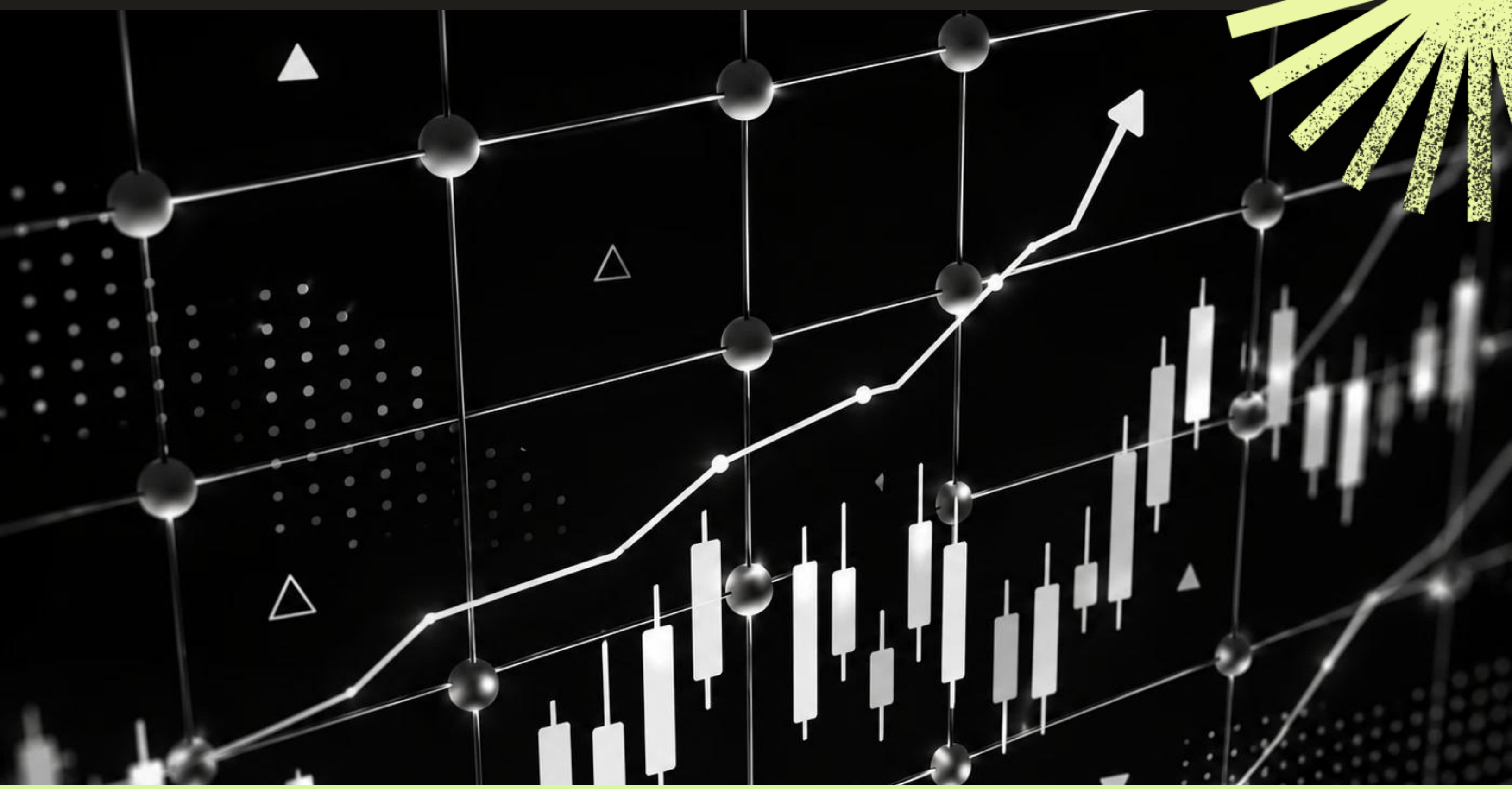
Reflections on Marketing in a Context of Digitalization and Artificial Intelligence

Book Tribute to Wagner A. Kamakura

Teodoro Luque Martínez (coordinator)



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Content

Vita fugit, facta manent.

In honorem Professoris Wagner A. Kamakura

Prologue

This book is an academic and personal tribute to Professor Wagner A. Kamakura, Doctor Honoris Causa of the University of Granada, a highly respected scholar in economics, business, and marketing, and someone closely connected to our university for almost two decades. His passing in 2025 represents an enormous loss but also leaves us with the responsibility to preserve and carry forward his intellectual, human, and academic legacy.

This volume brings together contributions from colleagues, , collaborators, and friends who shared research, teaching, and conversation with him. In addition to celebrating an exceptional academic, we wish to recognize his vision of the university: rigorous, generous, international, committed to data, oriented toward generating useful knowledge, and marked by enduring intellectual rigor and curiosity and a gift for illuminating what is essential.

For the University of Granada, and particularly for the Department of Marketing and Market Research and the Master's Degree in Marketing and Consumer Behavior, Wagner Kamakura was much more than a prestigious visiting professor. He was a leading authority on methodology, a long-standing collaborator, an inspiration to professors and students, a magnificent colleague, and a great friend.

Wagner A. Kamakura was born in São Paulo, Brazil, into a family of Japanese immigrants. His life reflects a multifaceted identity: Brazilian by birth, Japanese by ancestry, Latin American by culture, American by academic training, and a citizen of the world by vocation. He initially trained as a mechanical engineer, pursued studies in business administration, and obtained a master's degree in industrial engineering, a technical foundation that would shape his later research orientation.

His intellectual curiosity led him to the University of Texas at Austin, where he completed his PhD in Business Administration, specializing in marketing, under the supervision of Professor Rajendra K. Srivastava. From that point on, his career combined an exceptional sensitivity to substantive issues in consumer behavior with a rigorous command of the quantitative tools needed to analyze them.

After completing his doctorate, he pursued his academic career at prestigious universities, including the State University of New York, Vanderbilt University, the University of Pittsburgh, the University of Iowa, Duke University, and Rice University. His research has been published in some of the most influential journals in the field, establishing him as one of the world's leading researchers in marketing.

His work is grounded in a solid methodological foundation and a clear quantitative perspective. It addresses a wide range of issues, including market share prediction, innovation diffusion, segmentation, preference heterogeneity, brand equity, choice models, latent structures, and lifestyles. Yet his contribution lies not only in the breadth of topics he covered or in the quality of his publications. His deepest contribution is his approach to research: seeking patterns of behavior without ignoring heterogeneity, working with observable data, using advanced models without treating them as ends in themselves, and always placing the practical value of knowledge at the center of his work.

His excellence in research was matched by his qualities as a teacher. Those of us who worked with him in classes, seminars, or projects will always remember his warmth, ability to synthesize ideas, simplicity, understated humor, and gift for getting to the heart of the matter. Wagner did not need to dazzle to teach. He knew how to listen, organize, simplify, and help others think better. In short, he brought out the best in us.

The chapters in this volume are grouped into four blocks and reflect the breadth of Professor Kamakura's academic and personal legacy. They include contributions from thirty-seven researchers from seventeen universities in six countries, united in recognition of a career that played a decisive role in establishing marketing as a rigorous, empirical, international, and applied discipline.

Some contributions engage with his key methodological and analytical work; others focus on substantive issues in marketing, consumer behavior, value, segmentation, choice, innovation, or the relationship between firms and consumers. Many of them focus on digitalization and the emergence of AI in marketing. Indirectly, all of them pay tribute to Professor Kamakura. More directly, some contributions adopt a more personal and evocative tone, portraying the professor, colleague, and friend who accompanied so many on their academic journeys.

Professor Kamakura's relationship with our university, and with the professors and researchers who shared years of teaching, research, and friendship with him, represents a bond that has enriched our institution. His presence helped open new horizons and reminded us that the university is also built through personal relationships grounded in trust, generosity, and shared endeavor.

This book is, above all, an act of gratitude. Gratitude to Professor Wagner A. Kamakura for his work, teaching, and friendship. For teaching us that rigor can be exercised with simplicity, that academic excellence does not require arrogance, and that the true value of research lies in its ability to deepen our understanding of reality and help improve it.

Our warmest gratitude also goes to Cissa, his wife, an indispensable companion throughout his life and career. In her, we recognize an inseparable part of Wagner's personal story and of the bonds that both forged with so many people and universities, including our own.

We also wish to thank the authors who contributed to this volume, as well as those from the University of Granada, the Faculty of Economics and Business, the Department of Marketing and Market Research, and the Master's Degree in Marketing and Consumer Behavior who helped make this tribute possible.

I would like to believe that there is another life in which we may meet again and talk about so many things, for there is still so much to discuss, my friend.

Teodoro Luque-Martínez.
University of Granada (Spain)


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I.

Marketing Analytics, Modeling, and Consumer Behavior

Geotargeting Financial Mindsets: A Bayesian Spatial Factor Analytical Approach

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Abstract

Based on Wagner Kamakura's extensive work on factor analysis, we propose a new Bayesian spatial factor analytic model which allows extracting spatially correlated attitudes. We decompose the factors into regional and individual components, introduce demographic covariates at both levels and include spatial dependence at the regional level. The model can handle the problem of missing data at the zip-code level, arising because of the collection of survey data for a random sample of zip-codes. We apply the approach in an empirical study on consumer attitudes towards financial services in the Netherlands.

Keywords

geotargeting, mindset metrics, factor analysis, spatial models, Bayesian inference

1. Introduction

Wagner Kamakura's seminal contributions to marketing research include his extensive work on the development and application of factor analysis models. His work has shown that factor analysis, formulated and estimated in a (simulated) likelihood framework, is a powerful tool for imputing missing observations in survey data (Kamakura & Wedel, 2000), for exploring truncated data (Kamakura & Wedel, 2001), for examining data structures where latent variables are non-normal (Wedel & Kamakura, 2001), for enhancing cross-selling effectiveness in database marketing (Kamakura et al., 2003), for uncovering audience preferences for concerts from ticket sales data (Kamakura & Schimmel, 2013), and for mapping product reviews (Moon & Kamakura, 2017), amongst others. Inspired by this impressive body of work, we develop a factor analytic model for geotargeting in this study.

One of the challenges of geographical targeting is to identify the properties of a particular geographical area to optimally match marketing efforts. For instance, placement of local billboards, direct marketing, and sponsoring of local sports clubs are among many other decisions in which the properties of geographical areas play an important role. While transaction data have been shown to be very effective for targeting (Van Diepen et al., 2009), they are only available for existing customers and not for non-customers which are often of primary interest in geographical targeting. Zip-code level demographic variables are often used as proxies for unobserved consumer behavior, but unfortunately the relationships of these variables with the behaviors of interest are often weak.

On the other hand, mindset metrics such as consumers' perceptions, attitudes and interests have been successfully used to diagnose market performance in areas such as branding and advertising (Keller & Lehmann, 2006; Valenti et al., 2023)). They provide powerful diagnostics of interest in product offerings and often exhibit stable long-term relationships with consumers' behavioral responses. Customers' share-of-mind, assessed through these measures, has been shown to translate to improved performance in many categories and markets (Srinivasan et al., 2010). Mindset measures are obtained from consumer surveys (Srinivasan et al., 2010). Obtaining these measures for all target customers in a geographic area is prohibitively expensive, however, and therefore usually the survey is conducted among a small sample of consumers and zip-codes. The purpose of the present paper is to build on Kamakura's work and develop a factor analytic method that facilitates the use of survey-based mindset measures for geographical targeting, relating them to commonly used demographic variables, and exploiting their spatial dependencies to facilitate target selection.

We propose a new factor analytic approach for geographical targeting based on consumers' mindset metrics and demonstrate the approach in an application to customer acquisition for financial services. Specifically, we develop a confirmatory factor model to assess the underlying mindset measures. The confirmatory factor model accommodates spatial dependence between zip-code areas and decomposes observed and unobserved heterogeneity in the data into household and regional sources of variation. This enables demographic data to be used at both individual and regional levels (Steenburgh et al., 2003).

There are several challenges in predicting spatial dependence of attitudes. We address those with the proposed model. 1) Since in most applications large numbers of mindset variables are measured, dimension reduction is called for to condense these variables into a limited number of unobserved mindsets. If theory is available to condense a priori developed measurements into factors, confirmatory factor analysis is appropriate. 2) Such a factor analytic model needs to accommodate the fact that mindset metrics are measured on Likert scales. We therefore use a cut-point formulation to reflect that the observed ordinal responses derive from underlying continuous mindset factors. 3) The variation in factor scores is caused by regional-level and individual-level variation. We therefore model the scores on mindset factor scores as consisting of two components: regional and individual parts. 4) Spatial dependence of the factor scores at the regional level needs to be accommodated. Previously, Bronnenberg and Mahajan (2001) used spatially lagged intercepts, Mittal et al. (2004) used geographically weighted regression (GWR), Yang and Allenby (2003) and Jank and Kannan (2005) used a spatial lag model. In this paper we apply the spatial lag approach (Anselin, 1988) to capture the spatial dependence of unobserved factors at the regional level. 5) Demographic and geographic covariates will affect the factor scores at both regional and individual levels. In our approach we use a regression style formulation to enable regional variation in the factor scores to be driven by regional characteristics and individual consumer variation by individual characteristics. 6) A factor analytic approach to geographic targeting based on a survey sample needs to account for missing data at the regional level. Mindset metrics are typically collected through random or stratified samples of a population, which will often not cover all geographical regions of interest. Such missing data on regions hampers the ability to use model results to target regions, because for many regions no such information is available. Following Kamakura and Wedel (2000), our approach imputes regional effects for missing regions. Our approach addresses all these five issues simultaneously.

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2. Methodology

2.1. Model specification

We propose a Bayesian spatial factor analytic model that extracts latent and spatially dependent factors, extending the literature on likelihood-based (Kamakura & Wedel, 2000; Kamakura & Wedel, 2001; Wedel & Kamakura, 2001) and Bayesian and spatial factor analysis (Ansari et al., 2002; Christensen & Amemiya, 2002, Hogan & Tchernis, 2004; Stakhovych et al., 2012). Our contribution over these prior approaches is that we: 1) develop a spatial confirmatory factor model that accommodates separate region (zip-code) level and individual level effects; 2) utilize a cut-point formulation to accommodate the measurement scales of the mindset variables; 3) introduce exogenous covariates that influence factors at both zip-code and individual levels; and 4) impute data for regions that are missing from the sample.

Every consumer $j = 1,\ldots, J_i$ from region $i = 1,\ldots, I$ responds $\mathbf{x}_{ij}$ to K items on a rating scale with H ordered categories. We assume that the observed response x_{ijk} is driven by latent variable y_{ijk} where the response $x_{ijk} = h$ is observed if y_{ijk} is located between two cut-points, $x_{ijk} = h$ if $c_{h-1} < y_{ijk} < c_h$, for $k = 1,\ldots, K$ and $h = 1,\ldots, H$. The cut-points are ordered, i.e. $c_{h-1} < c_h$, and the first and last cut-points are fixed to $c_0 = -\infty$ and $c_H = +\infty$ for identification. All other $H-1$ cut-points ($c_1 \ldots c_{H-1}$) are estimated. The probability of the ordinal response is:

$$p\left(x_{ijk} = h\right) = \int_{c_{h-1}}^{c_h} f(y_{ijk})\, dy, \tag{1}$$

where f is a probability density function of the latent variable y_{ijk}.

We assume that the survey instrument is developed with the purpose of measuring a specific set of factors representing mindsets of consumers. Thus, the continuous variable y_{ij} is modeled according to a confirmatory factor model specification:

$$y_{ij} = \Lambda\xi_{ij} + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N_K(0, I_K). \tag{2}$$

Equation (2) represents a (reflective) factor analytic model, where y_{ij} is a K dimensional vector of latent unobserved values obtained from observed discrete responses x_{ij}. These values reflect unobserved mindsets in region $i = 1,\ldots,I$ for person $j = 1,\ldots,J_i$. The variation in variable y_{ij} (K×1) can be explained by L latent factors ξ_{ij} (L×1), the hierarchical and spatially dependent structure of which will be defined later. These latent factors are mapped to the observed variables by a K×L factor loadings matrix Λ. Theoretical constraints are imposed on the loading matrix, such that it reflects how the underlying factors are measured by the items in the survey. Typically, this involves constraints such that one item loads on one or limited number of factors, while for each factor one loading is constrained to be equal to 1 to identify its measurement scale. Finally, ε_{ij} are K-variate measurement errors, which are assumed to be standard normally distributed.

We decompose the factor scores to capture regional (ν_i) and individual (χ_{ij}) effects: $\xi_{ij} = \nu_i + \chi_{ij}$. This decomposition reflects the different sources of variation in the data and allows us to assess how much is lost by geo-targeting zip-code areas rather than individual consumers or households. We next introduce covariates at the individual and zip-code levels, as well as spatial autocorrelation at the zip-code level.

The matrix Q_l contains individual-specific covariates. We link those covariates to the factor scores as follows. Note that χ_{ij} is of the same dimension as ξ_{ij}, i.e. it can be represented by a L×1 vector. We combine the factor scores from all $n = \Sigma J_i$ individuals into one matrix $X = (\chi_{11} \ldots \chi_{1j} \ldots \chi_{1Ji} \ldots \chi_{ij} \ldots \chi_{IJi})'$ of size n×L. This matrix is partitioned into L vectors χ_l (n×1), such that χ_l is l-th column of $X = (\chi_1 \ldots \chi_l \ldots \chi_L)$ and contains all individual effects across all n individuals for factor l (l = 1,…,L). The vector of individual random effects for factor l follows a regression formulation: $\chi_l = Q_l\delta_l + \varphi_l$, where δ_l is a vector of parameters for factor l; and φ_l is a vector of error terms. If one stacks all χ_l in one vector, then for all factors simultaneously one obtains:

$$\mathrm{vec}(X) = \mathrm{vec}\{\chi_l\} = \mathrm{diag}\{Q_l\}\cdot\mathrm{vec}\{\delta_l\} + \mathrm{vec}\{\varphi_l\}; \qquad \mathrm{vec}\{\varphi_l\} \sim N_{Ln}(0,\Phi\otimes I_n), \tag{3}$$

where $\mathrm{diag}\{Q_l\}$ is a diagonal matrix with Q_l on its diagonals; Φ is a positive definite matrix of size L×L which captures the covariance of individual effects between factors; and $\otimes$ is the Kronecker product.

The matrix Z_l contains region-specific covariates The regional effects ν_i are contained in a vector of size L×1. We combine these effects into one matrix $V = (\nu_1 \ldots \nu_i \ldots \nu_I)'$ of size I×L. This matrix is partitioned into L vectors ν_l (I×1), such that ν_l is l-th column of $V = (\nu_1 \ldots \nu_l \ldots \nu_L)$ and contains the regional effects across all I regions for factor l. The vector of regional random effects for factor l has a regression structure, $\nu_l = \rho_l W \nu_l + Z_l\beta_l + \psi_l$, where β_l is a vector of parameters for factor l; ρ_l is a spatial dependence parameter; W is an I×I spatial weights matrix and ψ_l is a vector of error terms. The spatial weights matrix W is a nonnegative matrix that specifies the neighborhood set for each region. We thus use a first-order contiguity specification of W which is simple to construct and produces robust results (Stakhovych & Bijmolt, 2009). The contiguity weights matrix is constructed in such way that regions that have a common border have non-zero elements w_{is}. A nonzero matrix element w_{is} indicates the relation between region i and region s. Because self-neighbors are excluded the diagonal elements are zeros ($w_{ii} = 0$). Weights across each row sum to one: $w_{ii}^* = w_{is} / \Sigma_s w_{is}$, which facilitates interpretation because the weighted average of the neighboring values formulates a spatial lag operator which is applied to the unobserved variable ν_l and serves as a measure of clustering of regions with similar effects. The values of the spatial autocorrelation parameters ρ_l indicate the strength of spatial dependence between regions. A positive value indicates that the neighboring regions are more similar leading to distinct clustering. Because we use a standardized weights matrix W, the maximum value of ρ_l is 1 and the minimum is $1/\lambda_{min}$, where λ_{min} is the minimum eigenvalue of W. Thus, the sub-model of our confirmatory factor model is a mixed spatial autoregressive model in which the regional effects are: a) spatially correlated across regions via the structure $\rho_l W \nu_l$; and b) a function of region-specific explanatory variables Z_l. Stacking all ν_l we obtain the sub-model for the regional effects:

$$\mathrm{vec}(V) = \mathrm{vec}\{\nu_l\} = P\otimes W\cdot\mathrm{vec}\{\nu_l\} + \mathrm{diag}\{Z_l\}\cdot\mathrm{vec}\{\beta_l\} + \mathrm{vec}\{\psi_l\}; \mathrm{vec}\{\psi_l\} \sim N_{LI}(0,\Psi\otimes I_I), \tag{4}$$

where P is an L×L diagonal matrix with spatial correlation parameters ρ_l on its diagonal and Ψ (L×L) is a positive definite matrix which captures the covariance of regional effects between factors.

2.2. Model estimation, inference, and imputation

We adopt a Bayesian approach and estimate the model using Markov Chain Monte Carlo (MCMC) methods. A general factor analytic model suffers from location, scale and rotation indeterminacy (Wedel & Kamakura, 2001). We solve these indeterminacies by imposing identification constraints, which involve fixing some of the elements of Λ to zero and fixing at least one of the elements in every column of Λ to one. Further, we fix the covariance matrix of the error terms to an identity matrix. The sampler is run for 1,200,000 iterations, with a burn-in of 200,000 and subsequent thinning with factor 1,000, resulting in 1,000 target draws. Convergence is assessed using standard diagnostics tools. We consider the evidence for an effect very strong if the 99% Credible Interval of the corresponding parameter does not cover zero.

In the MCMC chain we sample from the posterior distributions of parameters for the regions with missing data, conditional upon the observed data. This approach achieves two very important goals. First, it improves the prediction of regional effects ν_m by not only using the covariates but also by borrowing information from nearby regions. If one ignores the spatial structure in the data, then the imputations would be biased. Second, it improves the quality of the estimated parameters by using not only the covariates from regions with observed data but also covariates from regions with missing survey data, for which the region-specific covariates are usually obtained from secondary data sources.

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We apply our approach to data from the financial services industry in the Netherlands. The data has been collected by the international market research company Growth from Knowledge (GfK), among a representative sample of 3,963 households. In face-to-face interviews, the respondents were asked to answer questions regarding perceptions and attitudes towards financial services on scales from 1 (= 'completely disagree') to 5 (= 'completely agree'). In the questionnaire, there are 25 questions that measure interest in financial matters ("Interest", 6 items), knowledge of financial matters ("Knowledge", 4 items), attitudes towards fees ("Fees", 3 items), attitudes towards new financial products ("Products", 5 items), attitudes towards risk ("Risk", 3 items), and preference for trusted banks ("Trust", 4 items). In addition, respondents were asked about ownership of financial products, including mortgage and income protection insurance. The data also contains information on 90 zip-code areas the households in the sample were located in. Available region-level covariates include the fraction of households in a zip-code region that owns a house, the fraction of households in a region that owns a business, and the fraction of households in a region that has a low socio-economic status. Individual-level covariates include household size, household income, gender, and age.

3.2. Model comparison

We estimate the confirmatory factor model with the six factors measured by the 25 items in the survey. We compare the proposed model with four nested benchmark models, using the WAIC (Watanabe-Akaike Information Criterion; Gelman et al. 2014) for model selection. Benchmark 1 ignores the spatial structure of regional effects, i.e. the spatial parameters ρ_l are set to zero. The mindset factors are decomposed into regional and individual parts, but regional effects are assumed independent. For this model, WAIC= 221,486. In benchmark 2 the regional effects are removed completely ($\mathbf{\nu}_i = 0$), i.e. factors only contain individual effects. This setup resembles a traditional confirmatory factor model, without a decomposition of factors. For this model, WAIC= 231,401. In benchmark 3 the individual effects are removed ($\boldsymbol{\chi}_{ij} = 0$) and only regional effects are kept. This setup reflects a situation in which region-level data is available only and used as input for a standard factor analysis. For this model, WAIC= 260,240. Finally, benchmark 4 has neither individual (Q_l) nor regional (Z_l) covariates. For this model, WAIC= 221,609. The proposed, full model has a WAIC = 221,473, which is the lowest among the five models estimated and thus WAIC statistic favors the full model over all benchmarks.

3.3. Factor loadings

The estimates for the cut-points are (–1.673; 0.157; 0.917; 2.534); note the large distance between the first and second, and between the third and fourth cut-points. Table 1 reports the estimates of the factor loadings. None of the 99% Credible Intervals of the free loadings covers zero, all loadings have the expected signs and have meaningful interpretations. The extracted factors explain a high fraction of the variance of the items, with many factor loadings being larger than 0.7. Importantly, the model correctly captures the expected directionality of effects. For example, item 20 captures risk seeking behavior and its estimated loading is positive, while items 18 and 21 measure risk aversion and the estimated loadings for these items are negative.

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Table 1. Posterior Means and Credible Intervals (CI) of Factor Loadings Λ

Factor		Item	Factor loadings Mean (99% CI)
Interest	1	I like to talk with friends about banking	1
	2	I am very interested in insurance products	**0.702** (0.678, 0.733)
	3	I like to talk with others about insurance	**0.932** (0.898, 0.968)
	4	I am very interested in banking (insurance, investments)	**0.704** (0.678, 0.732)
	5	If I see something about investments in newspapers or magazines, I will read it	**0.863** (0.831, 0.897)
	6	If I see something about insurance in newspapers or magazines, I will read it	**0.648** (0.621, 0.675)
Knowledge	7	I know a lot about banking (insurance, investments, etc.)	**0.551** (0.521, 0.581)
	8	I am well informed about various investment opportunities	1
	9	I believe I am well informed about various types of insurance	**0.367** (0.341, 0.392)
	10	I believe that I know well what banks can do for me	**0.258** (0.234, 0.284)
Fees	11	When it comes to information about banking and insurance, I do not try to save money	**0.749** (0.701, 0.800)
	12	I think it is reasonable that you have to pay for banking services	1
	13	If I need financial advice, I do not mind paying for that	**0.789** (0.745, 0.842)
Products	14	I am very interested in new investment opportunities	1
	15	If I see something in a newspaper or magazine about investment opportunities, I will read it	**0.927** (0.890, 0.962)
	16	If I see something in a newspaper or magazine about insurance products, I will read it	**0.664** (0.635, 0.693)
	17	I am very interested in the latest banking and insurance products	**0.716** (0.686, 0.745)
	18	I try to stay informed about new ways of saving	**0.587** (0.557, 0.615)
Risk	19	I try to avoid financial risk as much as possible	**−0.752** (−0.804, −0.693)
	20	When you invest it is exciting to take some risk	1
	21	I never invest in high-risk financial products, even if I could earn a lot of money	**−0.651** (−0.712, −0.590)
Trust	22	It is nice to be a customer of a bank where you know the people	**0.333** (0.292, 0.374)
	23	I trust my money matters only to a well-known bank	**0.793** (0.741, 0.853)
	24	The service that a bank provides is very important for me	1
	25	It is comfortable to be a customer of a bank or insurance company that provides you with good advice	**0.942** (0.886, 1.002)

Note: Bold indicates that the 99% Credible Interval does not contain zero.

3.4. Effect of demographic variables

The estimates of the effects of zip-code level covariates are presented in Table 2 and those of the individual level covariates in Table 3. There is very strong evidence for positive effects of home ownership on Interest, Knowledge and Products, and of low social class on Interest, Fees and Products (Table 2). Entrepreneurship does not play a major role.

Table 2. Posterior Means of Effects of Zip-code Covariates on Factors, β

Covariate\Factor	Interest	Knowledge	Fees	Products	Risk	Trust
Fraction of HHs in a region with:						
Own house	**1.186**	**1.449**	0.612	**1.115**	0.594	**−0.645**
Entrepreneurship	0.829	0.856	0.642	0.907	0.170	0.550
Low social class	**1.219**	1.046	**1.064**	**1.143**	0.763	−0.353

Note: Bold indicates that the 99% Credible Interval does not contain zero.

For individual covariates (Table 3), there is very strong evidence that household size has positive effects on all factors except Trust; that gender (male) has a negative effect on all factors except Trust; that age has a positive effect on all factors except Fees and Trust; and that household income has a negative effect on all factors except Trust.

Table 3. Posterior Means of Effects of Individual Covariates on Factors, δ

Covariate\Factor	Interest	Knowledge	Fees	Products	Risk	Trust
HH size	**0.053**	**0.061**	**0.082**	**0.068**	**0.064**	−0.011
Gender	**−0.496**	**−0.807**	**−0.202**	**−0.619**	**−0.478**	0.034
Age	**0.088**	**0.091**	−0.046	**0.109**	**0.159**	**−0.107**
HH income	**−0.120**	**−0.225**	**−0.057**	**−0.172**	**−0.059**	0.014

Note: Bold indicates that the 99% Credible Interval does not contain zero.

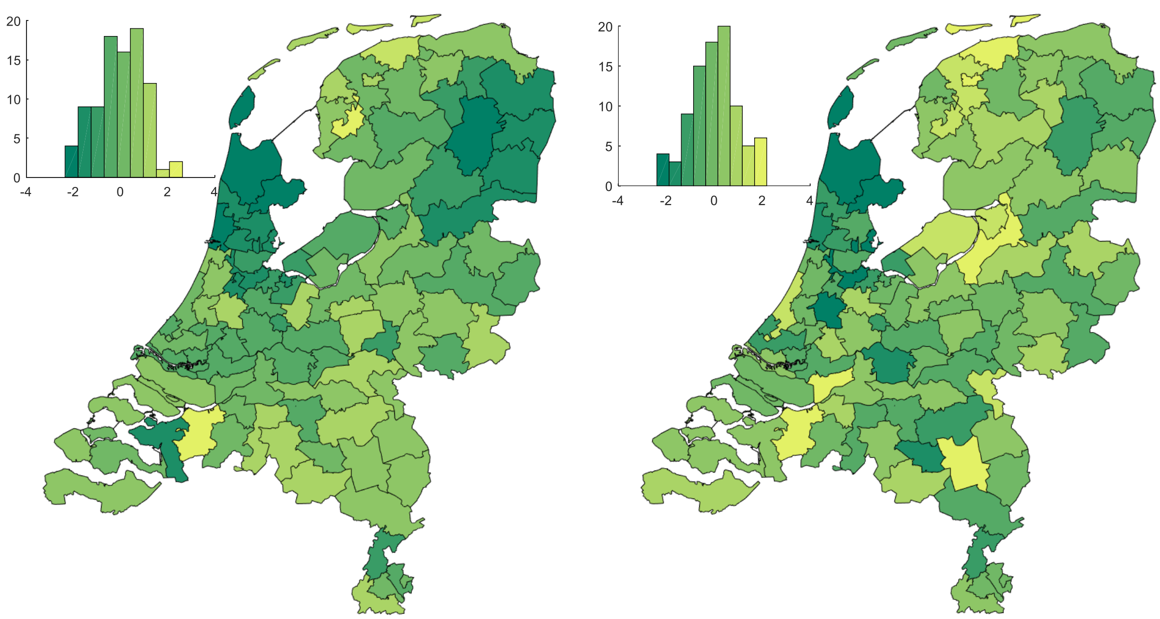
3.5. Spatial autocorrelation

There is very strong evidence for positive spatial correlation (ρ) across zip-code areas for four out of the six factors: *Interest* (0.434), *Products* (0.447), *Knowledge* (0.348) and *Fees* (0.410). These mindsets are extensively studied in finance (e.g. Roig et al., 2009), but their spatial correlation has not been previously documented. To illustrate the spatial correlation, we plot the regional effects $\boldsymbol{\nu}$ for the factor with the highest (Products = 0.447) and the lowest value of ρ (Risk = 0.149). Figure 1 plots the normalized regional factor scores by zip-code on a map of the Netherlands. A higher degree of spatial correlation for Products in Figure 1(a), leads to a more distinct spatial clustering, relative to the map for Risk in Figure 1(b), which is patchier. These results imply that in targeting households with offers for specific financial products at the zip-code level, regional clusters will impact the effectiveness of the campaign.

4. Conclusions

In this paper, inspired by the extensive work of Wagner Kamakura on factor models, we presented a method to support geotargeting based on mindset metrics. The Bayesian spatial factor analytic model we proposed considers the discrete measurement scale of the observed survey measures by using a cut-point formulation, models factor scores at regional and individual levels, includes demographic variables, allows for heterogeneity of parameters at both levels, and for spatial covariance of the factor scores at the regional level. The importance of considering spatial dependence was demonstrated on real data on mindsets towards financial services. The model can handle the problem of missing data at the zip-code level. In future research, the model could be extended to mixed-data outputs (Wedel & Kamakura, 2001).

The proposed model allows marketers to focus marketing activity on specific geographic areas tailored to consumers' local culture, needs, and mindsets. Its' application to financial services illustrated how local branches of financial institutions may use the model to implement customer relationship management (Kamakura et al., 2003) by target existing and new customers in their immediate zip-code area based on their mindsets, and customize marketing communications and financial offerings based on local knowledge of and interest in financial products, risk tolerance, and trust. The model imputation makes it possible to even target zip-code areas that are not included in the sample used to collect the financial mindset measures.



(a) Products factor, ρ = 0.447*** (b) Risk factor, ρ = 0.149

Figure 1. Normalized regional factor scores for (a) Products and (b) Risk.

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Interactive Relationships of Consumption Behaviors and Political Ideologies

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Abstract

This chapter examines the bidirectional relationship between political ideology and consumer behavior, arguing that ideology both shapes consumption and is shaped by it. The intersection of political ideology and consumer behavior raises several provocative questions for marketing scholars: Are liberals or conservatives easier to satisfy? How do their underlying cognitive processing styles lead to substantially different product preferences and brand loyalties? Drawing on political psychology, sociology, and marketing studies, the chapter synthesizes evidence that political identity organizes preferences, satisfaction, complaint behavior, brand attachment, regulatory reactance, and financial risk-taking. It also reviews theoretical accounts—Bourdieu's cultural capital, Giddens's life politics, and symbolic consumption—that explain how repeated consumption choices and experiential encounters can reinforce or transform ideological orientations. Thus, the chapter aims to: (1) summarize and evaluate the current state of research on the interactive relationships between political ideologies and consumption behaviors, and (2) provide a roadmap for future inquiry. The chapter concludes by proposing research avenues—two-dimensional segmentation, lifestyle catalysts of ideological change, symbolic goods and polarization, experiential interventions, and the role of AI and social media—offering an agenda for marketing scholars navigating an increasingly politicized marketplace.

Keywords

Consumption behaviors; political ideologies; consumer segmentation; lifestyle politics; symbolic consumption theory

1. Introduction

The intersection of political ideology and consumer behavior raises several provocative questions for the modern marketer: Are liberals or conservatives easier to satisfy? How do their underlying cognitive processing styles lead to vastly different product preferences and brand loyalties? While marketing research has long recognized that political orientation serves as a powerful driver of lifestyle and preferences (Jost, 2017), the relationship is far from a simple one-way street. It is a bidirectional, dynamic interaction where ideology shapes consumption choices, and consumption experiences, in turn, feed back into the evolution of political identity (Jung and Mittal, 2020).

Political identity functions as more than a demographic label; it is a deep psychological structure that organizes consumer behavior in predictable ways. Systematic differences in personality, cognitive processing, and motivational concerns create elective affinities between certain products and specific ideological positions. For instance, conservatives tend to be more satisfied with their purchases than liberals, a "satisfaction gap" rooted in a stronger belief in personal agency and free will (Fernandes et al., 2021). Conservatism is also associated with stronger brand attachment, greater psychological reactance toward government-mandated restrictions, and differential risk-taking behaviors depending on self-efficacy levels (Chan and Ilicic, 2019; Irmak et al., 2020).

While the influence of ideology on buying behavior is well-documented, the reverse direction—how consumption shapes ideology—remains a critical frontier, particularly in marketing research. Consumption is rarely a neutral act; it is a system of social signals that constructs and reinforces political belonging (Bourdieu, 2019). Through reflexive lifestyle choices—organic produce, fair-trade goods, or symbolic products—consumers cumulatively entrench and signal their political orientations (Giddens, 1990; Hetherington and Weiler, 2018). Experiential consumption, such as travel and cross-cultural interaction, can further serve as a catalyst for ideological change (Saha et al., 2017).

Despite substantial evidence from sociology and political science on how consumption influences political identity, marketing research has contributed comparatively little to this reverse direction. This chapter addresses that gap. Specifically, it aims to: (1) summarize and evaluate the current state of research on the interactive relationships between political ideologies and consumption behaviors, and (2) provide a roadmap for future inquiry. In doing so, we encourage marketing scholars to adopt frameworks such as consumer segmentation (Kamakura & Russell, 1989; Wedel & Kamakura, 2000) to better capture how political orientations differentially moderate responses to marketing activities.

2. Literature Review on the Relationships between Political Orientations and Consumption

This section reviews the existing literature on both directions of the relationships between political orientations and consumption behavior. Section 2.1 focuses on the influence of political orientations on consumption systematically shape their product preferences, brand relationships, satisfaction levels, complaint behaviors, responses to regulation, and financial decision-making. This direction has received considerably more scholarly attention in the marketing literature and is supported by a substantial body of empirical evidence.

Section 2.2 then turns to the less-explored but equally important reverse direction in the marketing field – the influence of consumption on political orientations. This direction examines how consumers' purchase experiences, lifestyle choices, experiential consumption, and exposure to goods, services, and cultural environments actively shape, reinforce, and in some cases transform their political identities and ideological positions. While this direction has been more extensively theorized in sociology and political science, it remains an underexplored area in marketing research, representing a significant opportunity for future scholarly inquiry.

2.1. Literature Review on the Influences of Political Orientations on Consumption

The influence of political orientations on consumer behavior represents a well-established and growing area of inquiry in marketing, consumer psychology, and related disciplines. A substantial body of empirical research demonstrates that individuals' political identities – whether liberal, conservative, or moderate – systematically shape their consumption preferences, decision-making processes, complaint behaviors, responses to regulation, and overall satisfaction with products and services. This section reviews the key findings in this domain, organized thematically to provide a coherent account of how political orientation functions as a driver of consumption behavior.

A foundational contribution to this area is provided by Jung and Mittal (2020), who offer a comprehensive conceptual treatment of political identity as a consumer behavior construct. They identify four key dimensions relevant to consumption: the definition and conceptual structure of political identity, practical approaches to its measurement, its role in consumer decision-making, and its influence across the consumer journey in retailing. Their framework establishes political identity not merely as a demographic variable but as a psychologically meaningful construct that systematically organizes consumer preferences and behaviors across a wide range of consumption contexts.

Complementing this framework, Jost (2017) provides a broad synthesis of political psychology research demonstrating that liberals and conservatives diverge systematically across personality characteristics, cognitive processing styles, motivational concerns, personal values, and even neurological structures. Jost (2017) argues that these deep psychological differences have direct and measurable implications for consumer choice, judgment, decision-making, persuasion, advertising responses, and customer satisfaction, establishing the psychological foundations through which political orientation shapes consumption at a fundamental level.

Caldwell, Elliot, Henry, and O'Connor (2020) extend this framework by examining the relationship between political ideology and consumers' attitudes toward their rights and responsibilities. Using two survey studies with consumers of the Uber ride-sharing service, they test a model mapping political ideology – liberalism, conservatism, and libertarianism – onto moral foundations including harm avoidance, fairness, in-group loyalty, authority and respect, and purity. Their findings demonstrate that political ideology is meaningfully associated with how consumers conceptualize their rights and responsibilities in the marketplace, suggesting that political orientation shapes not only what consumers buy but how they understand and enact their role as consumers within broader social and institutional frameworks.

One of the most extensively documented consumption outcomes of political orientation concerns customer satisfaction. Fernandes et al. (2021) synthesize evidence from nine studies employing diverse methodologies, data sources, product categories, and participant populations to demonstrate that conservatives are consistently more satisfied with the products and services they consume than liberals. The mechanism identified is belief in free will: conservatives are more likely to believe that individuals have genuine agency over their decisions and therefore trust their own consumption choices more readily, generating higher satisfaction. The downstream consequences of this effect are substantial, including higher repurchase intentions, stronger recommendation intentions, and measurable impacts on firm sales. Importantly, this satisfaction advantage is attenuated when belief in free will is externally weakened, when consumer choice is restricted, or when the consumption experience is overwhelmingly positive regardless of ideology. This finding is further contextualized by Jung and Mittal's (2020) observation that political identity shapes the entire consumer journey, suggesting that the satisfaction differential identified by Fernandes et al. (2021) is not an isolated phenomenon but part of a broader pattern of politically differentiated consumer experience.

Political orientation also systematically influences how consumers respond when consumption experiences fall short of expectations. Jung, Garbarino, Briley, and Wynhausen (2017) analyze three large consumer complaint databases from the Consumer Financial Protection Bureau, the National Highway Traffic Safety Administration, and the Federal Communications Commission, in conjunction with county-level political ideology data derived from the 2012 U.S. presidential election results. Their findings demonstrate that conservative consumers are significantly less likely than liberal consumers to file complaints and less likely to dispute complaint resolutions. The mechanism identified is system justification: conservatives' stronger motivation to justify and maintain existing social and institutional arrangements reduces their propensity to challenge firms or regulatory bodies through complaint behavior. This finding has important implications for firms' understanding of how political orientation shapes post-consumption behavior and customer relationship management.

Political orientation also shapes consumers' relationships with brands. Chan and Ilicic (2019) demonstrate across five studies that conservatism is associated with stronger brand attachment bonds. Their account attributes this relationship to conservatives' greater feelings of uncertainty, which motivate them to seek psychological security through the formation of strong attachments to familiar and trusted brands. This finding suggests that political orientation shapes not only discrete purchase decisions but the deeper relational bonds consumers form with brands over time, with significant implications for brand management and loyalty strategies.

Consumption of luxury goods represents another domain in which political orientation exerts a systematic influence. Kim, Park, and Dubois (2018) demonstrate that conservatives' desire for luxury goods is driven by the goal of maintaining social status. Drawing on survey data examining car purchases, desire for luxury car brands, and willingness to pay for eyewear products, they show that conservatives are more strongly motivated by status maintenance concerns in their luxury consumption, and offer insights into how luxury brands can effectively tailor their communications to conservative audiences. This finding connects political orientation to the symbolic and status dimensions of consumption, suggesting that conservative ideology amplifies the appeal of goods that signal social position and hierarchy.

Political orientation also powerfully shapes how consumers respond to government-imposed consumption regulations. Irmak, Murdock, and Kanuri (2020) investigate this relationship through a natural experiment and three laboratory experiments. Their natural experiment demonstrates that conservatives – but not liberals – increase their mobile phone use in cars following the enactment of a law prohibiting that behavior. Their experimental studies further show that when exposed to government-imposed consumption regulations such as usage restrictions or warning labels from the Food and Drug Administration, conservatives are more likely to use restricted products, purchase unhealthy foods, and view restricted behaviors more favorably. Critically, these reactance effects are specific to government sources and do not emerge when the source of the regulation is a non-governmental entity or when the message is framed as a notification rather than a warning. This body of evidence establishes that political orientation is a key moderator of consumer reactance to regulatory interventions, with conservatives exhibiting significantly stronger reactance to government-imposed consumption constraints.

Political orientation also structures consumers' financial consumption behaviors. Han et al. (2019), drawing on data from the Consumer Expenditure Survey and experimental studies using real financial products from the Vanguard Group, demonstrate that conservatives' financial risk-taking increases as their self-efficacy increases, driven by their greater social dominance orientation. In contrast, liberals' financial risk-taking is invariant to their self-efficacy levels. This finding reveals that political orientation moderates the relationship between psychological resources and financial decision-making, with important implications for financial services marketing and the design of investment products.

Kidwell, Farmer, and Hardesty (2013) examine how the alignment between political ideology and persuasive appeals shapes sustainable consumption behaviors. Their conceptual model demonstrates that when persuasive appeals are congruent with consumers' political ideologies, the effectiveness of those appeals in promoting sustainable behaviors is enhanced. This finding highlights political orientation as a key variable in the design and targeting of sustainability communications, suggesting that politically tailored messaging may be substantially more effective in driving environmentally and socially responsible consumption than politically neutral approaches.

Beyond product consumption, political orientation also shapes consumption decisions in the domain of education. Jung and Mittal (2021) examine how parents' political identity affects their preferences for supplemental educational programs — including tutorials, educational materials, and summer programs — contingent on their focus on self versus others. Their findings demonstrate that political identity systematically shapes educational consumption choices, extending the influence of political orientation beyond traditional product and service categories into consequential family investment decisions.

Crockett and Wallendorf (2004) contribute an important qualitative dimension to this literature through their study of African-American consumers living in a racially segregated midwestern city. Their findings demonstrate that normative political ideology is central to understanding shopping as an expression of social and political relations, particularly for households confronting constrained access to goods and services in contexts stratified by race, gender, and class. This work enriches the understanding of how political orientation shapes consumption by attending to the intersections of ideology, race, and structural inequality, showing that political ideology influences provisioning decisions in ways that are deeply embedded in social and political relations of power.

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At the organizational level, Kashmiri and Mahajan (2017) examine how CEOs' political ideologies influence firms' innovation propensity, measured by the rate of new product introductions. Analyzing data from 421 publicly listed U.S. firms from 2006 to 2010, they find that CEOs' degree of political liberalism positively affects their firms' rate of new product introductions, demonstrating that political orientation shapes consumption-related decisions not only at the individual consumer level but also at the level of organizational strategy and product development.

Taken together, this body of literature establishes that political orientation is a pervasive and consequential driver of consumption behavior across a remarkably wide range of domains — from brand attachment and luxury goods to complaint behavior, regulatory reactance, financial risk-taking, and sustainable consumption. The mechanisms through which political orientation shapes consumption are diverse, including belief in free will, system justification motivation, status maintenance goals, uncertainty and security seeking, and ideological congruence with persuasive appeals. These findings collectively demonstrate that political identity functions as a deep psychological structure that organizes consumer behavior in systematic and predictable ways, with significant implications for marketing strategy, market segmentation, and consumer policy.

2.2. Literature Review on the Influences of Consumption on Political Orientations

Taken together, this body of literature establishes that political orientation is a pervasive and consequential driver of consumption behavior across a remarkably wide range of domains — from brand attachment and luxury goods to complaint behavior, regulatory reactance, financial risk-taking, and sustainable consumption. The mechanisms through which political orientation shapes consumption are diverse, including belief in free will, system justification motivation, status maintenance goals, uncertainty and security seeking, and ideological congruence with persuasive appeals. These findings collectively demonstrate that political identity functions as a deep psychological structure that organizes consumer behavior in systematic and predictable ways, with significant implications for marketing strategy, market segmentation, and consumer policy.

The relationship between consumption and political ideology has attracted growing scholarly attention across political psychology, sociology, consumer behavior, and cultural studies. A substantial body of literature suggests that what people buy, experience, and consume does not merely reflect pre-existing political orientations but actively shapes, reinforces, and transforms them over time. This section focuses specifically on the directional influence of consumption on political orientation formation and change.

One of the foundational frameworks for understanding how consumption shapes political identity is Bourdieu's (2019) theory of cultural capital and distinction. Bourdieu (2019) argues that consumption patterns are never merely economic or aesthetic acts — they are deeply political. Taste in food, art, music, and material goods functions as a system of social signals that actively constructs and reinforces class-based political identities. From this perspective, consumption is not a passive reflection of pre-existing identity but an active mechanism through which political belonging is built and communicated over time. The repeated enactment of particular consumption choices gradually solidifies political alignment, making consumption a constitutive force in ideological formation rather than merely a symptom of it.

Giddens (1990) provides a complementary but distinct account of how consumption drives political identity formation in high modernity. His concept of Life Politics argues that as traditional structures of political identity – social class, union membership, and religious affiliation – have substantially dissolved, individuals are compelled to construct their political identities through reflexive lifestyle choices. In this framework, every consumption decision carries moral and political weight. Choosing organic produce, reducing plastic consumption, or purchasing fair trade goods are not simply personal preferences; they are political acts that cumulatively build and express a political orientation.

Crucially, Giddens (1990) argues that this process operates through sub-politics – political action that emerges outside formal governmental structures through the aggregation of individual consumption choices. Consumer boycotts, the fair-trade movement, and ethical investment are emblematic examples of how lifestyle consumption choices aggregate into collective political forces capable of driving large-scale change. In this sense, consumption does not merely signal political identity but actively generates and sustains it. The supermarket aisle, in Giddens' framing, effectively functions as a voting booth, where repeated consumption decisions cumulatively shape and entrench political orientations.

Social media has further amplified this dynamic by enabling individuals to publicly perform their consumption-based lifestyle choices to wide audiences, accelerating the process by which consumption crystallizes into stable political identity. However, critics caution that this framework may overstate individual agency, noting that lifestyle politics as a pathway to political identity formation is considerably more accessible to those with the disposable income to choose ethical or sustainable consumption options, raising important questions about the equity of consumption-driven political identity formation.

Symbolic consumption theory offers a further mechanism through which consumption shapes political orientation. Bird and Smith (2005) and Witt (2010) demonstrate that the acquisition and display of goods functions as a system of group membership signaling. As individuals align their consumption choices with particular social and political communities, these choices feed back into and reinforce their political orientations through in-group identification and out-group differentiation. The consumption of symbolically charged goods gradually pulls individuals deeper into the political orientations associated with those goods.

Hetherington and Weiler (2018) provide one of the most direct empirical treatments of this process, demonstrating that consumer lifestyle choices – emblematized by the contrast between Prius and pickup truck ownership – do not merely reflect political polarization but actively deepen it. Their account illustrates how consumption functions as a self-reinforcing cycle: initial consumption choices signal political affiliation, which draws individuals into communities that further reinforce those affiliations, leading to progressively more entrenched ideological positions. In this view, consumption is not simply a consequence of political orientation but also a driver of ideological sorting and polarization.

Beyond the symbolic dimensions of everyday consumption, lived experiential consumption has been identified as a particularly powerful mechanism through which political orientations are altered. Personal financial experiences represent one such pathway. Pocketbook voting theory (Tilley, Neundorf, and Hobolt, 2018; Welch and Hibbing, 1992), demonstrates that direct personal financial experiences – economic hardship, prosperity, or perceived financial threat – produce measurable shifts in partisan preferences and ideological orientations. Thus, the consumption of economic conditions directly reconfigures political alignment. Travel and cross-cultural experiential consumption represent another documented pathway of political change. Saha, Su, and Campbell (2017) find that exposure to diverse cultural environments through travel produces liberalizing effects on political attitudes, suggesting that the experiential consumption of cultural difference actively broadens and shifts ideological perspectives.

The Contact Hypothesis, empirically examined by Christ et al. (2014), further demonstrates that consumer and social experiences involving outgroup members function to modify prejudice and political attitudes. Direct intergroup contact – whether through shared consumption spaces, community environments, or social interactions – reduces intergroup hostility and shifts political orientations toward greater tolerance and openness. Taken together, these findings establish that experiential consumption is a significant and underappreciated driver of political attitude change.

Across these theoretical frameworks and empirical findings, the literature converges on a sequential mechanism through which consumption influences political ideology. Consumption experiences generate social identity signals that are reinforced through in-group interaction, leading to the gradual crystallization of ideological positions, which ultimately manifest in changed political behavior. This process is neither instantaneous nor unidirectional – routine consumption can entrench existing orientations while novel experiential consumption can, under the right conditions, catalyze ideological transformation. Understanding this mechanism is essential for analyzing how political identities are formed, sustained, and changed in contemporary consumer societies.

3. Literature Review on the Relationships between Political Orientations and Consumption

Building on the bidirectional relationship between political identity and consumer behavior established in the literature review, this section outlines future research opportunities. Following the chapter's two-way division, the following avenues are proposed to deepen the understanding of how marketing activities and consumption experiences interact with ideological formations.

3.1. Influences of Political Orientations on Consumption

Research in this direction has been robust, yet several areas remain ripe for exploration within the marketing discipline.

- The "Moderate" Consumer Journey: While significant research exists on the liberal-conservative binary, less is known about the "moderate" consumer. Future research should examine if moderates represent a distinct psychological profile or a fluid segment that shifts behavior based on the consumption context.
- Ideology and Digital/AI Interactions: Given that political identity shapes the entire consumer journey, researchers should investigate how algorithmic customization and AI-driven recommendations interact with ideological biases. For instance, do "fixed" worldviews respond differently to AI autonomy than "fluid" worldviews?
- Cross-Cultural and Global Ideologies: Much of the current literature is grounded in U.S. political contexts. Research should expand to examine how political orientations shape consumption in diverse cultural environments where traditional culture and different ideological structures (e.g., authoritarianism vs. democracy) may alter consumer reactance or luxury motivations.
- Corporate Strategy and Brand Activism: Expanding on CEO ideology research, research can explore how a firm's perceived political leaning affects long-term brand equity and "anti-consumption" manifestations among ideologically opposed segments.

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3.2. Influences of Consumption on Political Orientations

This reverse direction represents a significant underexplored area in marketing research and a major opportunity for future inquiry.

- Two-Dimensional Consumer Segmentation: Future studies should focus on segmenting consumers not just by their specific marketing responses (Kamakura and Russell, 1989; Moon, Jalali, and Erevelles, 2021; Moon, Russell, and Duvvuri, 2006; Wedel and Kamakura, 2000) but also their ideological orientations. This includes investigating differential segment relationships between varying degrees of political orientation and preference/consumption characteristics.
- Lifestyle as Ideological Catalyst: Research should move beyond correlation to investigate if specific consumption habits—such as a shift to organic/local food or the adoption of sustainable technologies—actively catalyze a shift toward progressive identities over time.
- Symbolic Goods and Polarization: Future inquiries should explore how the consumption of "symbolically charged" goods (e.g., gun ownership or religious products) reinforces and entrenches conservative political identities through in-group signaling.
- Experiential Consumption and Perspective Shifts: Building on the "Contact Hypothesis," marketers can study how shared consumption spaces or travel experiences involving diverse outgroups can reduce prejudice and shift political orientations toward greater openness.
- The Role of Social Media Performance: Studies are needed to determine how the "public performance" of lifestyle choices on social media platforms accelerates the crystallization of a consumer's political identity.
- Financial Experience and Ideological Sorting: Research can further examine how personal financial "consumption experiences"—such as sudden economic hardship or prosperity—act as "pocketbook" triggers that reconfigure a consumer's partisan preferences.

4. Conclusion

This chapter has examined the bidirectional and dynamic relationship between political ideology and consumer behavior—a relationship that is considerably more complex than traditional marketing frameworks have acknowledged. Two broad streams of evidence emerge from this review, each carrying distinct implications for both theory and practice. The first stream confirms that political orientation functions as a robust psychological architecture shaping consumer behavior across nearly every dimension of the customer journey. The second stream, though less developed within marketing, is equally important: consumption is not simply the output of political identity but also one of its inputs.

In sum, the marketplace is increasingly a political arena, and political identity is increasingly a marketplace phenomenon. Recognizing this interdependence is not merely an academic exercise—it is an essential competency for marketers navigating an era of deepening ideological polarization. Future research that integrates marketing's behavioral rigor with the theoretical richness of political psychology and sociology will be best positioned to illuminate this consequential relationship.

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Latent Structure, Dynamic Consumers, and Market Intelligence

A Reflection on Wagner A. Kamakura's Marketing Science and Mentorship

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Abstract

This chapter reflects on the scholarly and personal legacy of Wagner A. Kamakura, drawing on over two decades as his doctoral student, coauthor, and friend. Wagner's contribution to marketing science is best understood as a philosophy of inquiry: ask questions that matter, respect the structure of real data, and extract signal without inventing it. I trace this philosophy through our joint work on household life cycles, customer wallet, budget allocation, social contagion, economic cycles, quantitative trendspotting, and repeated cross-sectional tracking, and connect it to Wagner's broader research on factor analysis, missing data, and mixed-scale measurement. The common thread is the use of latent structure to understand dynamic consumers and markets. In the era of digitalization and artificial intelligence, this thread is more important, not less: today's foundation models, embeddings, and recommender systems are themselves latent-variable systems operating at scale, and they inherit the same identification, measurement, and credibility problems Wagner spent his career taking seriously.

Keywords

Marketing science; Latent structure; Consumer dynamics; Market intelligence; Artificial intelligence; Mentorship

1. Introduction

Wagner Kamakura was my doctoral adviser at Duke from 2001 to 2005. He was also a coauthor on seven papers, a colleague for nearly a quarter century, and a friend. To our field, he was a leading figure in quantitative marketing. To me, he was the person who taught me what marketing science is for. Writing this chapter is a way of saying thank you, and a way of articulating what I learned.

One of Wagner's standing admonitions was that we should do marketing science, not marketing science fiction. He meant that a model's value lies not in its technical sophistication or speculative reach, but in whether it explains a real phenomenon, respects the data-generating process, and produces inferences a reaso

nable scholar or manager can act on. For Wagner, marketing science was a craft of disciplined inference, not a performanc e of complexity.

The frame I use here—latent structure, dynamic consumers, and market intelligence—is one Wagner would have recognized as native to his research program. Many of the constructs marketers care about are not directly observable. Life stage, customer potential, category need, peer influence, emerging trend, latent preference: each must be inferred from partial traces in surveys, transactions, search logs, or repeated samples. Wagner's work showed how to do that inference honestly.

What follows is part synthesis, part personal reflection. The synthesis covers our coauthored papers on latent-variable modeling for households, customer analytics, diffusion, trendspotting, and tracking. The personal threads are pieces of advice that I received from Wagner and still pass on: don't prove that sugar is sweet; methodological research is worth doing when it solves a common data problem; talk to practitioners; and don't be afraid if being afraid will not help you.

These lessons take on new weight in the current era of digitalization and AI. We now have data streams Wagner could only have hoped for at the start of his career, and computational tools to match. But large language models, recommender systems, and foundation models do not eliminate the problem Wagner spent his life on. They are themselves latent-variable machines, fitted to messy partial observations, and they inherit, often at greater scale and with less transparency, the identification, measurement, and credibility problems that Wagner taught his students to take seriously. The chapter is, in part, an argument that his methodological standards are more useful in the age of digitalization and AI, not less.

2. Latent Structure as Methodological Craft

Wagner had an unusual gift for finding structure in data that looked too messy, too incomplete, or too heterogeneous for standard tools. He admired Michelangelo and sometimes used the sculptor's metaphor: form is revealed by removing what obscures it. Applied to modeling, the metaphor is a discipline. The analyst should impose enough structure to make the construct identifiable, but not so much that the model invents what is not there. Honest modeling sits between under-specification and fiction.

His factor-analytic work is a clear illustration. With Michel Wedel, Wagner developed factor-analytic procedures that could estimate factor structure and impute values under realistic patterns of missingness (Kamakura & Wedel, 2000). A few years later, Kamakura, Wedel, de Rosa, and Mazzon (2003) extended this with a mixed-data factor analyzer for cross-selling, combining survey responses, binary service ownership, satisfaction rankings, usage counts, and transaction volumes in a single latent-factor framework.

What made these papers durable is not their technical machinery but the empirical attitude behind them. Marketing databases rarely look the way textbook estimators want them to look. They are mixed in scale, incomplete by design or by nonresponse, and observed from one institutional vantage point. Wagner treated those features as defining properties of the problem, not as nuisances to be cleaned away.

That same attitude shaped the research we did together. The latent object varied by paper: life-cycle stage in a household's evolution (Du & Kamakura, 2006); a customer's total category demand and the firm's share of it (Du, Kamakura, & Mela, 2007); peer influence net of confounds (Du & Kamakura, 2011); dynamic factors beneath noisy digital indicators (Du & Kamakura, 2012); and population trajectories underlying repeated cross-sectional samples (Du & Kamakura, 2015). The task in each case was the same: recover what cannot be seen directly, given partial traces of what can.

Wagner also held a high but practical bar for methodology research: it is worth the hard work only when the method addresses a recurring data structure. Newness is not enough. A method earns its place when it lets researchers and practitioners answer common questions more credibly. This is why his methods traveled—the same latent-structure logic could be applied to customer databases, household panels, search histories, and repeated cross-sections.

Our papers can be read as exercises in matching method to phenomenon. Household life cycle calls for a hidden Markov model because the object is a latent state evolving over time. Customer wallet requires data augmentation because the firm sees only its own slice of the customer's category activity. Budget allocation needs a structural demand system because categories compete for a shared budget. Contagion calls for an individual-level hazard model with explicit confounders because influence must be distinguished from common exposure, geography, and homophily. Trendspotting uses dynamic factors because digital indicators coevolve and carry seasonality. Tracking studies need state-space treatment because repeated cross-sections inherit temporal dependence even when their respondents do not.

Beneath the methodological variety is a single question Wagner pressed us to ask of every project: what assumptions do we need so that the construct is identified, and are those assumptions defensible given how the data were generated? The model is not decoration. It is the answer.

That question is what makes Wagner's work continue to travel. Newer data sources are larger, faster, and less structured, but they are still partial. A click is not an interest. A search query is not a demand. A purchase sequence is not a preference. An adoption pattern is not influence. The translations from observation to construct require the same kind of work Wagner taught us to do.

3. Dynamic Consumers and the Household Economy

One thread of our coauthored work treats consumers as dynamic members of households and economies. Household life cycle had been a fixture of segmentation and consumer behavior research for decades, but the field had not converged on how life stages should be defined or how households move between them. In 'Household Life Cycles and Lifestyles in the United States,' we used 34 years of Panel Study of Income Dynamics data to fit a hidden Markov model in which life-cycle stages were latent states inferred from household demographics (Du & Kamakura, 2006). We then applied the estimated classifications to Consumer Expenditure Survey households to study lifestyle differences across the life cycle.

The contribution was to convert life cycle from a static demographic label into an estimated dynamic process. Households are not fixed units. They form, age, dissolve, expand, and reorganize, and their spending patterns track those transitions. Static segmentation can describe where a household is; it cannot describe how it got there. The hidden Markov treatment allowed us to see the household as a trajectory rather than a category.

The same view motivated 'Where Did All That Money Go?' (Du & Kamakura, 2008), in which we argued that consumer expenditures across categories ultimately compete for the same pool of household income. Industries treat themselves as separate markets, but households experience them as competing claims. We estimated a structural demand model over 31 expenditure categories using 22 years of Consumer Expenditure Survey data, which let us examine category trade-offs, the role of life stage and income in shaping expenditure shares, and how shocks such as price changes or tax rebates ripple across categories.

This line of work places marketing directly inside the household economy. Marketing is not only brand choice within a category; it is also how households allocate limited resources across categories. A price increase in one category can move expenditure in another. Macroeconomic policy can redistribute consumption across industries. A marketing action can alter both a firm's sales and a household's budget composition. Wagner believed marketing science could speak to such questions without giving up empirical discipline.

In 'How Economic Contractions and Expansions Affect Expenditure Patterns' (Kamakura & Du, 2012), we pushed this further into the macro cycle. The standard assumption is that tastes are stable across recessions and expansions, so expenditure shifts trace movements along fixed Engel curves. We proposed a relative-consumption framework instead: holding total consumption fixed, the share allocated to positional goods and services should fall during recessions, and the share allocated to nonpositional ones should rise. Economic contractions, on this view, change not just what households can afford but what kinds of consumption feel appropriate, necessary, or socially legible.

Read together, these papers treat consumers as adaptive actors embedded in households, markets, and macro conditions. Consumption is structured by household transitions, economic shocks, and social comparison; it is not just individual choice. Wagner's modeling made those structures measurable, and his framing made them part of marketing's purview.

4. Hidden Opportunity, Social Influence, and Market Intelligence

Another thread of our collaboration concerns what firms cannot see directly. A firm's CRM data captures its own transactions with the customer, not the customer's category demand or competitor relationships. The result is an inward, partial view of customer value. In 'Size and Share of Customer Wallet' (Du, Kamakura, & Mela, 2007), Carl Mela, Wagner, and I argued for an outward view. We showed that internal transaction volume can be weakly related to external category transactions, and that a small subset of customers often accounts for a large share of the external category opportunity.

The managerial implication is direct: observed internal value is not the same as customer potential. A small internal customer may be a large category buyer who allocates wallet to competitors; a large internal customer may already be near saturation. Methodologically, the paper offered a list-augmentation approach that enriches internal records with external category information. The broader lesson belongs to Wagner: talk to practitioners, because they tell you what methodological problems are actually worth solving.

Practitioners know where their data are blind. They can usually articulate what they observe and what they wish they could infer. Wagner did not treat such problems as merely applied; he treated them as fertile ground for science. The wallet problem itself has only become more relevant in a digital economy. First-party data are now abundant, but they remain bounded by platform, channel, and institutional relationship. More data inside the firm do not deliver a complete view of the customer. The inferential question is the same: how do we use partial observations to infer broader market reality?

A closely related inferential problem arises in diffusion. Consumers influence one another, but observed adoption can be driven by advertising, distribution, geography, seasonality, demographics, common shocks, and homophily. In 'Measuring Contagion in the Diffusion of Consumer Packaged Goods' (Du & Kamakura, 2011), we studied individual-level trial and repeat-purchase data for 67 newly introduced CPGs. Standard diffusion models did not detect contagion. After extending the model to absorb spatial and temporal heterogeneity along with cross-sectional and temporal confounds, we recovered statistically significant contagion for many products.

The contrast with naive analysis is the point. It is easy to claim contagion whenever adoption spreads, and equally easy to deny it when a simple model fails. Wagner's standard was to specify the alternative explanations that must be ruled out before an influence claim is trusted. The result is neither enthusiasm nor dismissal; it is credible measurement. In an environment of influencer marketing, online reviews, algorithmic recommendation, and platform-driven amplification, the lesson cuts harder, not softer. Social traces are abundant, but traces are not identification. The algorithmic substrate of modern platforms introduces new confounds—exposure decisions made by recommender systems, selection on engagement, and feedback between displayed content and user behavior—that did not exist when the contagion paper was written. Distinguishing influence from these is a harder problem now than it was in 2011, not an easier one.

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5. From Digital Traces to AI-Enabled Marketing Science

The current AI moment makes Wagner's intellectual program more, not less, central. Modern machine learning systems are themselves latent-variable systems. Word embeddings learn latent semantic dimensions; matrix factorization underlies most production recommender systems; transformer attention can be read as a learned weighting over latent associations; and large language models compress text into high-dimensional representations on which downstream prediction depends. The substantive vocabulary differs, but the conceptual move is one Wagner would have recognized—use observed data to recover unobserved structure that makes prediction possible. What has changed is scale, opacity, and stakes, not the underlying problem.

Several of Wagner's earlier methodological contributions read, with hindsight, as direct precursors to ideas now central in AI. The factor-analytic missing-data work (Kamakura & Wedel, 2000) sits in the same intellectual lineage as the masked-prediction objective that drives modern self-supervised learning, and as the matrix-completion methods that recommender systems still depend on. The mixed-data factor analyzer (Kamakura, Wedel, de Rosa, & Mazzon, 2003), which combined binary, ordinal, count, and continuous variables in a unified latent framework, anticipates the multimodal models now used to learn joint representations across heterogeneous inputs. The dynamic factor approach in Quantitative Trendspotting (Du & Kamakura, 2012) parallels modern dynamic-embedding and time-evolving topic models. None of this is to claim priority of invention; the point is that the conceptual moves Wagner taught are not artifacts of an earlier era of marketing science. They are core moves in contemporary AI, and the discipline he insisted on—identification, interpretation, and honest accounting of uncertainty—is what is most often missing when those moves are scaled up.

Our 'Quantitative Trendspotting' paper (Du & Kamakura, 2012) is a useful concrete example. Trendspotting can be qualitative—observers reading early signs of changing consumer needs—or quantitative, drawing on indicators such as search volume, blog mentions, or social posts. We proposed a structural dynamic factor model that could ingest many time series at once, compress them into a small number of latent dynamic factors, and separate seasonal cycles from nonseasonal, nonstationary trends. The application used 81 months of Google Trends data for 38 major light-vehicle makes to extract common trends in consumer shopping interest. The contribution was not just prediction; it was interpretation. The model gave analysts a way to move from many noisy indicators to a smaller set of common trajectories whose meaning could be examined. That distinction—prediction versus interpretation—has only grown in importance. Modern machine learning will reliably find patterns in large marketing data. The harder questions are whether those patterns reflect real consumer constructs, whether they generalize beyond the training distribution, and whether they support decisions that improve value for firms and consumers. Wedel and Kannan (2016) describe the methodological challenges of data-rich marketing environments, and Huang and Rust (2021) lay out a strategic framework for AI in marketing across mechanical, thinking, and feeling tasks. Both perspectives implicitly require what Wagner explicitly required: a defensible theory of the construct being measured, attention to identification, and a willingness to say what the evidence cannot support.

Our paper on tracking studies applies the same logic to a research design that is common in marketing and the social sciences (Du & Kamakura, 2015). Repeated cross-sectional samples are often cheaper and more practical than longitudinal panels, but standard analyses either treat each wave independently or aggregate to sample means. We proposed a multivariate state-space model that operates on individual-level data from repeated cross-sections and exploits three sources of information jointly: intertemporal dependence in population means, temporal co-movement across variables, and cross-sectional covariation across individual responses. State-space modeling is conceptually adjacent to the recurrent and sequential architectures now common in machine learning, but with one important difference: the latent states are interpretable as constructs the analyst defined.

The broader argument is that common data structures, e.g., repeated surveys, search time series, customer databases, behavioral streams, deserve serious methodological attention because they are the environments in which firms and institutions actually make decisions. AI can accelerate analysis, but it can also amplify noise, bias, and spurious correlation, and it can do so at speeds that outrun the analyst's ability to notice. Generative models add a further failure mode that Wagner would have called marketing science fiction in its purest form: plausible-sounding outputs that are unmoored from any data-generating process. Wagner's program offers an antidote, not by rejecting computational power, but by insisting that computation be paired with theory-defined constructs, identification arguments, and an honest account of what the evidence can and cannot support.

6. Marketing's Role in the Economy and Society

Reflecting on marketing's role in the economy and society is not separate from Wagner's research program; it is part of what made it serious. Marketing allocates attention, information, and resources. It shapes how firms find opportunities, how consumers learn about offerings, how households spend, and how innovations diffuse. The models reviewed here therefore address more than technical questions. They address how marketing systems work.

The household consumption work shows that marketing operates inside everyday economic constraints. Consumers do not make isolated category choices in a vacuum; they reallocate limited budgets across transportation, food, apparel, leisure, and housing-related services, and the priority among these categories shifts when economic conditions shift. Marketing therefore has societal consequences. It affects not only which firm wins a sale but also how households experience abundance, scarcity, and security.

The wallet and cross-selling work raises a related question about the relationship between firms and consumers. Better inference about customer potential can both reduce wasted targeting and surface consumers whose needs are underserved. Sharper inference also increases the responsibility to use data carefully. Customer analytics should be evaluated not only on lift and profitability, but on the honesty of its measurement, the transparency of its assumptions, and the value it actually creates for the customer.

The contagion and trendspotting papers show that markets are social and informational systems. Diffusion can depend on interpersonal influence; shifts in search behavior can register emerging interest before traditional measures move. These are exactly the settings where AI now appears most powerful, and exactly the settings most prone to mistaking correlation for influence, treating platform artifacts as consumer demand, or accepting an algorithmic signal as self-explanatory. The corrective is Wagner's: define the construct, understand the data-generating process, and separate stable structure from noise.

In this respect, Wagner's legacy provides a working standard for responsible AI in marketing. AI can automate repetitive tasks, support prediction, personalize communication, and assist with market sensing. It cannot, on its own, decide what counts as a meaningful consumer construct, a fair target, a welfare-improving recommendation, or a credible causal claim. Those judgments require marketing science, and the intellectual habits Wagner cultivated: skepticism toward trivial findings, respect for common data structures, openness to problems practitioners actually face, and refusal to make claims the evidence cannot support.

The opportunity, then, is not to replace marketing science with AI, but to make AI more scientific. Latent-variable models, state-space methods, structural demand systems, and factor analyzers continue to matter because they encode assumptions about markets and consumers in interpretable form. Newer systems can expand the data and tasks, but they do not eliminate the work of recovering latent structure. The question for the next generation is how to pair computational scale with theoretical clarity and empirical humility. Wagner's work is one place to start.

7. Mentorship, Courage, and Paying It Forward

Wagner's legacy is not only methods and publications; it is also the scholars he shaped. His standards were demanding and his generosity was real, and the two were not in tension. He wanted students to ask real questions, to avoid trivial contributions, to learn from practitioners, and to find the courage that difficult research requires. One of his lines has stayed with me: don't be afraid if being afraid will not help you. It is a working version of scholarly courage. Fear does not estimate the model, sharpen the theory, or improve the evidence. Work does.

As an adviser, Wagner combined rigor with clarity. He did not let students hide weak ideas behind methodological ornament, and he did not let them off the hook for messy empirical problems. He pressed us on whether the question mattered, whether the data structure was common enough to be worth a method, whether the model was faithful to the phenomenon, and whether the findings would survive alternative explanations. These are habits of judgment more than technical skills, and they are habits one scholar passes to another.

My last email exchanges with Wagner were around Thanksgiving 2024. I am grateful that I had the chance to thank him directly before his passing. In one of his final messages to me, he wrote:

That's the way the system works: you are mentored as a young scholar and then pay forward mentoring others, and everyone benefits from it! This way, you keep up to date with the field and take advantage of your experience, along with the new energy from the students.

That sentence captures the human infrastructure of scholarship. Marketing science is sustained not only by articles and models but by mentoring chains through which judgment and standards are passed along. Wagner also reframed mentorship as reciprocal: senior scholars contribute experience, students contribute new energy, new questions, and new data environments. Everyone benefits when the system works as he described.

For me, the best way to honor Wagner is to keep paying forward what he gave. That means encouraging students to pursue nontrivial questions, take methodology seriously, listen to practice, avoid both hype and cynicism, and keep their work on the science side of the line. It also means showing them, by example when one can, that rigor and kindness are not opposing virtues. Wagner embodied both.

8. Conclusion

Wagner's legacy lies in the models he built and in the discipline behind them. He taught us not to prove the obvious, to invest methodological effort where the data structure recurs, to listen to practitioners, and to pursue inference with both courage and humility. His scholarship was rarely flashy. It was methodologically precise, theoretically grounded, managerially useful, and honest.

Our coauthored research traces one path through that legacy. Hidden Markov models made household dynamics visible. Structural demand systems linked marketing to consumption, welfare, and macro shocks. Augmented latent-variable models turned hidden customer potential and obscured peer influence into measurable quantities. Dynamic factor and state-space models turned noisy indicators and repeated samples into market intelligence. The constant in these papers is that marketing constructs worth caring about are usually unobserved, and they can be recovered only when theory, data, and method are brought together responsibly.

This reflection is selective. It emphasizes our joint work and one slice of Wagner's methodological legacy, particularly his factor-analytic contributions. Many other scholars could tell different stories. The selectivity is a limitation and also, I think, the right form for a tribute. Each of us carries the part of Wagner we knew most directly.

Looking ahead, the case for Wagner's standards is, if anything, stronger. Digitalization has expanded the volume, velocity, and variety of marketing data. AI has expanded the computation available to make sense of it. Neither has eliminated the need for theory-driven constructs, credible measurement, causal caution, or models that clarify rather than obscure. The risk of marketing science fiction grows when the tools grow more powerful, and so does the opportunity for marketing science to do better.

I close where Wagner himself would have closed, with mentorship paid forward. The best tribute I can offer is to keep asking questions that matter, build models that can be trusted, teach students to respect evidence, and help the next generation find its own way. That is how Wagner's legacy continues—not only in citations, but in the standards we hold and the scholars we help shape.

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AI in Marketing: Learnings and Future Directions

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Abstract

One of the drivers of new advances in marketing models and tools is the emergence of new data sources that shed light on the motivation and behaviors of consumers and firms. In this chapter, I discuss the evolving role of marketing in the global economy and society in the era of AI models and tools, and its implications for researchers. Three important areas in which AI can impact marketing are (1) market research, (2) content creation and job changes, and (3) personalization and modeling of customer journeys. First, market research has the potential for considerable automation using AI in the coming years. However, human participants are still likely to play a role in data collection as Large Language Models have limitations when representing the preferences of humans. Second, content creation, in the form of text and images can be readily automated by AI, which will likely cause job losses for some marketing functions. However, AI's capabilities for higher-order tasks are uneven and likely requires human judgment to use AI appropriately to improve productivity. Lastly, AI has vast potential for personalization given its ability to consider the entire history of an individual customer's interactions with the firm when making recommendations or composing marketing messages. However, the capabilities of AI models should be balanced against the cost of using AI if simpler models can deliver reasonable performance.

Keywords

Artificial Intelligence, Large Language Models (LLMs), Market Research, Content Creation, Personalization, Customer Journeys

1. Introduction

One of the drivers of new advances in marketing models and tools is the emergence of new data sources that shed light on the motivation and behaviors of consumers and firms. When Universal Product Codes (UPCs) were developed in the 1970s, scanner data could be collected as consumers checked out at retail stores, which spawned a vast literature in marketing in the 1980s that utilized data sets based on UPC scans (e.g., Guadagni and Little 1983). Marketers soon realized that while aggregate data of what products were moving off the shelves were useful, additional data were needed to track individual customers.

Tesco, a UK supermarket chain, was one of the pioneers in launching a loyalty card that customers could scan at checkout[1], such that individual-level data on purchases could then be collected and analyzed. Importantly, Tesco (and dunnhumby, which provided the data analysis) realized the value of individual panel data as a primary benefit of such loyalty cards. Firms such as Nielsen and IRI in the United States developed household panel data (Keane 2015) by recruiting households, who would use handheld scanners to more accurately capture the entirety of their retail purchases, providing the ability to track purchases across competing stores (e.g., Bell et al. 1998). Crucially, household panel data allowed for quantitative segmentation of consumers into relatively homogeneous groups, as Kamakura and Russell (1989) showed in their pioneering work on uncovering latent classes in brand choice probabilities. A plethora of ensuing work quantified managerially important parameters such as price elasticities (see Bijmolt et al. 2005 for a review)

In the 1990s, the internet brought a new data source of clickstream data to the marketing domain. Unlike purchase data readily available from household panels, the clickstream offered the possibility of understanding consumer search and pre-purchase activities with greater clarity. Firms such as comScore (founded by former IRI executives) recruited households which agreed to allow tracking of their clickstream history using cookies and provided such data to researchers. The literature soon leveraged such clickstream data (e.g., Montgomery et al. 2004; Moe and Fader 2004) to build models of dynamic consumer behavior. Further, consumer use of search engines and online social media led to models that could spot trends in what people were looking for (e.g., Du and Kamakura 2012) using dynamic factor-analytic models.

The 2010's brought yet another source of highly personalized data: usage of mobile devices. While mobile phones had been around for several years prior to the 2010's, their ascent to becoming peoples' go-to device (overtaking desktops and laptops) in the mid 2010's meant that consumer location data could be combined with shopping and purchase data in unprecedented ways. Insights from geofencing (e.g., Luo et al. 2014), and targeting based on time and location (e.g., Danaher et al. 2015) paved the way for a new wave of research on mobile marketing (e.g., Grewal et al. 2016).

In the 2020's, the advent of Large Language Models (LLMs) and the popularity of Artificial Intelligence (AI) chatbots such as ChatGPT, Claude, and Gemini has unlocked the potential to generate and analyze multimodal data sets with ease. As Davenport et al. (2020) point out, the marketing discipline arguably has a great deal to gain from AI. Further, Grewal et al. (2025) note

[1] https://www.thetimes.com/business/companies-markets/article/tesco-clubcard-at-30-the-loyalty-scheme-that-changed-retail-6v6qmwnnl

that Generative AI can create novel outputs in a variety of marketing tasks such as advertising copy, personalized customer emails, personalized web landing pages, and customer service chatbots.

In this chapter, I discuss the evolving role of marketing in the global economy and society in the era of AI models and tools, and its implications for researchers. In Section 2, I review a selection of the AI marketing literature. In Section 3, I suggest directions in which marketing will evolve or be disrupted by AI, including societal implications of such changes.

2. AI Marketing Literature

In this section, I focus on subsets of the AI marketing literature, keeping in mind the connections to Professor Wagner Kamakura's work. In Section 2.1, I discuss the literature on using AI for market research. In Section 2.2, I discuss AI's impact on content creation and jobs. Lastly, in Section 2.3, I discuss AI for personalization and customer journeys. Importantly, there are several other AI methods and applications that are relevant to marketing, but which I do not include in this chapter. Please refer to Sudhir and Toubia (2023) for a broader review.

4.1. Using AI for market research

Arora et al. (2025) compare the performance of LLMs with and without augmented data in qualitative and quantitative market research tasks, finding that LLMs, on average, performed as well as humans when appropriately tuned. Goli and Singh (2024) apply LLMs to an intertemporal choice task of choosing between a smaller and sooner reward and a larger but distant reward. They find that LLMs are more impatient than humans, with larger discount rates, even when prompting LLMs to explain decisions.

Toubia et al. (2025) take the different approach of collecting a data set of over 2,000 participants answering more than 500 questions covering a wide range of measures. They then use this data to create digital twins that would reflect their human counterpart as much as possible by prompting OpenAI's GPT model with "personas" obtained from the survey data. They show the "silicon" counterparts produce similar preferences as humans. Importantly, this paper provides data on heterogeneous customers that can be helpful with segmentation.

Yet, Gui and Toubia (2025) warn of challenges when LLM-simulated subjects are blind to the experimental design, suggesting that unambiguous prompting strategies (unblinding the study to the LLM subject) work better. Misra (2025) points out that prompting engineering inherently has potential for bias, as the user's anticipation can lead to the results they expect.

Timoshenko et al. (2026) explore the capabilities of a supervised fine-tuned LLM to automate the identification of customer needs from Voice of Customer studies. Importantly, they leverage professionally formulated customer needs from an industry partner as ground truth to show their fine-tuned LLM is on par with professional analysis and defeats foundational LLMs. Further, while few-shot prompting improves performance compared to zero-shot prompting (i.e., no examples provided), prompting is dominated by their fine-tuned LLM.

Brand et al. (2026) use OpenAI's GPT model to evaluate the performance of LLMs on a conjoint task. Using willingness-to-pay estimates from human-based conjoint studies, the corresponding estimates from LLMs were compared. They find that fine-tuning LLMs with prior human surveys from the same product category improved performance. However, while average population willingness-to-pay was readily improved by such fine tuning, heterogeneity was far less likely to be captured by even their best-performing LLM. In related work, Wang et al. (2026) propose a data augmentation approach to combine LLM-based estimates with true human labels available for a subset of the data.

Put together, the practice of fine tuning (i.e., retraining) LLM parameters using data containing relevant information about the target population appears to lead to better LLM-based market research, as compared to prompting strategies alone. In one sense, this is not entirely surprising given that prompting can be more prone to user bias (which is almost considered a "feature").

However, as Kamakura and Russell (1989) showed, the market is very unlikely to be composed of a homogeneous group of consumers. Segmentation and customer heterogeneity are often key insights managers look to obtain from market research, and LLMs appear to have better success with average estimates compared to heterogeneous ones. Stepping back, that LLMs get sensible average estimates is a sign of their value, given the plethora of potential biases in the data they are trained on, and that training is based on linguistic patterns, is encouraging. However, more research is needed to ensure that market and customer segmentation is better captured by these models.

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4.2. AI Impact on Content Creation and Jobs

Content creation is a major application of AI (Grewal et al. 2025). Hundreds of variations in text and images can be generated within seconds with AI, allowing for the development of marketing campaigns (e.g., email, mobile, print, or display ads). As Kang and Yoganarasimhan (2025) point out, the bottleneck for marketing campaigns has shifted from ad generation to ad evaluation. These authors also propose an algorithm for self-improving AI that leverages the Twin-2k-500 personas developed by Toubia et al. (2025) to conduct synthetic experiments to continually improve ad content and performance.

These improvements in AI models' ability to create and evaluate content, often with limited human supervision, can have implications for the job market. Demirci et al. (2025) study the impact of AI tools on an online freelance platform with three main job types: manual-intensive jobs (e.g., data management), automation prone jobs (e.g., writing, coding), and image generation jobs (e.g., graphic design). They find the introduction of ChatGPT reduced job posts for automation prone jobs (as compared to manual-intensive jobs), especially those involving writing and coding. The launch of GenAI tools for image creation such as Midjourney and DALL-E 2 reduced job posts for image creation and graphic design. Hui et al. (2024) similarly show freelancers have reduced employment and earnings after the introduction of generative AI models. Further, they do not find moderating effects by worker quality and suggest that top freelancers are not spared by AI introduction. Overall, these findings suggest "low-hanging" automation tasks involving text and image generation are being shifted from human workers to AI.

Dell'Acqua et al. (2026) show mixed results of AI tools for management consultants in a randomized field experiment. They suggest a "jagged AI frontier" where tasks of similar difficulty (as perceived by humans) have differing levels of fit with AI capabilities. Within the frontier, AI tools complement human work, while outside the frontier AI tools degrade human performance. The challenge these authors point out is that any given worker may find it hard to classify which tasks are within or outside the frontier, especially for projects that involve multiple tasks.

As such the "human-in-the-loop" continues to be important in AI-Human hybrid settings, to be able to discern when AI can help speed up tasks or improve quality, versus when it may hinder performance.

4.3. AI for Personalization and Customer Journeys

There is a rich literature in stochastic modeling (e.g., Netzer et al. 2008) for capturing dynamic customer journeys. The Transformer architecture (Vaswani et al. 2017) that underpins LLMs offers potential to model rich customer data (both structured and unstructured). In other words, customer interactions can be modeled with a Transformer architecture similar to how LLMs model a sequence of words (Lu and Kannan 2026).

Lu and Kannan (2026) show their heterogeneous Transformer architecture can capture relationships between customer interactions that Hidden Markov Models (HMMs) can miss. Unlike HMMs which assume a first order Markovian property, the Transformer architecture considers non-linear relationships between inputs at all points in time. By converting a vector of customer behaviors into a low-dimensional embedding space, akin to a "factor model" that is dynamic and non-linear, their model can "connect the dots" between similar behaviors, while the self-attention mechanism of the Transformer searches for intertemporal patterns. Because the data of Lu and Kannan (2026) do not corresponding to the text data used to train LLMs, they estimate the embeddings along with the overall model. By allowing customers to be heterogeneous (e.g., Kamakura and Russell 1989), this paper brings the Transformer architecture closer to the marketing literature, and is a valuable starting point for additional research on customer journeys.

Rafieian and Yoganarasimhan (2023) provide a detailed review of personalization of marketing actions using AI and machine learning algorithms. The posterchild for personalization is the Netflix recommendation algorithm, which is considered to have a significant role in keeping the churn rate low for the company. The Netflix algorithm has influenced other streaming services and retailers (e.g., Wayfair as highlighted by Korganbekova and Zuber 2023) in using personalization algorithms to improve customer outcomes. However, Rafieian and Yoganarasimhan (2023) point out that personalization does not always improve performance, especially if "noise" ends up guiding policies. Because promotion effects are typically small, the signal-to-noise ratio requirements are high for personalization to work effectively. In some cases, the authors suggest a simple uniform policy may yield better results.

3. How AI May Impact Marketing

In this section, I suggest directions in which marketing will evolve or be disrupted by AI in the areas of market research, content creation and jobs, and personalization.

Market research is likely to be transformed by AI in the coming years. Firms typically use market research firms to conduct surveys and to produce analyses from research data. Such functions are prone to AI automation such that a 3-month project could be undertaken in hours or days at a fraction of the cost. AI agents can be developed to provide an end-to-end solution, where a prompt is given to state the research objective, and the agent can then (1) summarize secondary research, (2) design studies to collect primary data, (3) collect primary data using silicone or human subjects, and (4) analyze and present the data in an easily-consumable style. At a minimum, such AI-based market research can be used for pre-testing or developing priors. When relevant data are hard to obtain for fine-tuning, human participants may well be required. This raises questions about the ethics of studies designed by AI for human subjects. While a human-in-the-loop overseeing and approving AI outputs may mitigate concerns that an Institutional Review Board (IRB) may have (especially for academic or pharmaceutical market research), full automation may lead to inappropriate questions or content being developed.

Overall, the direction of market research points towards partial or full automation, which will likely have an effect on jobs in the industry. Analysts who primarily collate information and write reports may be displaced by AI which can do these tasks efficiently.

In addition, content creation tasks in digital marketing and personalization can be readily accomplished with AI. While factorial designs for email marketing campaigns have been commonplace, such campaigns can now be personalized using AI at the individual level using a customer's entire history of interactions. As a result, jobs that involve creating text and images for digital campaigns are at considerable risk of being eliminated. Since millions of people currently perform these jobs, the societal impact of AI automation of these tasks requires careful study and debate. Demonstrating the societal implications of AI can be a mantle that researchers take on to help advance public policy in this area.

As Dell'Acqua et al. (2026) point out, AI has nonuniform capabilities that can complicate its use by workers to enhance productivity and quality since the knowledge to separate tasks that AI can and cannot do well is not widespread. Yet many companies are encouraging, incentivizing, or requiring their workforce to adopt AI tools[2] without necessarily tracking the value gained from these tools. Some report a phenomenon called "workslop" in which workers spend considerable time to fix or revise content generated by AI[3], which may result in reduced productivity. Therefore, an important direction for research and practice is to understand whether AI usage should be mandated in a top-down manner, or allowed to grow organically based on where it adds value. The jagged frontier may be discovered through trial and error, and it would be important for organizations to have a learning mindset when facing a technology as new as LLMs.

In terms of AI for personalization and customer journeys, foundation models may need to be developed, leveraging data from multiple firms. Unlike LLMs, AI for customer journeys involve customer behaviors and interactions, and any one firm may face sparsity issues when building a model only using their own data. These models may provide greater predictive power should there be non-linear intertemporal patterns that standard models cannot capture. On the other hand, per the principle of Occam's Razor, it is worth considering if the complexity of AI models is worth the training and computation cost for any given application. From a societal standpoint, the demands of AI computation is spurring the construction of new data centers which consume large amounts of electricity and water. It is estimated that large data centers can consume up to 5 million gallons of water a day, which is about what a town of 10,000 to 50,000 people would use[4]. Electricity grids are reportedly strained when data centers are constructed in a town. As a result, responsible use of AI should also involve the choice of these models when appropriate, and the selection of simpler models when they would perform well enough. Of course, researchers need to explore the jagged frontier of model selection to help guide when AI models are justified for a given application.

In summary, the marketing field has evolved as new data sources have emerged such as scanner data, clickstream data, and mobile devices. Like any new technological advance, AI has brought new capabilities for individuals and firms to incorporate. While it is natural in the "exploration" stage of AI to incorporate it into as many marketing applications as possible, researchers have a crucial role to play in establishing where AI helps marketing productivity and where it does not. Rather than using AI as a sledgehammer for every problem, a classification tree of when AI or LLMs can help and when tasks may lead to workslop or decreased productivity would be a helpful next step. From a societal standpoint, this nuanced understanding which needs to develop as the technology matures can guide job design as well as judicious use of natural resources that AI requires for computation.

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[2] https://www.cnbc.com/2026/05/05/ai-use-work-employee-monitoring-tech-surveillance.html
[3] https://hbr.org/2025/09/ai-generated-workslop-is-destroying-productivity
[4] https://www.eesi.org/articles/view/data-centers-and-water-consumption

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II.

Markets, Relationships, and Marketing Applications

Actional Self Activation in Continuous Shared-Use Services: The Role of Warm Relationships and Clique Dynamics in Consumer Loyalty

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Abstract

We examine how relational dynamics shape consumer loyalty in continuous shared-use services (CSSU), moving beyond traditional dyadic perspectives toward a triadic and culturally embedded framework. Drawing on Social Exchange Theory (SET), Service-Dominant Logic (S-D Logic), and cogenetic triadic relationships (CTR), we propose the actional self as a key mechanism linking relational experiences to behavioral outcomes. We test a model in which warm relationships and clique dynamics influence loyalty through the mediating role of the actional self. Data were collected from 120 university students in Brazil and Mexico and analyzed using PLS-SEM. The results show that warm relationships positively affect both actional self activation ($\beta = .58$, $p < .001$) and loyalty ($\beta = .22$, $p = .03$), while clique dynamics negatively affect warm relationships ($\beta = -.23$, $p = .02$) and indirectly reduce actional self ($\beta = -.13$, $p = .03$). Actional self strongly predicts loyalty ($\beta = .57$, $p < .001$), confirming its central role as a behavioral activation mechanism. Mediation analysis reveals full mediation between clique dynamics and actional self and partial mediation between warm relationships and loyalty. Multigroup analysis indicates structural invariance across Brazil and Mexico, supporting cross-cultural stability within Latin American contexts. These findings advance the literature on triadic relationships by demonstrating, through CTR, that loyalty emerges from relational activation processes rather than from direct relational conditions.

Keywords

Continuous Shared-Use Services; Actional Self; Warm Relationships; Clique Dynamics; Cogenetic Triadic Relationships; Consumer loyalty

1. Introduction

The contemporary consumption environment has become increasingly interactive, connected, and relational, marking a significant transformation in how organizations create value with consumers (Kumar et al., 2025). Across sectors such as education, fitness, food delivery, ride-hailing, apartment rentals, and subscription-based services, the growing diffusion of digital platforms has intensified the interdependence among users, technological systems, and service providers (Chou et al., 2022). In this context, customer experience no longer depends solely on the core offering; instead, it is strongly shaped by recurring interactions and the quality of relationships developed over time (Kandampully et al., 2023). Consequently, interactive marketing assumes a central role by emphasizing continuous processes of dialogue, personalization, participation, and value co-creation (Chou et al., 2022; Hollebeek & Macky, 2019).

This transformation aligns with Service-Dominant Logic (S-D Logic), which posits that value is not embedded in offerings but emerges through use and interactions among multiple actors within the ecosystem (Vargo & Lusch, 2017). Recent studies on consumer engagement demonstrate that interactive experiences positively influence satisfaction, trust, advocacy, and loyalty when they enable meaningful participation and relevant social connections (Kandampully et al., 2023; Lim et al., 2022). However, despite these advances, much of the literature still conceptualizes consumer loyalty through predominantly dyadic relationships centered on the firm–customer nexus (Munaier & Mazzon, 2025; Sahhar et al., 2021; Sarkar & Banerjee, 2019).

Such an approach is limited in environments where experiences are shared with other consumers and strongly influenced by social norms, group belonging, and relational interdependence (Sarkar & Banerjee, 2019; Storbacka et al., 2016). Recent research highlights that, in contemporary ecosystems, multiple actors simultaneously co-create or co-destroy value, requiring broader analytical lenses (Hardcastle et al., 2025; Munaier & Mazzon, 2025). This gap is particularly salient in continuous shared-use services (CSSU), where consumers repeatedly engage within the same environment and interact with other users over time.

In such contexts, the consumer experience extends beyond functional attributes, price, or convenience, incorporating social and symbolic dimensions related to belonging, acceptance, and legitimacy (Sarkar & Banerjee, 2019). As a result, consumer loyalty depends not only on organizational performance but also on the quality of interpersonal relationships throughout the consumption journey (Munaier & Mazzon, 2025; Wang & Yang, 2024). Although this relational dimension is widely acknowledged, understanding of how these processes are structured and sustained across cultural contexts remains limited.

Addressing this gap, this study proposes the concept of the actional self (Simão, 2020) as an explanatory mechanism for consumer behavioral activation in CSSU contexts. Rooted in cultural psychology, the actional self refers to the individual's disposition to act, participate, and engage within the environment, being continuously shaped by interactions with other actors and by the emergent culture of the context (Simão, 2020; Tateo, 2016). Unlike approaches centered on attitudes or intentions, the actional self offers a deeper understanding of how relational experiences translate into active behavior.

Two relational forces are posited as particularly salient in these ecosystems. The first pertains to warm relationships, characterized by inclusion, closeness, friendship, and interpersonal support. Their importance is consistent with the human values literature, which identifies positive relational bonds as a foundation for enduring preferences and relational commitment (Kamakura & Mazzon, 1991; Kamakura & Novak, 1992). The second refers to clique dynamics, understood as dense, cohesive subgroups with strong internal ties that concentrate interactions within the group and restrict access to external actors (Sasidharan, 2026). While they foster cohesion, trust, and shared interpretations, they also create relational closure, limiting exposure to diverse perspectives and reducing the inflow of novel information. While such dynamics reflect the need for belonging, they may also generate exclusion and constrain participation (Kim et al., 2023; Sasidharan, 2026).

In this context, this study examines how warm relationships and clique dynamics influence consumer loyalty through the mediating role of the actional self. Additionally, the model is tested from a cross-cultural perspective, comparing two national contexts to assess structural stability and cultural moderation effects.

The educational services setting is adopted as the empirical context, representing a prototypical CSSU ecosystem in which social interactions are central to experience formation and value co-creation. This study also advances understanding of whether relational mechanisms underlying loyalty are universal or context-dependent.

This article offers three main contributions. First, it moves beyond dyadic logic by adopting an ecosystemic and socially embedded perspective. Second, it introduces the actional self as a mechanism linking relational experiences to loyalty. Third, it provides evidence on the stability of these mechanisms across cultural contexts. From a managerial perspective, the findings suggest that fostering loyalty requires actively managing the social architecture of the experience, promoting inclusion, mitigating exclusion, and expanding opportunities for meaningful participation.

2. Theoretical Background

2.1. Social Exchange Theory and S-D Logic

Understanding consumer behavior in CSSU servicescapes requires a relational perspective that extends beyond transactional structures (Chou et al., 2022; Munaier & Mazzon, 2025). Social Exchange Theory (SET) posits that individuals remain in relationships when perceived benefits outweigh costs, with reciprocity and perceived value serving as central mechanisms sustaining engagement (Lai et al., 2020). In service contexts, this implies that the quality of social interactions directly influences individuals' willingness to participate in and invest in the experience (Munaier & Mazzon, 2025).

However, in shared-use settings such as universities, language schools, fitness centers, and similar service ecosystems, relational dynamics extend beyond dyadic interactions to encompass multiple actors who jointly shape the experience (Munaier & Mazzon, 2025; Sahhar et al., 2021; Sarkar & Banerjee, 2019). The extant literature indicates that consumer–firm (B2C), consumer–employee (E2C), and consumer–consumer (C2C) interactions are critical for value creation and perceived service outcomes, particularly in continuous-use environments (Kumar et al., 2025; Lim et al., 2022; Zou & Wang, 2022). In these contexts, engagement is influenced not only by functional attributes but also by the quality of social relationships and the sense of belonging derived from such interactions (Kumar et al., 2025; Lim et al., 2022; Sasidharan, 2026).

S-D Logic complements this perspective by proposing that value is not delivered by the organization but is co-created by the consumer through use, resource integration, and lived experience (Hollebeek et al., 2019; Vargo & Lusch, 2017). This approach emphasizes the active role of consumers in value creation, with their participation contingent upon interactions with other actors within the service ecosystem (Hardcastle et al., 2025; Kumar et al., 2025; Wang & Yang, 2024). Thus, in service ecosystems characterized by continuous and shared experiences, value emerges as a processual outcome, continuously constructed and reconstructed through ongoing interactions.

The convergence of SET and S-D Logic enables the understanding of value co-creation as a dynamic process of relational evaluation, wherein positive interactions reinforce engagement, while negative interactions may reduce participation or even lead to value co-destruction (Hardcastle et al., 2025; Wang & Yang, 2024). In university settings, for instance, this dynamic is reflected in how social relationships, marked by acceptance or rejection, shape student involvement, underscoring that the service experience is inseparable from the quality of the social exchanges that sustain it (Hardcastle et al., 2025).

2.2. CSSU and Triadic Relationships

The analysis of contemporary service environments has evolved from dyadic structures to more complex relational configurations, in which multiple actors interact simultaneously, requiring new analytical lenses for understanding value formation (Kumar et al., 2025; Zou & Wang, 2022). In this context, triadic relationships highlight that behavioral outcomes are not solely a function of direct relationships but also of interdependencies among actors (Munaier & Mazzon, 2025; Zou & Wang, 2022). Such structures have been widely examined in service and digital contexts, where consumers interact with other users, platforms, and organizations, increasing the complexity of the consumption experience (Munaier & Mazzon, 2025; Sarkar & Banerjee, 2019; Zou & Wang, 2022).

This complexity is particularly evident in CSSU ecosystems, defined as environments in which multiple users recurrently share the same space and continuously interact with one another and with the organization (Munaier et al., 2025). In these contexts, the consumer experience is constructed over time through repeated interactions, whereas in transactional services, value is perceived at discrete points. Accordingly, value emerges as a relational trajectory, continuously shaped and reshaped through interactions (Kumar et al., 2025; Lim et al., 2022; Wang & Yang, 2024).

Within CSSU, C2C, E2C, and B2C interactions form a relational ecosystem that directly influences value co-creation. The literature indicates that the quality of these interactions affects engagement, sense of belonging, and active participation, potentially generating or destroying value (Hardcastle et al., 2025; Kim et al., 2023; Sasidharan, 2026). In this sense, other consumers shift from peripheral elements to co-determinants of the service experience.

Despite these advances, traditional triadic approaches treat actors as relatively static entities, overlooking the role of emergent culture (Sarkar & Banerjee, 2019; Zou & Wang, 2022). Recent literature incorporates cultural psychology, suggesting that relationships are simultaneously structural and symbolic, and continuously constructed through interaction (Munaier & Mazzon, 2025). Within this perspective, cogenetic triadic relationships (CTR) extend the traditional view by incorporating the interdependence between self, others, and emergent culture (Herbst, 1976; Simão, 2020).

Unlike conventional approaches, culture is conceptualized as a dynamic boundary that defines belonging and exclusion, continuously negotiated (Simão, 2020). Applied to CSSU ecosystems, this suggests that norms and meanings emerge from interactions and guide behavior (Munaier & Mazzon, 2025). Entry into environments such as universities involves symbolic negotiation of belonging, shaped by the quality of social interaction. Inclusive relationships facilitate integration, whereas rejection reinforces barriers and limits participation. Moreover, the CTR perspective introduces the actional self, representing the individual in continuous interaction with others and culture, activated or inhibited by environmental dynamics (Boesch, 2001; Herbst, 1976; Simão, 2020). This concept is central to understanding the motivation to act and co-create value, as behavior derives from relational quality and a sense of belonging (Munaier & Mazzon, 2025; Simão, 2020).

2.3. Actional Self, Warm Relationships, and Rejection Dynamics

Understanding engagement in CSSU environments requires mechanisms linking social interactions to action. The actional self describes the individual in a state of relational activation, shaped by interactions and emergent culture (Simão, 2020). In shared ecosystems, activation depends on perceived belonging and legitimate opportunities for participation.

The literature on the List of Values (LOV) indicates that warm relationships with others are a relevant value in explaining consumer behavior and should not be treated as an isolated preference but rather as part of a broader value system that guides perceptions, motivations, and actions (Kamakura & Novak, 1992). Kamakura and Novak (1992) argue that values operate within hierarchical structures and that "warm relationships with others" may assume substantive importance in the individual's motivational organization, integrating dimensions of maturity and relational pleasure. Evidence shows that inclusive interactions strengthen a sense of belonging and increase willingness to co-create value (Kumar et al., 2025; Munaier & Mazzon, 2025; Sasidharan, 2026). Conversely, rejection dynamics, represented by cliques, function as social closure structures restricting interaction and recognition (Kim et al., 2023; Sasidharan, 2026). From a SET perspective, this reduces relational benefits and increases participation costs, discouraging engagement. These dynamics also undermine warm relationships by limiting relational openness and weakening inclusion.

Thus, the actional self emerges from a relational ecology that combines values, inclusion experiences, and exclusionary barriers. Based on this logic, the following hypotheses are proposed:

H1: The greater the presence of warm relationships, the higher the activation of the actional self.

H2: The greater the occurrence of rejection dynamics ("cliques"), the lower the formation of warm relationships.

H3: The greater the occurrence of rejection dynamics ("cliques"), the lower the activation of the actional self.

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2.4. Consumer Loyalty in CSSU

Consumer loyalty, traditionally associated with relationship continuity and favorable attitudes, assumes broader contours in CSSU ecosystems (Munaier et al., 2025). In these contexts, loyalty extends beyond formal retention to encompass active engagement with the ecosystem, reflecting individuals' willingness to participate, contribute, and derive value over time (Kumar et al., 2025; Lim et al., 2022; Wang & Yang, 2024). Accordingly, loyalty incorporates both behavioral and relational dimensions, aligning with the value co-creation perspective.

As discussed previously, the actional self represents the individual's activation to act within the service environment and is shaped by social interactions (Kumar et al., 2025; Munaier et al., 2025). In this sense, loyalty can be understood as an outcome of such activation, as individuals with higher levels of the actional self tend to engage more deeply, increasing participation and loyalty (Munaier & Mazzon, 2025). Thus, active engagement emerges as a central indicator of loyalty in CSSU contexts. Additionally, the literature on human values underscores the role of interpersonal relationships in shaping continuity behaviors. As argued by Kamakura and Novak (1992), values such as warm relationships with others operate within broader value systems that consistently guide behavior. In CSSU environments, warm relationships serve as a relational foundation for enduring bonds, positively influencing loyalty. Therefore, loyalty emerges from the interaction between self-activation and the quality of social relationships.

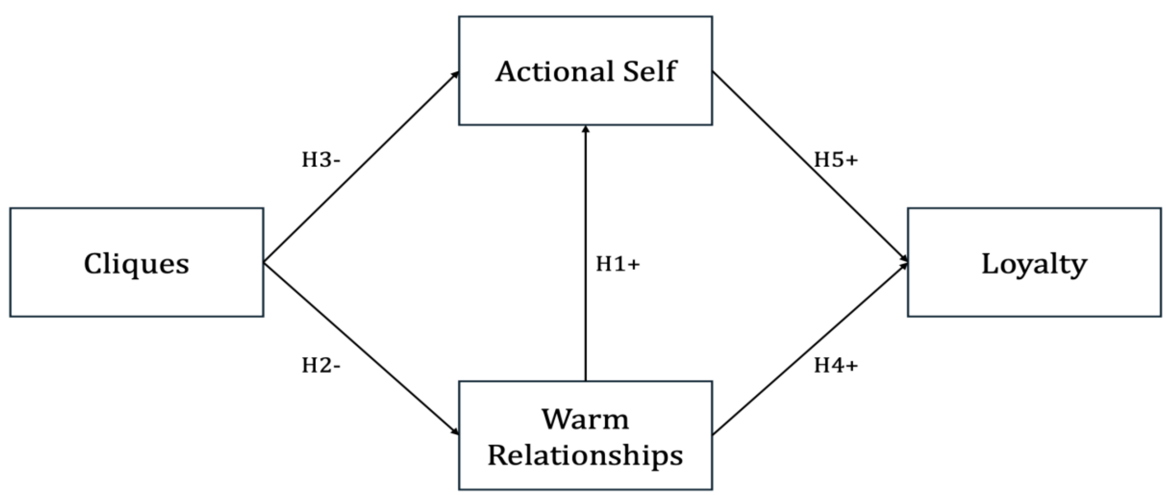
Based on this reasoning, the following hypotheses are proposed:

H4: The greater the presence of warm relationships in the service environment, the higher the level of consumer loyalty.

H5: The higher the activation of the actional self, the higher the level of consumer loyalty.

Figure 1 presents these proposed hypotheses.

Figure 1. Theoretical Model



Source: Author's elaboration

2.5. Latin American Relational Patterns in CSSU

The Latin American cultural context reinforces the role of warm relationships, clique dynamics, and the actional self in CSSU environments. The cultural script of simpatía, characterized by interpersonal warmth, emotional expressiveness, and a preference for harmonious interactions, functions as a shared normative framework guiding social behavior (Acevedo et al., 2020). In such contexts, warm relationships are not only desirable but socially expected, whereas clique dynamics represent forms of social closure that violate norms of inclusion and increase relational costs.

Given these shared cultural patterns, the relationship between the actional self and loyalty is expected to remain stable across Latin American contexts. Norms emphasizing belonging and interpersonal validation shape how relational experiences are translated into engagement and loyalty behaviors. Accordingly, in culturally similar settings such as Brazil and Mexico, the mechanisms linking actional self activation to loyalty are expected to operate consistently. Thus, the following hypotheses can be supported:

H6: The structural relationships between warm relationships, rejection dynamics (cliques), and the formation of the actional self, as well as the relationship between the actional self and consumer loyalty, are equivalent across Latin American contexts (Brazil and Mexico).

3. Method

This study adopted a quantitative survey-based approach to examine patterns, attitudes, and perceptions of students in CSSU environments, specifically within the university context, allowing inferences to this target population (Hair et al., 2022; Malhotra et al., 2014). The model constructs were operationalized using multi-item scales adapted to the university setting. The instrument comprised five latent constructs and 21 items measuring the main variables. All items were assessed using a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”).

Warm relationships were measured using three items adapted from Beatty et al. (1985), whereas the clique construct was operationalized with four items adapted from Munaier and Serralvo (2022). The actional self was measured with six items adapted from Shulga et al. (2021), reflecting its multidimensional and relational nature. Finally, student loyalty was assessed using eight items adapted from Lin and Wong (2020) and Yoo and Donthu (2001), capturing the individual’s willingness to actively engage with the institution. Given the inherently relational and contextual nature of the phenomenon under investigation, the scale adaptation was intended to ensure alignment with the university environment. A pretest was conducted with students to inform semantic and clarity adjustments, and additional validation was carried out with academic experts. Demographic questions were also included to characterize the sample, covering variables such as gender, age, major, and personal income.

The sample consisted exclusively of students currently enrolled in higher education institutions. This choice does not represent a limitation but rather a theoretical and empirical requirement, as universities constitute a prototypical CSSU context in which social interactions are central to experience formation and value co-creation. As a control criterion, respondents with current or prior employment relationships with educational institutions were excluded to avoid bias arising from multiple roles within the analyzed ecosystem. Data were collected through an online questionnaire distributed directly to students via faculty members and institutional networks, involving one private institution in Mexico and another in Brazil, in accordance with data protection guidelines. The dissemination strategy aimed to expand sample reach within the target population by leveraging network effects. Data collection took place between March and April 2026, resulting in a convenience sample.

Measurement quality was assessed through tests of multicollinearity and convergent and discriminant validity (DeVellis, 2016). Reliability was evaluated using Cronbach's alpha ($\alpha \geq .70$), composite reliability ($CR \geq .70$), and average variance extracted ($AVE \geq .50$), while discriminant validity was assessed using the Fornell-Larcker (1981) criterion. The factor structure was examined based on factor loadings greater than .70 (Hair et al., 2022).

Additionally, a multigroup partial least squares (PLS-MGA) analysis was conducted to examine differences in structural relationships across national contexts, enabling the assessment of cross-cultural robustness.

4. Results

The sample comprises 120 valid respondents, with no missing data. Participants are evenly distributed across countries, with 50.0% from Brazil and 50.0% from Mexico. The gender distribution is predominantly female (69.2%); the average age is 23.0 years (SD = 7.73; median = 21), with ages ranging from 18 to 58 years. Income was reported in mixed formats and standardized into U.S. dollars to ensure comparability. The distribution is concentrated in lower-income brackets, with 25.8% earning less than USD 500 and 21.7% earning between USD 500 and USD 1,000 per month. Higher income ranges are less frequent, suggesting a predominantly low- to middle-income profile, which is consistent with a student sample. Regarding marital status, most respondents are single (90.0%). In terms of academic background, all respondents are enrolled in undergraduate programs, primarily in business-related fields such as marketing, management, and related majors. Geographically, the sample is highly concentrated in two major regions: the state of Querétaro (Mexico) and the state of São Paulo (Brazil), which together account for the vast majority of respondents. Both regions are economically dynamic, urbanized, and characterized by strong industrial and service sectors, as well as significantly higher education ecosystems. Querétaro stands out as a rapidly growing hub for manufacturing and innovation in Mexico, while São Paulo represents the largest economic and financial center in Brazil.

4.1 Measurement Model Assessment

The assessment of the measurement model followed established PLS-SEM guidelines, ensuring construct reliability and validity prior to structural interpretation (Hair et al., 2022). Table 1 presents item quality indicators, including VIF for multicollinearity, internal consistency (Cronbach's alpha and composite reliability), and AVE, along with factor loadings.

Table 1. Convergent Validity and Reliability of the Measurement Model

Construct	Item	VIF	VIF Adjust	Load
Clique	Clique1	2.47	2.47	0.80
α=0.87: CR=0.91: AVE=0.77	Clique2	2.80	2.80	0.92
	Clique3	2.24	2.24	0.90
	Clique4	1.49	1.49	0.65
Loyalty	Loyal1	7.43	4.28	0.93
α=0.93: CR=0.95: AVE=0.78	Loyal2	5.30		
	Loyal3	7.04	4.24	0.91
	Loyal4	6.45		
	Loyal5	4.93	3.73	0.91
	Loyal6	6.27		
	Loyal7	3.13	2.91	0.87
	Loyal8	2.23	2.03	0.78
Actional Self	Self1	2.45	2.45	0.83
α=0.88: CR=0.91: AVE=0.67	Self2	2.04	2.04	0.78
	Self3	2.48	2.48	0.84
	Self4	1.89	1.89	0.75
	Self5	1.39	1.39	0.63
	Self6	2.46	2.46	0.84
Warm Relationships	WR1	2.01	2.01	0.87
α=0.86: CR=0.92: AVE=0.78	WR2	2.24	2.24	0.87
	WR3	2.47	2.47	0.91

Source: Authors, based on the analyzed data

After examining multicollinearity, items with elevated VIF values were identified and eliminated: Loyal2 (5.30), Loyal4 (6.45), and Loyal6 (6.27). Most items exhibited adequate factor loadings (λ > .70), except Clique4 (λ = .65) and Self5 (λ = .63), which were removed due to lack of convergent validity. Model re-specification resulted in improved fit indices, with SRMR decreasing from .089 to .085, d_ULS from 1.35 to 0.98, and d_G from 0.59 to 0.48. The chi-square value decreased (χ^2 = 389.70 to χ^2 = 328.65), while NFI increased from .76 to .78, indicating better model fit and alignment between observed and estimated matrices.

Discriminant validity was assessed using the Fornell–Larcker criterion, as presented in Table 2 (Fornell & Larcker, 1981).

Table 2. Discriminant Validity (Fornell–Larcker Criterion)

Constructs	1	2	3	4
Actional Self (1)	**0.82**			
Clique (2)	-0.16	**0.88**		
Loyalty (3)	0.70	-0.13	**0.88**	
Warm Relationships (4)	0.58	-0.23	0.55	**0.88**

Source: Authors, based on the analyzed data

4.2 Hypotheses Testing

Following confirmation of convergent and discriminant validity, the proposed hypotheses were tested. Table 3 presents the results of the structural model.

Table 3. Hypotheses Testing Results

Hypotheses	Relationship	β	Mean	SD	T-statistics	P-value
H1	Warm Relationships -> Actional Self	0.58	0.57	0.09	6.73	0.00
H2	Clique -> Warm Relationships	-0.23	-0.25	0.10	2.37	0.02
H3	Clique -> Actional Self	-0.02	-0.02	0.07	0.30	0.76
H4	Warm Relationships -> Loyalty	0.22	0.22	0.10	2.24	0.03
H5	Actional Self -> Loyalty	0.57	0.58	0.09	6.13	0.00

Source: Authors, based on the analyzed data

For model interpretation, indirect effects provide important insights into the mediating mechanisms. The indirect effect of Clique on Actional Self is negative and statistically significant ($\beta = -.13$; $t = 2.15$; $p = .03$), indicating that the influence of rejection dynamics operates indirectly through the deterioration of warm relationships. This result, combined with the absence of a significant direct effect (H3 not supported), characterizes full mediation of Warm Relationships in the relationship between Clique and Actional Self.

In the relationship between Clique and Loyalty, the indirect effect is marginally significant ($\beta = -.14$; $t = 1.85$; $p = .07$), suggesting a tendency toward mediation, although without robust statistical support at the conventional 5% level. Finally, the indirect effect of Warm Relationship on Loyalty via Actional Self is positive and significant ($\beta = .33$; $t = 4.14$; $p < .001$). Given that the direct effect between Warm Relationship and Loyalty is also significant ($\beta = .22$; $p = .03$), this indicates partial mediation, in which the impact of warm relationships on loyalty occurs both directly and indirectly through the actional self.

Beyond standard statistical assessments, additional tests were conducted to address two critical issues in structural equation modeling for consumer behavior: endogeneity and common method bias.

To assess endogeneity, the Gaussian Copula approach was employed, as recommended by Hult et al. (2018) for PLS-SEM applications. The results indicate no statistical evidence of endogeneity in the proposed structural model (Figure 1), with non-significant coefficients for Warm Relationship ($p = .965$), Clique ($p = .184$), and Actional Self ($p = .748$).

Regarding common method bias, the full collinearity test proposed by Kock (2015) was applied using variance inflation factors (VIFs) across latent constructs. The results show that Clique presented a VIF of 3.01, which is acceptable under the conservative threshold of 3.3, indicating no common method variance. The constructs Warm Relationship, Actional Self, and Loyalty exhibited VIF values above this threshold, suggesting potential redundancy. However, this does not necessarily indicate methodological bias; rather, it reflects strong theoretical and empirical relationships among these constructs. Given the model's sequential theoretical structure, in which Warm Relationship influences Actional Self, which in turn affects Loyalty, higher VIF values can be interpreted as a consequence of nomological proximity rather than measurement bias.

To further examine discriminant validity, the Heterotrait–Monotrait ratio (HTMT) was applied. Following the conservative criterion of HTMT < .85 (Henseler et al., 2015), the results indicate satisfactory discriminant validity: Actional Self–Loyalty (.751), Actional Self–Warm Relationship (.666), Clique–Warm Relationship (.250), and Loyalty–Warm Relationship (.602). Together with the Fornell–Larcker criterion and cross-loadings, these findings confirm that the elevated VIF values do not reflect construct overlap but rather strong theoretical linkages among distinct constructs.

Finally, three additional analyses were conducted: out-of-sample predictive power, Importance–Performance Map Analysis (IPMA), and robust mediation analysis via bootstrapping. The predictive assessment showed an average RMSE of 1.104, compared to a benchmark of 1.476, indicating substantially lower prediction error and suggesting good predictive performance. In the IPMA, the importance and performance values were as follows: Actional Self (.569; 85.9), Warm Relationship (.212; 88.6), and Clique (.023; 30.0). These results indicate that Actional Self exerts the strongest impact on Loyalty, emerging as the primary strategic driver. Thus, increasing students' actional self, belonging, and behavioral activation is likely to significantly enhance loyalty. Warm Relationship shows high performance but moderate importance, suggesting that it represents a foundational relational condition that should be maintained. Clique exhibits low performance and low direct impact, indicating a need to monitor and reduce exclusionary dynamics.

Robust mediation analysis via bootstrapping revealed a significant indirect effect for the pathway Warm Relationship → Actional Self → Loyalty ($\beta = .495$; 95% CI [.268, .784]), indicating that warm relationships increase loyalty primarily through the activation of the actional self. A second serial mediation pathway, Clique → Warm Relationship → Actional Self → Loyalty, also showed a significant indirect effect ($\beta = -.056$; 95% CI [−.142, −.003]), suggesting that clique dynamics reduce loyalty indirectly by weakening warm relationships and diminishing actional self activation.

Overall, the findings indicate that loyalty is socially constructed through relational mechanisms activated by psychological processes. While clique dynamics contribute to relational deterioration and reduced actional self activation, warm relationships are necessary but not sufficient; the actional self emerges as the key mechanism driving loyalty.

In summary, although full collinearity VIF values exceeded recommended thresholds for some constructs, multiple discriminant validity tests indicate that these results are driven by substantive theoretical relationships rather than common method bias.

4.3 Multigroup Analysis: Brazil and Mexico as Moderators

To assess the role of country as a moderating variable, a multigroup analysis was conducted, considering Brazil and Mexico as distinct contexts of investigation. Prior to comparing structural path coefficients, the measurement model was evaluated separately for each group to ensure adequacy and comparability of the constructs (Toldos et al., 2025). Internal consistency was assessed using Cronbach's alpha and CR, with results indicating satisfactory levels in both countries, exceeding the .70 threshold. Convergent validity was evaluated using AVE, which presented adequate values for most constructs. Although the Clique construct in the Brazilian sample showed an AVE slightly below the recommended threshold, the remaining indicators exhibited satisfactory loadings and reliability, supporting the construct's adequacy. Taken together, these findings indicate that the measurement model achieves acceptable reliability and convergent validity across groups, enabling valid comparison.

For cross-group comparisons, the permutation test was used to assess the statistical significance of differences in parameters. The results indicated that no differences between Brazil and Mexico were statistically significant ($p > .05$) for reliability and convergent validity indicators (see Table 4).

Table 4. Permutation Test: Brazil vs. Mexico

Construct	α BR	α MX	Diff. A	p α	CR BR	CR MX	Dif. CR	p CR	AVE BR	AVE MX	Diff. AVE	p AVE
Actional Self	0.88	0.87	0.01	0.87	0.91	0.91	0.01	0.89	0.68	0.66	0.01	0.89
Clique	0.86	0.88	-0.02	0.81	0.62	0.92	-0.3	0.09	0.39	0.8	-0.41	0.08
Loyalty	0.94	0.9	0.04	0.16	0.96	0.93	0.03	0.16	0.82	0.72	0.1	0.16
Warm Relationship	0.79	0.9	-0.11	0.3	0.87	0.94	-0.06	0.3	0.7	0.83	-0.14	0.31

Source: Authors, based on the analyzed data

Table 5. Country Moderation (Brazil vs. Mexico)

Hypothesis	Relationship	Difference (BR–MX)	p-value (two-tailed)	Result
H6	Actional Self -> Loyalty	0.09	0.58	No moderating effect
	Clique -> Actional Self	-0.17	0.32	No moderating effect
	Clique -> Warm Relationships	-0.02	0.79	No moderating effect
	Warm Relationships -> Actional Self	-0.09	0.55	No moderating effect
	Warm Relationships -> Loyalty	-0.17	0.39	No moderating effect

Source: Authors, based on the analyzed data

Taken together, these results support measurement invariance, thereby allowing us to proceed with multigroup analysis in the structural model. Accordingly, it is methodologically appropriate to compare structural path coefficients across countries, enabling the examination of the moderating effect of national context. Country moderation (Brazil vs. Mexico) was assessed using partial least squares multigroup analysis (PLS-MGA), following established guidelines. The decision regarding moderation was based on bootstrap MGA results using two-tailed p-values. The results indicate that none of the differences in structural coefficients were statistically significant ($p > .05$). Specifically, differences for Actional Self → Loyalty ($\Delta\beta = .09$; $p = .58$), Clique → Actional Self ($\Delta\beta = -.17$; $p = .32$), Clique → Warm Relationships ($\Delta\beta = -.02$; $p = .79$), Warm Relationships → Actional Self ($\Delta\beta = -.09$; $p = .55$), and Warm Relationships → Loyalty ($\Delta\beta = -.17$; $p = .39$) did not reach statistical significance (see Table 5).

Additionally, robustness tests (parametric and Welch–Satterthwaite; see Table 6) corroborated these findings, revealing consistent patterns of non-significance and reinforcing the stability of the results and the absence of structural differences between groups.

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Table 6. Robustness Tests

Relationship	Difference (BR–MX)	t-value (Parametric)	p-value (Parametric)	t-value (Welch)	p-value (Welch)
Actional Self -> Loyalty	0.09	0.54	0.59	0.54	0.59
Clique -> Actional Self	-0.17	0.98	0.33	0.98	0.33
Clique -> Warm Relationships	-0.02	0.04	0.97	0.04	0.97
Warm Relationships -> Actional Self	-0.09	0.57	0.57	0.57	0.57
Warm Relationships -> Loyalty	-0.17	0.87	0.39	0.87	0.39

Source: Authors, based on the analyzed data

The results indicate that the country does not exert a moderating effect on the proposed structural relationships, suggesting structural invariance of the model between Brazil and Mexico. In other words, the explanatory mechanisms involving warm relationships, rejection dynamics, actional self activation, and loyalty operate similarly across both contexts. These findings support H6, which posits the equivalence of these relational mechanisms across Latin American settings, particularly in two countries sharing a common cultural framework.

10. Conclusions

This study advances the literature on CSSU by demonstrating that consumer loyalty is not directly driven by relational conditions but by a relationally activated mechanism (actional self) that emerges within triadic and cogenetic interactions. By integrating SET, S-D Logic, and the CTR perspective, the findings clarify how relational experiences are translated into behavioral outcomes.

From a SET perspective, our results show that relational benefits and costs operate asymmetrically through distinct mechanisms. Warm relationships significantly increase actional self activation ($\beta = .58$; $p < .001$), indicating that inclusion, interpersonal support, and proximity do not merely sustain exchange, but trigger behavioral readiness to engage. In contrast, clique dynamics do not directly suppress the actional self ($\beta = -.02$; $p = .76$) but significantly reduce warm relationships ($\beta = -.23$; $p = .02$), with a negative indirect effect on actional self ($\beta = -.13$; $p = .03$). This pattern refines SET by showing that relational costs are not internalized as immediate disengagement; rather, they operate by eroding the relational substrate through which engagement becomes possible. Thus, participation in CSSU is not a direct response to exclusion, but a mediated outcome contingent on relational conditions.

Our results advance CTR by providing empirical evidence that the self is shaped less by discrete relational events and more by the structure of relational accessibility within the ecosystem. The absence of a direct effect of clique dynamics on actional self, combined with their indirect influence via warm relationships, indicates that the self is not independently responsive to isolated social signals. Instead, it is cogenetically constituted through ongoing relational configurations, in which the quality of interactions with others defines the individual's capacity to act. The study also advances the triadic relationship literature by empirically demonstrating that C2C interactions are structurally constitutive of value formation. Warm relationships and clique dynamics, both rooted in C2C interactions, directly shape the emergence of the actional self, thereby influencing downstream outcomes. This finding challenges the implicit assumption that C2C dynamics are contextual moderators, showing instead that they are core drivers of engagement within service ecosystems.

Our findings shift the understanding of co-creation from a relational condition to an activation process, in which value is realized through the individual's capacity to act within the ecosystem. From an S-D Logic perspective, the results clarify the process through which value co-creation is enacted. The strong effect of actional self on loyalty ($\beta = .57$; $p < .001$) indicates that value does not emerge directly from relational experiences, but from the activation of the individual as an integrating actor within the service system. While warm relationships also exhibit a direct effect on loyalty ($\beta = .22$; $p = .03$), their stronger indirect effect through actional self ($\beta = .33$; $p < .001$) demonstrates that relational quality becomes consequential only when it enables participation.

The serial mediation (Clique → Warm Relationships → Actional Self → Loyalty; $\beta = -.056$; CI [−.142, −.003]) further refines this process by specifying how value co-destruction unfolds. Rather than producing immediate disengagement, exclusionary dynamics propagate through the system by weakening relational bonds, which in turn reduce behavioral activation and ultimately undermine loyalty. This finding contributes to the literature by showing that co-destruction is not episodic, but processual and cumulative, operating through relational degradation rather than direct behavioral withdrawal.

The cross-cultural results provide an additional theoretical contribution. The absence of significant differences between Brazil and Mexico supports the structural invariance of the model, indicating that the mechanisms linking relational conditions, actional self, and loyalty operate consistently across both contexts. This finding is coherent with the cultural script of *simpatía* (Acevedo et al., 2020), which reinforces norms of interpersonal warmth, relational embeddedness, and harmony. Within such contexts, warm relationships function as a normative baseline for interaction, while clique dynamics represent deviations from expected relational conduct. Consequently, the processes by which relational experiences translate into behavioral activation and loyalty remain structurally stable. Importantly, this result does not imply universal generalizability but suggests that relational activation mechanisms may exhibit stability within culturally proximate environments.

From a measurement standpoint, the study provides evidence of the robustness of the proposed scale for capturing relational and behavioral dynamics in CSSU. Multiple validity assessments indicate that these reflect strong theoretical interconnections rather than methodological bias.

This reinforces the adequacy of the measurement model for studying complex relational systems in shared-use services.

Managerially, the findings suggest a shift in how loyalty should be approached in educational services. While fostering warm relationships remains necessary, it is insufficient on its own. The central role of the actional self indicates that institutions must design environments that activate participation, not merely support it. This involves creating conditions that enhance agency, legitimacy of participation, and opportunities for contribution. At the same time, clique dynamics must be actively mitigated, as their impact unfolds indirectly yet systematically, undermining the ecosystem's relational foundation. We identify actional self as the primary driver of loyalty, highlighting that behavioral activation, rather than relational satisfaction alone, is the key mechanism of long-term relationships.

5.1 Limitations and Suggestions

This study presents some limitations that define clear avenues for theoretical advancement.

First, the empirical context is restricted to higher education, which, although appropriate for CSSU, may limit generalizability to other service ecosystems. Future research should test the model in contexts such as fitness, co-working, or digital platforms. Second, the cross-cultural analysis between Brazil and Mexico reflects cultural proximity rather than global generalizability. Both contexts share the script of simpatía, which likely explains the invariance observed. Future research should contrast Latin American settings with Anglo-Saxon and East Asian contexts, where relational norms differ significantly, enabling a more rigorous test of the model's cultural boundaries. Third, an additional limitation concerns the restricted scope of relational constructs included in the model. Although the study captures warm relationships and clique dynamics, it does not explicitly model interactions between students and staff/professors. Future research should extend the model by differentiating C2C and E2C interactions, allowing for a more precise understanding of how distinct relational interfaces influence actional self activation and loyalty. Finally, additional constructs, such as psychological safety or identity processes, could extend the model's explanatory power, refining the understanding of relational dynamics in CSSU.

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Appendix. Scale

Item	Actional Self Adapted from Shulga et al. (2021)
Self1	When I think about this educational institution, I feel inclined to talk about it
Self2	I reflect on the experiences I have at this educational institution
Self3	I think about new experiences I could have at this educational institution
Self4	I feel motivated to contribute to the development of new experiences at this educational institution
Self5	I talk to others about my experiences at this educational institution
Self6	I try to encourage others to also experience this educational institution with me
Item	**Cliques (Rejection Dynamics)** Adapted from Munaier and Serralvo (2022)
Clique1	I feel excluded from WhatsApp groups of students who attend the same courses as I do
Clique2	When I arrive at this educational institution, I do not feel part of that "tribe"
Clique3	I have difficulty integrating into this educational institution because students already have their own closed groups
Clique4	It bothers me that there are gatherings outside the institution and that students from my courses do not invite me
Item	**Loyalty** Adapted from Lin and Wong (2020) and Yoo and Donthu (2001)
Loyal1	I truly love this educational institution
Loyal2	I will genuinely miss this educational institution when I complete my academic program
Loyal3	This educational institution is special to me
Loyal4	This educational institution is more than just a service to me
Loyal5	I am fully satisfied with this educational institution
Loyal6	I consider myself loyal to this educational institution
Loyal7	When I think of an educational institution, this is my first choice
Loyal8	I fully intend to study again at this educational institution after completing my current academic trajectory
Item	**Warm Relationships (List of Values – LOV)** Adapted from Beatty et al. (1985)
WR1	Enthusiasm is very important in my daily life
WR2	A sense of belonging is very important in my daily life
WR3	Having warm relationships with others is very important in my daily life

Effects of the economic crisis and pandemic on the structure of consumption according to socioeconomic strata. The case of Spain

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Abstract

This study examines how the Great Recession and the COVID-19 pandemic reshaped household consumption in Spain across socioeconomic strata. Using Permanent Income (PI), households are classified into six groups based on Spanish Household Budget Survey (EPF) data from 2006–2020. A budget allocation approach tracks spending patterns across expansion, recession, recovery, and pandemic periods. Results show that essential goods (food at home, energy, communication) remain stable, while non-essential items (clothing, leisure, dining out, transport) are more affected by crises. Lower-income households concentrate spending on essentials, whereas higher-income groups adjust discretionary expenses more. The COVID-19 shock caused sharper and more immediate changes than the 2008 crisis, including shifts from leisure services to goods and a stronger decline in public transport use. While differences between groups narrow in essential categories, inequalities persist in discretionary spending. A limitation is that the pandemic is observed for only one year.

Keywords

Consumption structure, Socioeconomic strata, Permanent income, Economic crisis, COVID-19 pandemic, Household budget, Spain

1. Introduction

When trying to explain recent economic fluctuations, it is worth remembering, as Durant & Durant (2012) said, that the past is the present unrolled for understanding and the present is the past rolled up for action.

In times of difficulty or problems, fears emerge in consumer behavior (Campbell, et al. 2020). Therefore, it is necessary to unwind the recent past of changes in consumption to understand it and activate or at least understand the action by economic agents. Together with the evolutionary changes that have been taking place (Del Barrio-García, Kamakura & Luque-Martínez, 2019), the 21st century has been characterized by two disruptive phenomena: the great crisis of 2008 and COVID-19 that have affected the world and, in particular, Spain (Luque-Martínez, Kamakura & Del Barrio-García, 2024).

In Spain, big changes have taken place in the household, such as a decrease in household size, a greater role of women as breadwinners, aging and higher level of education of the head of household, or a growth of the middle and upper social classes at the expense of the lower and lower middle classes (Aldás & Solaz, 2019). During the great economic recession (2008-2014), the greatest changes in consumption occurred in households with the lowest per capita consumption, which delayed the purchase of durable goods as a reaction mechanism to the crisis. Likewise, total consumption decreased slightly in the lowest classes, with no notable changes in the rest of the classes (Anghel et al., 2018). According to Alonso et al. (2015), the wealthiest classes put the emphasis on irrational spending as the cause of the crisis without assuming responsibility for it.

This study examines how these two disruptions reshaped consumption priorities overall and across socioeconomic strata. Considering the pandemic effect, it tries to measure the importance of the economic impact (recession) and the structural impact (restrictions on movement, shifts in work, education and entertainment options, etc).

To the best of our knowledge, prior research has not examined in comparable detail how these two crises altered consumption priorities across product categories and socioeconomic strata in Spain. Luque-Martínez, Kamakura & Del Barrio-García (2024) have examined the consequences of these two important disruptive phenomena on changes in consumption by socioeconomic strata are examined, but the analysis does not include product categories, nor the extent to which these effects differ across product categories.

[†] Sadly, Professor Kamakura passed away on March 11, 2025. This work is a continuation of the work by Luque-Martínez, Kamakura & Del Barrio García (2024). Professor Kamakura's contribution was fundamental to the research design and model, as well as to the analysis and visualization of the data. We believe that the best place to share this final collaboration with Wagner is in this tribute book. Always with affection in our memory.

In order to study these shifts in consumption priorities during the dynamic beginning of the 21st century in Spain (with fast economic growth followed by a major recession, a relatively fast recovery, and a major pandemic), we use a concatenation of 15 EPF surveys conducted by INE from 2006 to 2020 (Spanish National Statistics Institute's household budget survey INE-EPF). This series of surveys present two valuable features for our study. First, about half of the households participating each year also participated in the subsequent year, allowing us to understand the dynamics of social mobility. Second, all reported expenditures could be aggregated into consumption categories that were harmonized throughout the entire 15-year period, allowing us to track consumption across categories by each socioeconomic class over time.

We use a budget allocation model (Kamakura & Du, 2012; Du & Kamakura, 2008) to isolate these two impacts and to verify how consumption priorities changed over time for each socioeconomic stratum, and to detect structural shifts in these priorities due to two major disruptions (the Great Recession of 2008 and the pandemic of 2020).

The results confirm that crises have heterogeneous effects across product categories and social strata. Essential products are more stable during the crisis. The pandemic crisis has accelerated the digitalization of consumption and has had more abrupt effects.

2. Consumption, economic crisis, and pandemic crisis

The literature above suggests that the concept of social class is complex; there are differences in self-image, social horizons and consumption goals between classes. But as Coleman (1983) indicates, the fundamental question is not whether social class is more determinant than income, but how it affects their use, that is, the consumption of goods and services. This is the question at hand. The stratification of any society or market is not an easy matter, as highlighted by Dominquez & Albert (1981) when warning about the need for new scales and greater sophistication when it comes to its delimitation in socioeconomic strata, even more so with the evolution of forms of consumption in post-industrial societies.

Williams (2002) concluded that social class is a significant predictor of the importance of the evaluation criteria for many products, being moderated by the objectivity of the criteria and the social sensitivity of the product. For socially insignificant products, the importance of utilitarian criteria was related to income; while for Rengs and Scholz-Wäckerle (2019) consumption depends endogenously on the change in social class and on signals such as the Snob and Veblen effects (namely, conspicuous consumption where social rank determines consumer preferences).

Katz-Gerro et al. (2017) obtained a decrease in spending on food (meat, fresh fruit), hygiene products and cosmetics, clothing and footwear, eating out, vacations or leisure activities, in addition to an increase in the shadow economy. These same authors distinguish different strategies depending on whether households operate as consumption units or as production units, or whether they adopt a proactive or reactive approach. Proactive households involved in production have more sustainable, self-provisioning practices, as is the case with farmers or industrial workers in towns. Proactive households as consumption units are more frequent among households with assets, professionals and they place the emphasis on investments in economic activities. While reactive households are of two types. On the one hand, those who present passive resistance mainly composed of older people or a single member who resist without trying to mitigate the effects of the crisis. On the other hand, there are those who reduce their consumption and savings, go into debt or sell properties. There are also households with a mixture of both strategies.

At the beginning of the crisis there are changes in consumer behavior, both in volume and quality, and later this will also be affected by government measures. In this sense, Kaytaz & Gul (2014) found that consumers switched to cheaper products at the beginning of the crisis, reducing their total consumption expenses. Subsequently, after the measures adopted by the governments, there was an increase in consumption. However, also in these cases the behavior of consumers is heterogeneous, depending on demographic, psychographic and attitudinal variables, as well as the involvement of consumers (Tilikidou & Delistavrou, 2014).

Also, changes in consumption during the crisis can have consequences on eating habits and, in short, on health (Jabakhanji et al., 2017) find that obesity is associated with the perceived effects of the economic recession but not with social class, so they defend a greater public health effort for a healthy weight of the population, instead of doing so towards specific social classes

According to Fritsche et al. (2017), economic crises threaten the sense of control of individuals and lead to certain collective responses such as class protests, nationalism or xenophobia. In short, there is an adaptation of consumers to the new situation, spending less, looking for alternatives or substitutes or more durable products (Katz-Gerro et al. 2017).

On the other hand, crises also cause consequences of a psychological nature that have effects on consumption. The results obtained by Oh (2021) show a negative relationship between self-esteem and conspicuous consumption among those who consider themselves to be of high social class.

Also, the perceived economic inequality, not only the objective one, has its effects. According to Velandia-Morales et al. (2022), perceived economic inequality influences consumption preferences, specifically favoring preferences for products that provide desirable symbolic values associated with status.

Meyer & Sullivan (2013) find different patterns of income and consumption inequality during the first decade of the 21st century. Inequality in consumption increases in the growth period while it decreased during the economic recession. The Great Recession according to the meta-analysis carried out by Jenkins et al. (2021) was associated with a reduction in mean calories per adult equivalent per day in high-income countries and an increase in calories per adult per day in middle-income countries. The intake of fruit and vegetables, fast food, sugary products, and soft drinks was also reduced. Ballester & Velazco (2015) reach similar conclusions for Spain.

Some research points to the effects of the 2008 economic crisis in Spain on consumption. Using focus group Alonso et al. (2015) confirm the different perceptions by class. On the one hand, those who have a dominant position did not articulate a critical discourse on consumption. Moreover, they identify it as the engine of the economy and in terms of well-being, only excessive consumption "by others" is criticized, without seriously considering other alternative forms of consumption or questioning the sustainability of the current consumption model. The crisis is seen as the consequence of mistakes by “others” who accumulate debts and live beyond their means. Although with skepticism, the remoralization of consumption and saving habits is seen as a possible solution.

Some studies analyse the effects of COVID on the consumption of certain products. Coibion et al. (2020) find that recreation, travel, and entertainment expenses, clothing and footwear, housing expenses including rent and maintenance, transportation, and debt payments including mortgages, auto, and student loans see the largest declines in spending. Instead, for utilities, food, or education and childcare, they only observe modest drops. And intermediate drops for small durables such as furniture and medical expenses. Regarding expenditures on durable goods, Coibion et al. (2020) do not find differences in the purchases of durable products, but they do find a sharp decrease in future purchases of these products, both in the probability of buying in the next twelve months and in the quantity to buy.

On the other hand, Chronopoulos et al. (2020) showed the changes produced in the consumption of different products during the different phases of the pandemic. Groceries increased a lot in fever-lockdown phases and remained at higher levels afterwards, while dining and drinking fell drastically in fever-lockdown and remained at lower levels afterwards (stay alert phase). In both cases, differences were found due to socio-demographic characteristics.

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More specifically, in the case of Spain, Luque-Martínez (2020) points out that the confinement caused drastic changes in supply and demand, as well as in prices, commercial distribution and consumption with heterogeneous effects by products, sectors and territories. The drastic fall in consumption was generalized in all types of products during confinement and rebounded once it ended. The prices of goods and services that rose the most during confinement were unprocessed food, food and non-alcoholic beverages, beverages, non-durable goods for the home or products for pets. On the contrary, the prices that fell the most were those of electricity, gas and other fuels; and recorded media.

In short, the review of the literature shows that socioeconomic classes are social spaces, modulated by the context, in which consumption patterns and the consequences derived from crises are reflected in a heterogeneous way. The factors that determine these changes can be divided into intrinsic and extrinsic. The former includes the more or less proactive nature of the households that comprise it, their self-image/self-esteem or the need for assimilation and the need for differentiation that can lead to ostentatious consumption, or the perceived inequality that gives symbolic value to consumption. Among the extrinsic aspects, it is worth highlighting whether the products are basic necessities, their character as available goods or relative equity, durability and sustainability, as well as government measures (fiscal measures, promotion or consumption stimulus measures).

In summary, crises provoke behavioral reactions in different directions as has been observed in different countries and habitats (Kumar & Abdin, 2021).

Socioeconomic strata are instruments for market segmentation and estimation of the evolution of product consumption. The 2008 economic recession led to a general decline in consumption, which affected households depending on their composition and economic vulnerability. The crisis derived from COVID-19 had even more abrupt consequences in all products, especially in those most directly affected by the confinement of the population and which corresponded to non-essential activities. The drastic change was not always downward, although a large drop was observed in the intention to purchase future durable products.

Thus, for example, Yan, Keh & Chen (2021) find a curvilinear effect of social class on green consumption, according to which the middle classes have a greater propensity to green consumption than the upper classes and the lower classes. This can be explained by the tension between need for assimilation (NFA) and need for differentiation (NFD) that differ between classes according to their identity.

After an in-depth analysis of the literature, we have not found relevant studies that analyze the effects of the economic crisis on the evolution of consumption by specific categories of products, not on the changes caused in their consumption according to the different classes. However, and in general terms, derived from the review of the literature, we can conclude that consumption fell for a longer time in the 2008 economic recession than in the COVID-19 pandemic, particularly in non-essential goods (clothes and footwear, vacations or leisure activities or food outside the home because those at home would increase due to confinement). The consumption of basic necessities seems not to be so affected during economic crises; some studies have even observed an increase during the pandemic (food at home). The consumption of energy and that related to communications is maintained during the economic crisis, it is relatively more insensitive to it, it would even increase in the home due to confinement.

The (economic and pandemic) crises are also crises of confidence, in addition to the fall of the GDP, the consumer confidence index falls (Luque-Martínez, 2020).

During the COVID-19 crisis, three dimensions of consumers' online behavior stood out: increased digital participation, transformative capacity of digital technologies, and socioeconomic adaptability to the crisis (Jiang, & Stylos, 2021).

In addition, the perception of food insecurity increased (Parekh, et al. 2021). Fear for health and economy is associated with changes in consumer behavior, in traditional and online shopping. During COVID-19 this occurs in different generations of consumers (Eger, et al 2021). More, "the poorest deciles increased their environmentally destructive behavior, while wealthier deciles showed modest improvements. All deciles displayed greater frugality in purchasing. Support was greater for policy interventions framed as environmental than for taxes on daily consumer products. The findings confirm the need for environmental programs which make sustainable consumption more readily accessible to poorer socioeconomic groups" (Peleg-Mizrachi & Tal, 2021). Consumers are subject by product scarcity and/or to resource scarcity (Hamilton, et al. 2019).

An historical analysis of articles published in the Journal of Consumer Research highlights that research on family decision-making has declined over time now the focus is on households (Wang et al., 2015).

In light of the existing literature and the two major crises of the 21st century, the following research questions arise: How did the Great Recession of 2008 and the COVID-19 crisis affect the structure of consumption by product category in Spain? To what extent do these effects differ across socioeconomic strata defined by Permanent Income? Which categories of goods display resilience in the face of crises, and which are more vulnerable? Do consumption differences between socioeconomic strata narrow or widen in times of crisis?

The general hypothesis is that the effects of crises are heterogeneous (Kumar & Abdin, 2021; Jenkins et al., 2021), with specific particularities associated with the pandemic crisis (Coibion et al., 2020; Chronopoulos et al., 2020; Jiang & Stylos, 2021). Such effects manifest unevenly across strata (Tilikidou & Delistavrou, 2014; Jabakhanji et al., 2017; Yan, Keh & Chen, 2021) and by product type (Ballester & Velazco, 2015; Katz-Gerro et al., 2017; Luque-Martínez, 2020; Velandia-Morales et al., 2022).

Accordingly, the following hypotheses can be formulated:

H1 (Essential vs. non-essential goods). During crises, the budget share devoted to essential goods remains stable or increases, while the share of non-essential goods declines substantially.

H2 (Socioeconomic gradient in essentials). Households with lower Permanent Income allocate a greater proportion of their budget to essential goods than higher-income households, both in normal periods and during crises.

H3 (More abrupt effects of the pandemic than of the 2008 recession on mobility and leisure). COVID-19 generated a more abrupt adjustment than the 2008 recession in categories related to mobility and leisure.

H4 (Digital acceleration). The pandemic-driven digitalization of consumption led to increased spending on communication equipment and services, particularly among middle- and lower-income classes.

H5 (Inequality in essentials vs. discretionary goods). The disparity between strata narrows in essentials and widens at the upper end in discretionary goods during the pandemic.

H6 (Leisure substitution). During the pandemic, consumers substituted leisure services with leisure equipment at home.

H7 (Transportation: private car vs. public). Car use displayed a relatively countercyclical pattern in 2008 but declined in 2020; public transportation fell more sharply in 2020 than car use.

3. Data and method

As summarized in Table 1, the study builds on the concept of *Permanent Income* (PI), defined as "the ability of the household to maintain a certain standard of living" (Friedman, 1957). Since current income may be misleading with respect to socioeconomic status, PI is measured as a latent variable derived from observable indicators. Although some authors (Bollen et al., 2007) have approached PI through formative indicators, the authors highlight methodological issues of collinearity and instead adopt a framework based exclusively on reflective indicators. Moreover, this formulation "is robust to missing values, as demonstrated by Wedel and Kamakura (2001)." The same procedure was employed by Luque-Martínez, Kamakura, and Del Barrio-García (2024).

The proposed model is a Latent-Trait measurement model that adjusts indicators according to household composition and life-cycle stage. This model accommodates binary, continuous, and count indicators, while also correcting for household characteristics—such as number of members and family structure—to avoid biases in the comparison of living standards.

Table 1. Methodological outline

Basic concepts

Permanent Income (PI): "the ability of the household to maintain a certain standard of living" (Friedman, 1957). Measured as a latent variable with reflective indicators

Indicators of PI

- Total net monthly income (at 2015 avg. prices) of the household (natural logarithm).
- Annual monetary spending (at 2015 avg. prices) of the household temporarily elevated (natural logarithm).
- Highest studies completed (categorical in 4 levels – primary, first cycle, second cycle, higher education).
- Occupation (categorical in 5 levels – Management, Professional or Technical, Administrative, Qualified Worker, Non-qualified Worker).
- Socioeconomic situation (reduced classification) of the main breadwinner
- (categorical in 6 levels – manual labor, non-manual labor, independent worker, unemployed, retired, other active).
- Tenure regime (categorical in 6 levels – owned, own with mortgage, rent, reduced rent, partially paid concession, free concession).
- Number of rooms in the house (ordinal in 8 levels).
- Area of the dwelling in m2 (natural logarithm).
- Access to hot water (binary).
- Access to Central Heating (binary).
- Neighbourhood (categorical in 7 levels – urban deluxe, urban high, urban medium, urban low, rural industrial, rural fishing, rural agriculture).

Statistical Model

Latent-Trait measurement model $\mathbf{u_{i(t)j} = \alpha_j + \Sigma_k\beta_{jk}x_{i(t)k} + \lambda_j\tau_{i(t)} + \varepsilon_{i(t)j}}$

$u_{i(t)j}$= latent value for household i interviewed (nested) in year t measuring the propensity to respond with the observed value $y_{i(t)j}$ for indicator j. This latent value is linked to the value $y_{i(t)j}$ via n identity (for continuous indicators), logarithm (for counts) or logit (for multichotomous observed indicators) link function.

α_j = intercept for indicator j.

β_{jk}= regression coefficient for indicator j on the k-th covariate (eg, household type).

$x_{i(t)k}$= background characteristic (regressor) k of household i interviewed in year t.

λ_j =factor loading for indicator j on the latent PI.

$\tau_{i(t)}$=Latent Permanent Income score for household I (nested) in year t.

$\varepsilon_{i(t)j}$ =random error.

Household Composition and Life Cycle Adjustment

Data

Encuesta de Presupuestos Familiares (EPF) - Household Budget Survey - is an annual survey of Spanish National Statistics Institute (INE) among 24,000 households

6 socioeconomic strata based on standardized permanent income:

- A (Permanent Income score in the top decile).
- B (top second and third deciles).
- C1 (top fourth and fifth deciles).
- C2 (bottom fourth and fifth deciles).
- D (bottom second and third deciles).
- E bottom decile).

Results

Analysis of consumption trends by product in period:

- Expansion (2006-2008)
- Big-recession (2008-2013)
- Recovery (2014-2019)
- COVID-19 pandemic (2020)

The PI indicators are drawn from the Spanish Household Budget Survey (EPF) conducted annually by the National Statistics Institute (INE), which collects information from 24,000 households each year. Based on this information, the PI of each household is measured over a 15-year period, consistent socioeconomic strata are defined across the entire timeframe, and mobility between social classes is tracked during phases of expansion (2006–2008), financial crisis (2008–2013), recovery (2013–2019), and the pandemic (2020). This approach also enables analysis of evolution across product categories.

4. Data analysis. Socioeconomic Class and Consumption Priorities in Spain in the 21st Century

We look at how consumption priorities (share of consumption budget) changed over time across socioeconomic strata for major consumption categories. Figure 1 displays budget shares allocated to *Food at Home* in the past 15 years, showing a reduction in disparity among socioeconomic classes since the Great Recession. The difference in allocation to *Food at Home* between class E and A was 21 points in 2008, down to 14 points in 2020. As one would expect for essential goods, wealthier classes (A and B) devote a smaller portion of their consumption budgets to *Food at Home* than poorer classes (E and D).

As for *Food away from Home*, typically a non-essential discretionary expense, the difference between upper and lower classes increased over time, particularly during the recovery from the Great Recession. However, the disparity decreased considerably with the pandemic, because richer households reduced their allocation to this category at a higher rate than poorer households. This probably happened because *Food away from Home* might be discretionary for the upper classes, but an unavoidable necessity for poorer households (e.g., lunch at work), who could not reduce consumption at the same rate as richer households since they already had it at a very low subsistence level. Another evidence that *Food away from Home* might be an unavoidable necessity for poorer households is the fact that budget allocations to this category are much less volatile for the lower classes than the wealthier ones, as shown over time in Figure 2.

Home Energy (Figure 3) is a clear essential expense, because poorer households allocate a higher share to it. The disparity in budget allocations to *Home Energy* across classes has increased since the Great Recession and even more so during the recovery phase (by almost 3 points), but decreased during the pandemic; all classes devoted a higher share of their budgets to *Home Energy* in 2020, except for the lowest class. All other classes stayed at home more and used more energy, while the lowest class probably could not afford to spend more.

Clothing (Figure 4) is a non-essential expense (higher budget allocation by the wealthier classes), and a smaller portion of the consumption budget has been devoted to it over time, surely motivated by globalization that favors marketing with lower prices. There was also a dramatic reduction in allocated budget to *Clothing* in 2020 due to mobility restrictions that led consumers to spend much more time at home, reducing the need for new clothing.

As one would expect, wealthier classes devote a higher share of their budgets to *Vacations* (Figure 5) than the poorer classes, typical for non-essential consumption. Surprisingly, budget allocations to *Vacations* show a decreasing long-term trend during the 15-period across all classes, suggesting that Spanish consumers are spending less of their budgets on vacations. The drop in allocated budget is more dramatic during the pandemic across all classes, probably due to mobility restriction and fear of contagion (why risk it?) rather than economic reasons, especially in the wealthier classes because they have much more room to save on it.

Leisure Equipment (Figure 6) is a non-essential and not very relevant category that represents less than 1.5% of the consumption budget in the sampling period, with a declining trend across all socioeconomic classes, except for 2020, which shows a clear growth for *Leisure Equipment* for all classes. The pandemic and confinement increased the need for leisure at home, hence the increase in this type of equipment across all social classes, although the increase is more accentuated in the wealthier classes.

Leisure Services (Figure 7) is a non-essential category, with stable behavior observed during the Great Recession in all socioeconomic classes, with a slight downward trend in the recovery, except for 2020. In this pandemic year, we see a large generalized drop in *Leisure Services* across all classes. This drop in *Leisure Services* is in direct contrast to the increase observed in *Leisure Equipment* (Figure 6), again confirming that consumers stayed at home more often, replacing *Leisure Services* with home entertainment, leading to increasing expenses in *Leisure Equipment*.

There was little diversity in the budget allocations to *Communication Equipment* (Figure 8) across socioeconomic classes until 2013, when this consumption category became clearly discretionary, with the wealthier classes spending a larger portion of their budgets in this category than the poorer classes. This increase is striking, although the share of total expenditure is still small. This is probably due to the increased spending on digital devices, both because of the diversity of the supply and the demand of an increasingly digitized society, both at work and in daily life.

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In contrast to *Communication Equipment* (Figure 8), *Communication Services* (Figure 9) has always been an essential expense, with the poorer classes devoting a higher share of their budgets to it than the wealthier classes. The year 2013 has also been a turning point for this consumption category as seen with *Communication Equipment*. As mentioned, an increasingly digitalized society needs more space for leisure and for work. However, in the case of *Communication Services* the poorer socioeconomic classes increased their allocation to this category after 2013 at a higher rate than the wealthy classes. Allocations to *Communication Services* increased dramatically in the pandemic year (2020) as consumers were forced to substitute in-person contacts with telecommunications.

Budget allocations to *Use of Personal Car* (Figure 10) increased during the Great Recession, particularly among the poorer classes. This behavior is somewhat surprising, especially for the poorer classes who have less discretionary income to spend on non-essentials and therefore rely more on public transportation. Possibly because the trips made are more concentrated in their own car instead of other alternatives, especially for leisure trips or vacations. As expected, all consumers reduced their budget allocations to *Use of a Personal Car* in the pandemic year of 2020, due to mobility restrictions.

It is somewhat surprising that budget allocations to *Public Transportation* (Figure 11) characterize this category as a non-essential discretionary expense, with wealthier classes devoting a higher share of their budgets to this category than poorer classes. This unexpected result might be due to the fact that *Public Transportation* includes inter-city transportation (beyond *Vacations*).

Similar to *Use of Personal Car*, and for the same reasons, all socioeconomic classes reduced their allocation to *Public Transportation* during the pandemic year of 2020. However, the drop in *Public Transportation* was much more dramatic, suggesting that consumers preferred to drive their own car than taking public transportation whenever necessary and possible.

Figure 1. Share of Consumption Budget by Socioeconomic Strata – Food at home

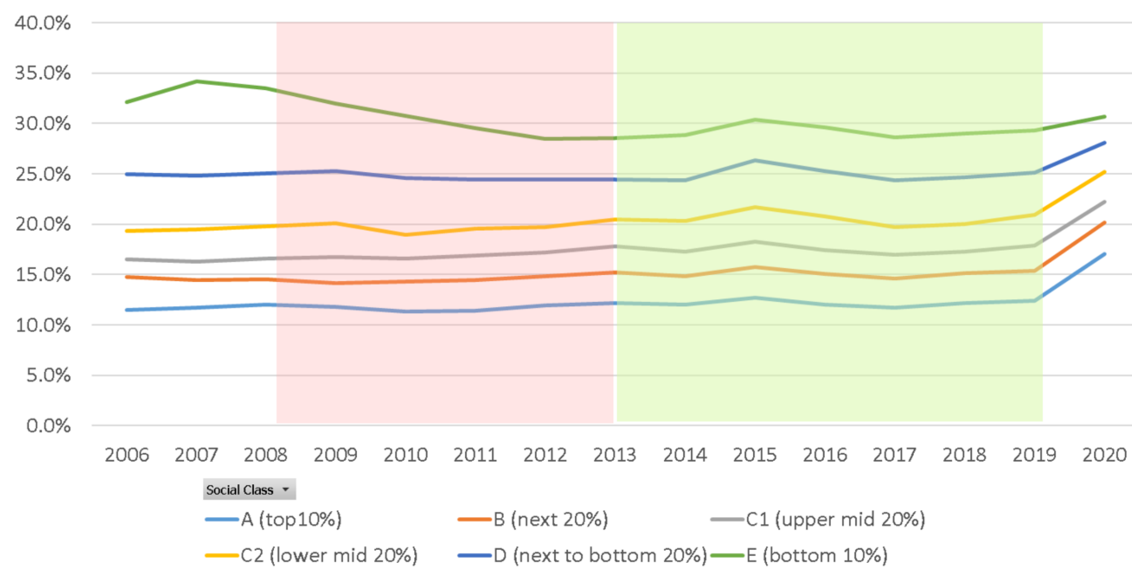


Figure 2. Share of Consumption Budget by Socioeconomic Strata – Food away from home

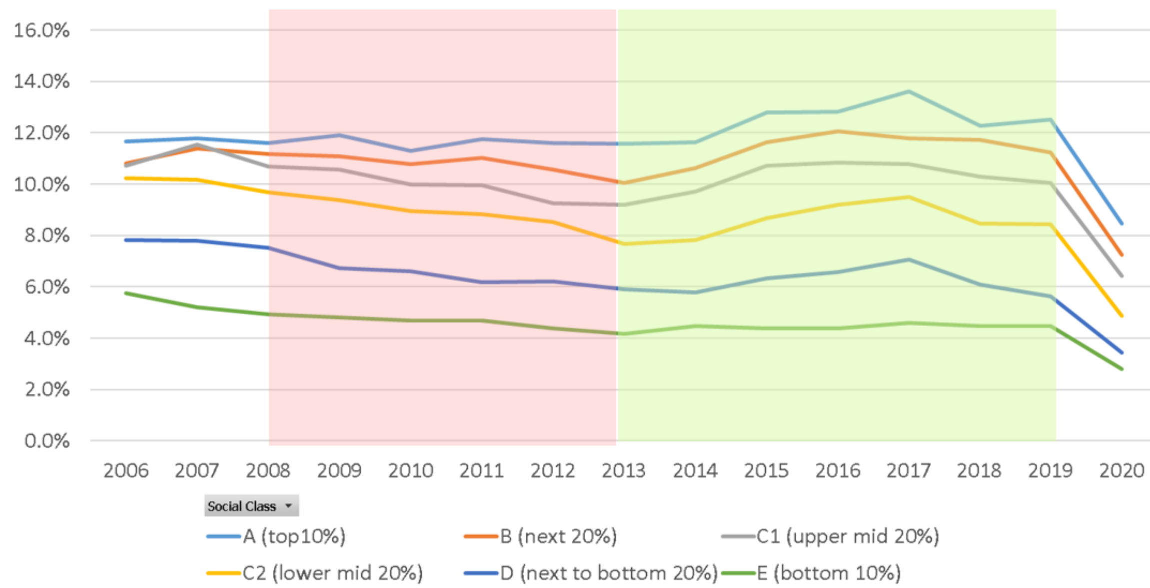


Figure 3. Share of Consumption Budget by Socioeconomic Strata – Home Energy

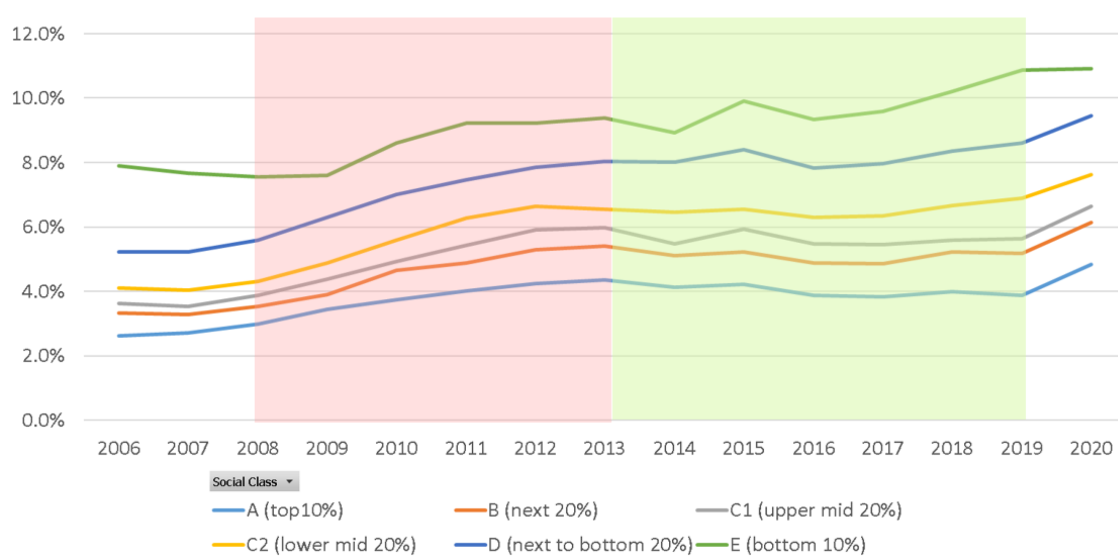


Figure 4. Share of Consumption Budget by Socioeconomic Strata – Clothing

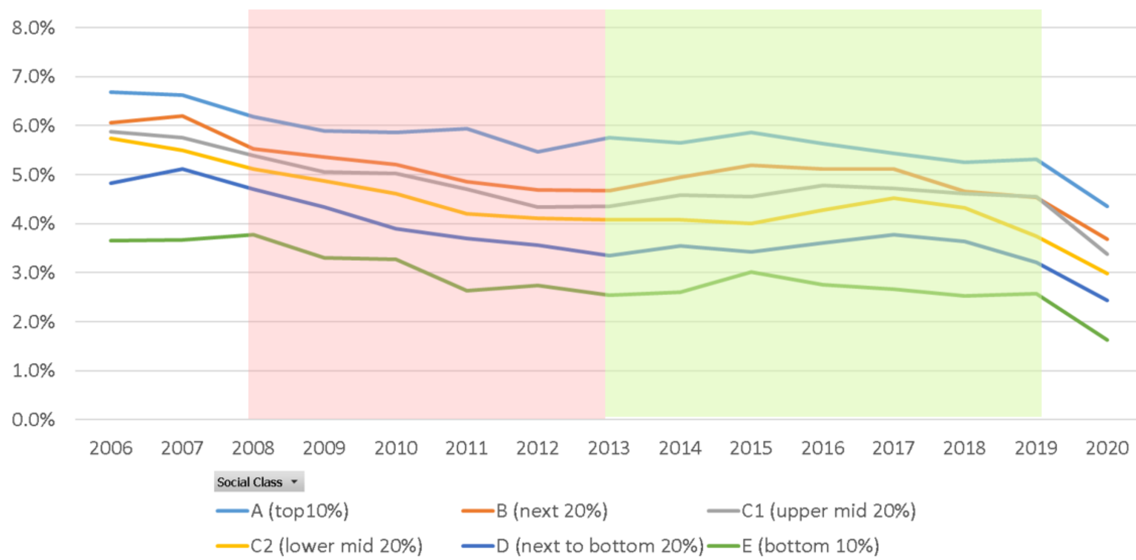


Figure 5. Share of Consumption Budget by Socioeconomic Strata – Vacations

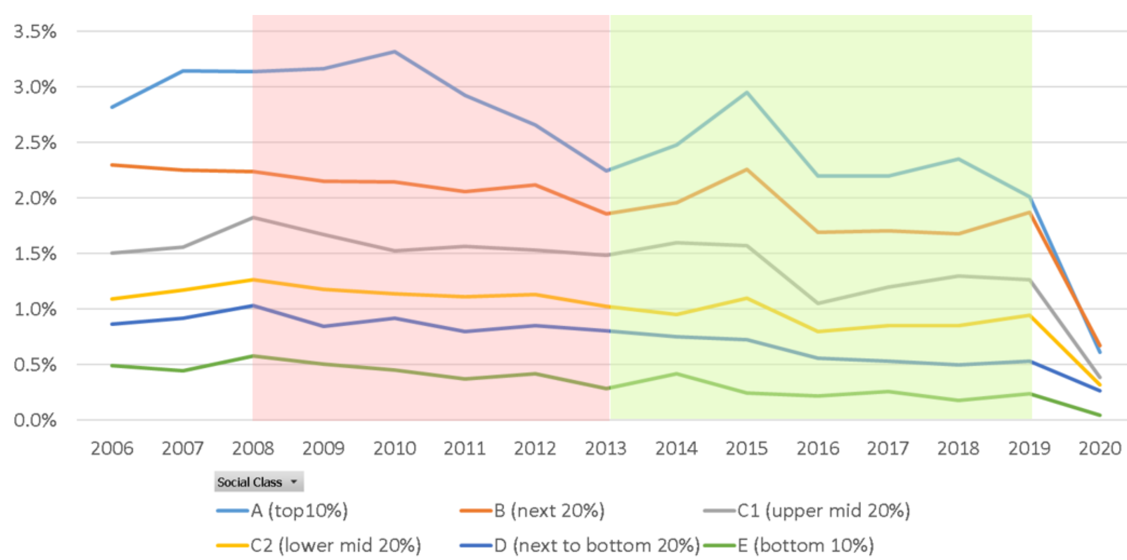


Figure 6. Share of Consumption Budget by Socioeconomic Strata – Leisure Equipment

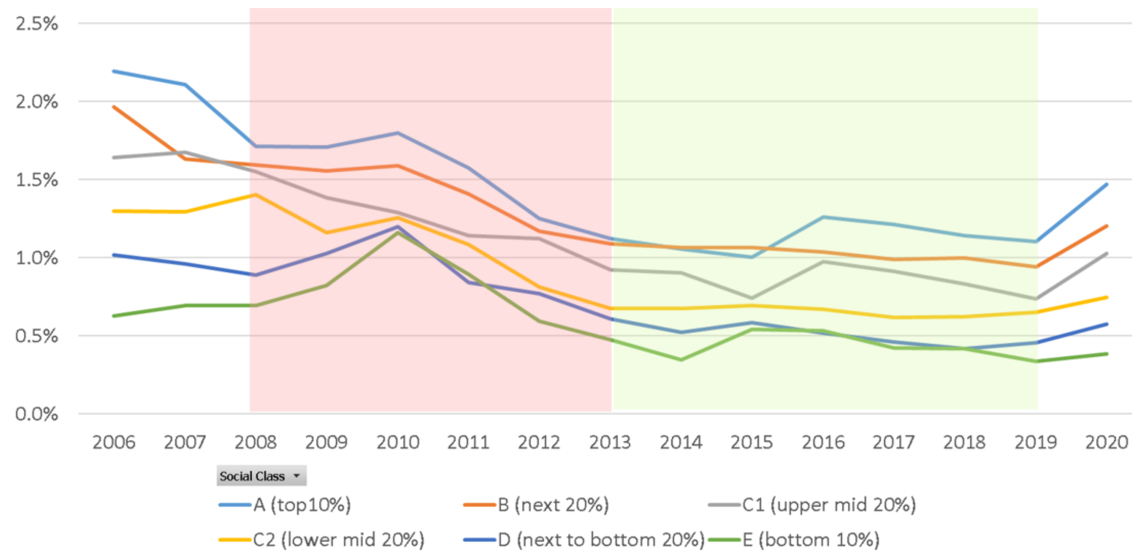


Figure 7. Share of Consumption Budget by Socioeconomic Strata – Leisure Services

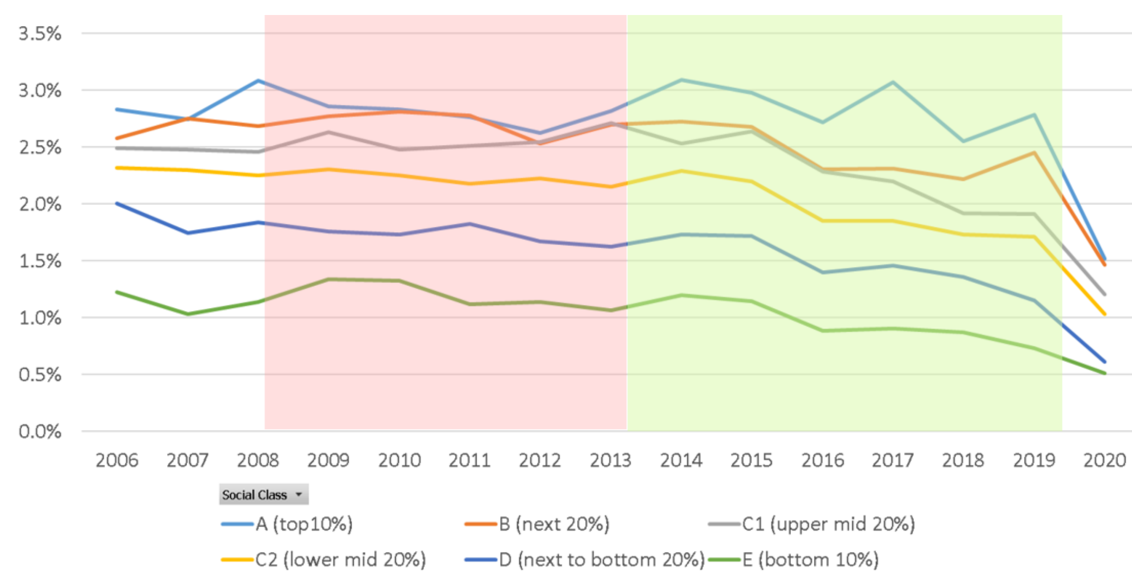


Figure 8. Share of Consumption Budget by Socioeconomic Strata – Communication Equipment

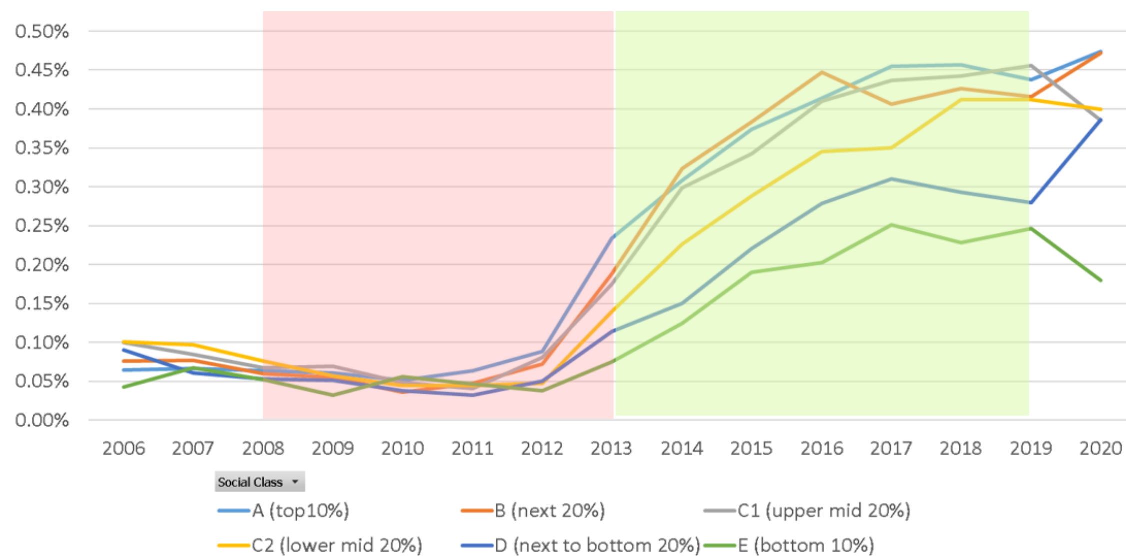


Figure 9. Share of Consumption Budget by Socioeconomic Strata – Communication Services

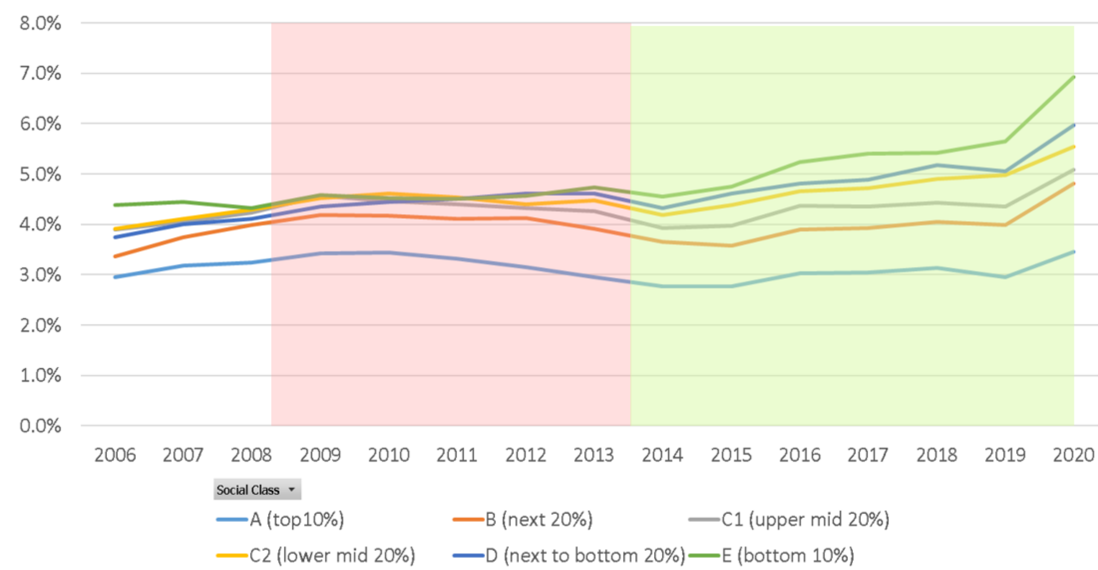


Figure 10. Share of Consumption Budget by Socioeconomic Strata – Use of Personal Car

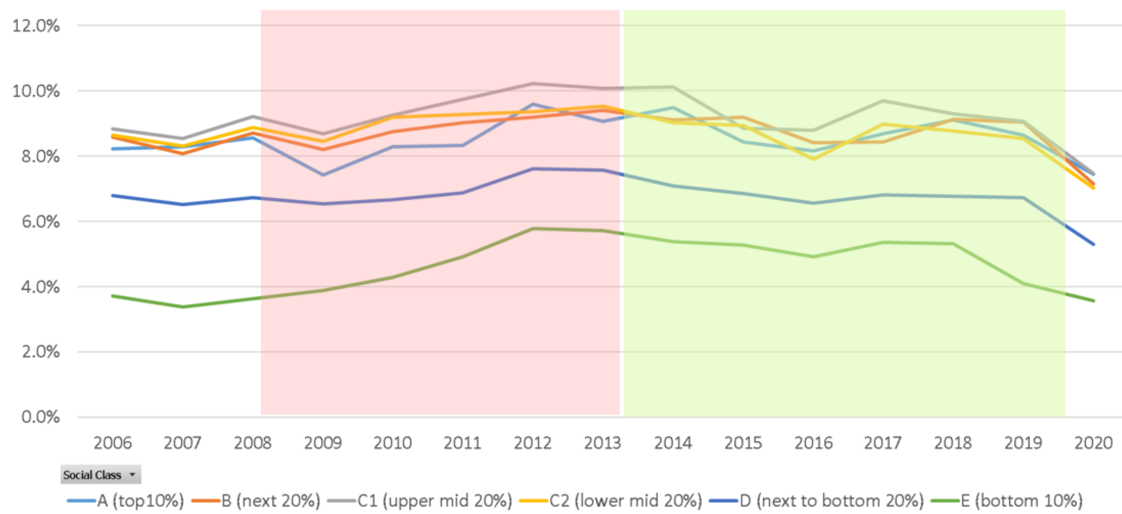
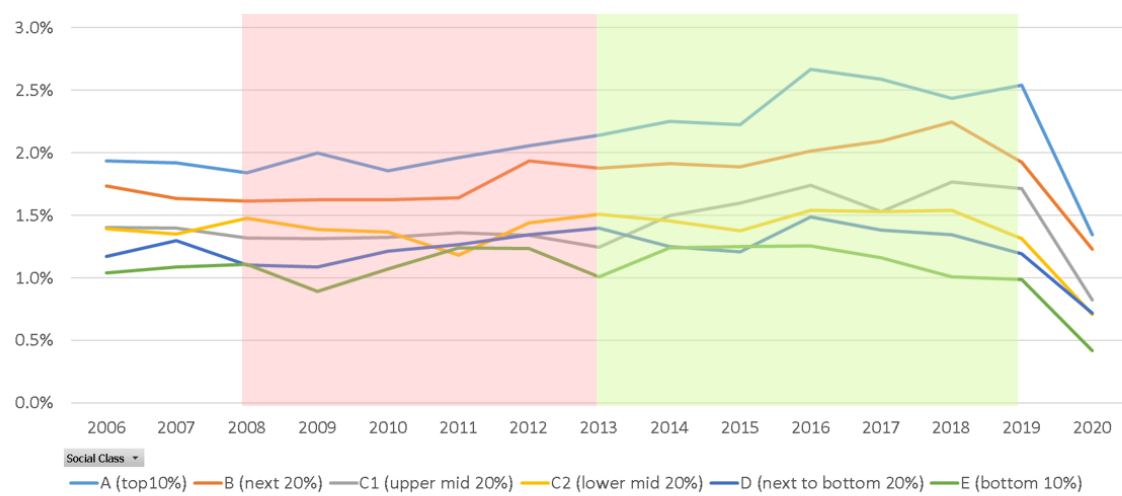


Figure 11. Share of Consumption Budget by Socioeconomic Strata – Public Transportation



As a summary, Table 2 shows the changes in the share of consumption budget by socioeconomic strata throughout the period of time analyzed and for each of the selected product categories, distinguishing two periods: (1) 2006 to 2019, which would correspond to the beginning of the analysis period, the economic crisis of 2008 and its subsequent recovery; (2) 2006-2020, which corresponds to the entire period analyzed, including the two great economic disruptions that occurred in the 21th century.

The evolution of the share of the product categories analyzed can be seen according to the variability within each stratum over the period, measured by the coefficient of variation (CV) or normalized root-mean-square deviation (NRMSD).

Products with high variability over the period (NRMSD>0.20)

The highest variability over the period and also the highest growth, by far above the rest, occurs in Communication equipment with enormous growth both before and after the pandemic. The variation affects all strata but to a greater extent the higher strata (A and B) and the lower strata (E).

Vacations and Leisure equipment have lost importance in both periods (pre-pandemic and pandemic) but especially vacations accelerated the fall for obvious reasons during the pandemic, and it was especially noticeable in the lower stratum (E) higher in the lower strata.

Products with intermediate variability during the period (0.12<NRMSD<0.20).

Home energy is the second fastest growing category, significantly during the whole period and even more accelerated during the pandemic, with by far the least growing stratum being the least wealthy (E).

Clothing has a path of significant decline, accelerated during the pandemic and especially in the lower strata (C2, D and E). Leisure services also show a downward trend but reduced in the upper strata and accentuated in the lower strata in the period prior to the pandemic. During the pandemic, the fall accelerates in a generalized way, somewhat more in the lower strata.

Public transportation shows a considerable increase in the three upper strata, while it tends to decrease, albeit slightly, in the lower strata. The pandemic causes a sharp and generalized decline in all strata, more so in the lower strata.

Products with low variability during the period (in general NRMSD<0.12).

Food at home is the category with the lowest variability, with a increase during the pandemic, except for the lowest stratum.

Food away from home increased somewhat before COVID in the top two strata but declined in the rest. The pandemic led to a decrease in its importance in all strata, but even more so in the lower strata.

Table 2. Changes in Share of Consumption Budget by Socioeconomic Strata

	Period	A (top10%)	B. (next 20%)	C1 (upper mid 20%)	C2 (lower mid 20%)	D (next to bottom 20%)	E (bottom 10%)
Food at home	2019-2006	8.30	4.26	8.61	7.96	0.57	-8.84
	2020-2006	48.67	36.76	34.75	30.20	12.40	-4.51
	NRMSD	0,11	0,09	0,08	0,07	0,04	0,06
Food away from home	2019-2006	7.24	3.88	-6.12	-17.61	-28.08	-22.28
	2020-2006	-27.47	-32.91	-39.92	-52.33	-56.25	-51.16
	NRMSD	0,09	0,10	0,11	0,14	0,16	0,13
Home Energy	2019-2006	48.23	55.81	55.37	68.27	64.30	37.75
	2020-2006	84.59	84.41	82.56	85.94	80.49	38.23
	NRMSD	0,16	0,17	0,17	0,18	0,17	0,12
Clothing	2019-2006	-20.50	-25.15	-22.73	-34.64	-33.47	-29.58
	2020-2006	-34.72	-39.07	-42.51	-48.02	-49.50	-55.45
	NRMSD	0,10	0,12	0,12	0,15	0,17	0,19
Vacations	2019-2006	-28.60	-18.56	-15.70	-13.05	-38.92	-51.48
	2020-2006	-78.31	-70.74	-74.45	-70.60	-69.81	-90.78
	NRMSD	0,26	0,21	0,24	0,22	0,27	0,41
Leisure equipment	2019-2006	-49.57	-51.98	-55.12	-49.76	-55.19	-46.38
	2020-2006	-32.84	-38.68	-37.43	-42.64	-43.67	-38.92
	NRMSD	0,26	0,23	0,27	0,32	0,33	0,37
Leisure services	2019-2006	-1.58	-5.03	-23.12	-26.29	-42.47	-40.56
	2020-2006	-46.41	-43.32	-51.65	-55.53	-69.56	-58.12
	NRMSD	0,13	0,13	0,16	0,17	0,21	0,21
Communication equipment	2019-2006	576.29	443.77	358.85	310.82	211.68	482.43
	2020-2006	633.21	517.67	288.20	298.50	330.20	325.52
	NRMSD	0,72	0,74	0,71	0,71	0,73	0,67
Communication Services	2019-2006	0.18	18.42	11.53	27.29	35.00	29.02
	2020-2006	17.26	42.90	30.49	41.89	59.43	58.18
	NRMSD	0,07	0,08	0,07	0,08	0,11	0,14
Use of Personal Car	2019-2006	5.06	5.43	2.74	-1.40	-0.96	10.64
	2020-2006	-9.57	-16.71	-15.39	-18.91	-21.94	-3.63
	NRMSD	0,07	0,06	0,08	0,07	0,07	0,18
Public transportation	2019-2006	31.12	10.85	21.95	-5.78	1.74	-5.12
	2020-2006	-30.60	-29.11	-41.45	-49.32	-38.61	-59.80
	NRMSD	0,16	0,13	0,16	0,15	0,14	0,19

Communication services shows an increasing evolution, especially in terms of their share in the expenditure of the poorest strata. Its growth with the pandemic also accelerated, especially in the poorest strata.

Use of Personal Car is the category that presented less strong changes, in general increasing. The pandemic changes this and represents a generalized decline in all strata in the importance of this category.

5. Conclusions and implications

In relation to the changes in the structure of consumption by product category and by class, a distinction is made between goods designated as COVID-19 goods by Eurostat and INE and the rest of goods and services.

Among the COVID-19 goods and services, there are basic needs whose difference in consumption between classes has been reduced in the period, their level of consumption was maintained in the financial crisis of 2008 but has increased with the pandemic. This is the case of *Food at Home* for which the largest stratum presents more heterogeneity. Something similar occurs with *Home Energy* and *Communication Services*, although in these cases the general trend is growing both during the 2008 crisis and much more so in the pandemic as a result of confinement. The middle classes are the most heterogeneous in their behavior for *Home Energy* and the lower ones for *Communication Services*.

Communication equipment had a very similar consumption share between the different classes and it remained the same until the recovery phase of the 2008 crisis, after which there was a great growth, greater in the higher classes and with a contradictory evolution in the response to the pandemic crisis. It is the category with the most heterogeneous consumption in all social classes.

Although it is not essential but can be included among the COVID-19 goods and services, the consumption of *Leisure equipment* fell during the 2008 crisis and grew quite a bit in 2020 as a result of confinement, with greater heterogeneity in classes of lower rent.

Other goods not included in the previous category (non-COVID-19 goods) and non-essentials show a downward trend, more accentuated in the lower classes during the 2008 economic crisis, and a sharp drop in the pandemic period. This is the case of *Food away from Home*, *Clothing* and *Vacations*, whose consumption remained the same or increased during the recovery phase, the behavior of consumption being more heterogeneous as the income level decreased. To these must be added *Leisure services* whose consumption remained stable during the 2008 crisis and had a drastic drop in 2020 as a result of the confinement, increasing the heterogeneity in the middle and lower classes.

The most countercyclical behavior is presented by the consumption share of *Use of Personal Car*, as Goodwin & Van Dender (2013) have already noted. It grew during the 2008 crisis, fell in the recovery and, for obvious reasons, fell during the pandemic. It is not a category with much heterogeneity in consumption behavior during the period.

Public transportation shows a growing trend during the 2008 crisis and the subsequent recovery until 2018, since it decreased in 2019 and, of course, it does so strongly in 2020. There are no great differences in the heterogeneity of this category.

Finally, regarding the transformations that have occurred in the structure of consumption by categories according to socioe-conomic strata, the evolution of consumption quotas shows changes in the structure of consumption. There is a shift towards energy consumption and related communication, both in equipment and especially in services, this increase being more accentuated in the lower income classes. On the other hand, the consumption shares dedicated to *Clothing*, *Vacations* and *Leisure* lost weight, the sharpest drop is due to the crisis due to the pandemic.

In sum, as evidenced by Figures 1–11 and Table 2, the 2008 recession entailed more prolonged declines in consumption, while the pandemic caused a more abrupt and generalized impact across all strata, with sharp reductions in *Food away from Home, Clothing, Vacations, Leisure Services,* and *Transportation,* and increases in *Food at Home, Home Energy, Leisure Equipment, Communication Services, Use of Personal Car,* and *Public Transportation.*

Lower strata devoted a greater share of their budgets to essential goods (*Food at Home, Home Energy, Communication Equipment, Communication Services*), whereas higher strata primarily reduced discretionary expenditures (*Food away from Home, Clothing, Vacations, Leisure Services*). Indeed, some products displayed resilience or growth, such as *Food at Home, Home Energy,* and *Communication Services,* while others proved vulnerable, notably *Food away from Home, Clothing, Vacations, Leisure Services,* and *Public Transportation,* with a marked substitution from leisure services to leisure equipment in 2020.

The results reveal a narrowing of differences in essential goods (e.g., *Food at Home, Communication Services*), but an expansion in certain discretionary categories (e.g., *Vacations, Leisure*).

Directly addressing the hypotheses: The results confirm the relative stability or growth of essential goods such as *Food at Home, Home Energy,* and *Communication Equipment and Services,* contrasted with widespread declines in non-essential goods, such as *Food away from Home, Clothing, Vacations, Leisure Services,* and *Public Transportation* (see Figures 1–7). H1 is confirmed.

Households with lower Permanent Income devoted more than 25% of their budget to *Food at Home* in strata D and E, compared to less than 15% in strata A and B (except during the pandemic). A similar pattern emerges in *Home Energy*, while upper strata A and B show larger reductions in leisure, vacations, and clothing (Table 2). H2 is empirically supported.

In 2020, much sharper declines were observed in *Vacations, Leisure Services,* and *Transportation* (both public and private) (Figures 5, 7, 10, and 11). H3 is confirmed.

The pandemic accelerated the digitalization of consumption, increasing expenditures on *Communication Equipment* and, more markedly among middle- and lower-income classes, on *Communication Services* (Figures 8 and 9). H4 receives partial empirical support.

As hypothesized in H5, the disparity between strata narrowed in essentials and widened at the top end in discretionary products during the pandemic. Greater dispersion is observed in stratum E for food and communication, and greater variability in higher strata for vacations and leisure.

The gap between strata narrowed in essential goods (e.g., *Food at Home*, with the A–E difference shrinking from 21 points in 2008 to 14 in 2020), whereas in discretionary goods higher strata adjusted more strongly during the pandemic (Table 2). The evidence for H5 is mixed and category-specific

For all strata, the pandemic led to sharp declines in leisure services and increases in leisure equipment, consistent with confinement and greater time spent at home (Figures 6 and 7). H6 is confirmed.

Finally, consistent with H7, car use rose in 2008 and declined across all strata in 2020. The sharper collapse in public transportation suggests a preference for private vehicles whenever possible (Figures 10 and 11).

But perhaps the most interesting contribution of this work, and from which, in our opinion, important implications for policymakers are derived, is the quantification of the effects of the two economic crises that occurred in this century, which can contribute to understanding the more or less successful of the political decisions that were taken during these events on the socioeconomic well-being of citizens in terms of mobility between the different strata and consumption of different categories of products. As has been shown, the consequences on mobility and the drop in product consumption turned out to be much more drastic and with greater consequences in the 2020 crisis than in the 2008 crisis. The adjustments and economic policies in the first crisis were much harder and affected the socioeconomic well-being of citizens to a greater extent than the policies adopted during the pandemic crisis, less oriented towards spending and investment cuts and more social policies to maintain employment and consumption. This is reflected in a lower inequality between strata according to the findings obtained.

However, we must consider an important limitation of this work and that is that the data series allows us to examine the immediate and more delayed effects of the 2008 crisis, while to examine the effects of the crisis of the pandemic of COVID-19 we only have data for one year. Future research should corroborate our findings and their evolution over time with consumption data several years after the pandemic.

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Relationship Marketing Today and Tomorrow: Insights from the Intellectual Legacy of Wagner A. Kamakura

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Abstract

This chapter provides a comprehensive overview of the current state and future evolution of relationship marketing (RM) through the intellectual legacy of Wagner A. Kamakura. Moving beyond its traditional focus on loyalty and retention, RM is conceptualized as a complex, data-driven system in which firms orchestrate customer relationships at scale across multiple channels, platforms, and touchpoints. The chapter highlights how digitalization, artificial intelligence (AI), and the proliferation of data have transformed RM into a real-time, multi-actor process, encompassing both B2C and B2B contexts. Drawing on Kamakura's foundational contributions—particularly in modeling heterogeneity, advanced segmentation, and customer value measurement—the chapter argues that these ideas constitute a critical analytical infrastructure for contemporary RM. At the same time, it identifies key tensions shaping the discipline, including personalization versus privacy, automation versus trust, and efficiency versus relational sustainability. The chapter examines current practices in B2C and B2B settings, emphasizing the rise of extreme customization, omnichannel interaction design, and network-based relationship management. Finally, it proposes a forward-looking research agenda focused on AI-enabled capabilities, hybrid human–AI relationships, privacy-constrained personalization, and causal approaches to RM. As key idea, in this chapter we propose RM as an evolving discipline that requires the integration of analytical rigor, managerial relevance, and long-term relational value—principles that define Kamakura's enduring legacy.

Keywords: Relationship marketing (RM); Customer value measurement; Unobserved heterogeneity; Artificial intelligence in marketing; Customer relationship management (CRMic crisis, COVID-19 pandemic, Household budget, Spain

1. Introduction: Why Relationship Marketing remains a relevant strategic pillar

In recent years, Relationship Marketing (RM) has maintained a prominent role. However, what we currently understand as RM differs substantially from its original formulation, which was primarily focused on loyalty, repeat purchase, and relationship duration. In an environment characterized by digitalization, the proliferation of platforms, automation driven by artificial intelligence (AI), and increasing interdependence among actors, market relationships have evolved from simple bilateral ties into complex, dynamic, and multi-actor systems.

Today, firms manage relationships at scale: millions of customers in B2C contexts and thousands of strategic accounts in B2B settings, interacting in real time across multiple touchpoints, channels, and devices. This reality has profoundly transformed the nature of RM, shifting the focus from individual interactions to the orchestration of relationships, where data, technology, organizational processes, and strategic decisions are interdependently intertwined.

The name of **Wagner A. Kamakura** will always be closely associated with RM. His contributions have been—and continue to be—foundational for understanding its evolution, particularly in explaining unobservable consumer behavior and the value, for firms, of anticipating changes in such behavior. In this context, revisiting his intellectual legacy is especially timely. His work has played a decisive role in providing marketing with a solid analytical foundation to understand customer heterogeneity, measure relationship value, and link methodological rigor to managerial decision-making. Far from being merely a historical reference, Professor Kamakura's ideas constitute a powerful intellectual framework for addressing contemporary challenges in RM.

Accordingly, this chapter pursues a dual objective. First, it offers a concise overview of the current state of RM in both B2C and B2B contexts, addressing key phenomena such as advanced personalization, data management, relational sustainability, and the intensive use of AI-based technologies. Second, it proposes a future research agenda which, inspired by the spirit of Professor Kamakura's work, combines analytical rigor, practical relevance, and a clear long-term orientation.

2. Relationship Marketing as a system: From interaction to the orchestration of relationships

One of the main transformations in RM has been the shift from viewing relationships as discrete ties to understanding them as complex systems of dynamic interaction. Traditionally, RM has been built around constructs such as satisfaction, trust, and commitment as key drivers of relationship continuity. However, in the current context, these elements—while still necessary—are insufficient to fully capture the complexity of contemporary relationships.

This shift is largely driven by the structural transformation of markets. Digitalization, the proliferation of channels, platform intermediation, and the development of AI-based technologies have profoundly altered the nature of interactions between firms and customers. In this new environment, relationships no longer evolve through linear sequences of contacts, but rather through interconnected networks of interactions that develop nonlinearly and in real time (e.g. Verhoef et al., 2015).

From this perspective, RM can be understood as a process of orchestrating relationships, in which firms manage multiple touchpoints—both physical and digital—in an integrated manner to build consistent and sustainable experiences over time. This approach implies a significant shift in managerial logic: it is no longer sufficient to respond to individual interactions; instead, firms must design systems that jointly coordinate decisions related to content, service, pricing, communication, and user experience. The following elements help define this context:

Relationships at scale and in real time. One of the defining features of contemporary RM is scale. In B2C contexts, firms simultaneously manage millions of relationships, whereas in B2B environments, the number of relationships is smaller but typically deeper. In both cases, interactions occur in real time, requiring analytical and operational capabilities to process large volumes of information and translate them into immediate decisions.

This reality introduces a central challenge: the impossibility of managing all relationships in a homogeneous manner. Scale requires prioritization, segmentation, and efficient resource allocation. Here, the legacy of Professor Kamakura becomes particularly relevant, as it provides tools to model customer heterogeneity and design differentiated strategies based on customer value and behavior (Kamakura and Russell, 1989; Kamakura et al., 2005). In other words, managing relationships at scale does not eliminate the need for personalization; rather, it makes it more analytically demanding.

Omnichannel management and relational complexity. Omnichannelness has been one of the main catalysts of this transformation. Customers interact with firms by combining multiple channels, which significantly influence both the quality and profitability of the relationship (Neslin et al., 2006). However, as empirical evidence shows, more channels do not necessarily lead to better outcomes. In a study we conducted with Professor Kamakura (Cambra-Fierro et al., 2016), we demonstrated that certain multichannel interaction patterns can even reduce customer profitability, highlighting the need to manage relational complexity rather than simply expanding it.

This finding has important implications. Instead of maximizing the number of interactions, firms should focus on optimizing channel combinations, taking into account both the value generated and the associated costs. In this way, omnichannel management ceases to be an objective in itself and becomes a strategic design problem, where efficiency and relational coherence play a central role.

Extreme customization and automation. Advances in analytics and AI technologies have enabled unprecedented levels of personalization. In B2C contexts, this translates into the ability to tailor offers, content, and experiences at the individual level. In B2B settings, customization materializes in client-specific solutions that integrate products, services, and organizational processes.

However, this evolution toward extreme customization also introduces new challenges. On the one hand, it increases operational complexity and dependence on algorithmic systems. On the other, it raises concerns related to intrusiveness, privacy loss, and the potential emergence of biases in decision-making. The literature on AI in marketing suggests that the value of these technologies depends not only on their predictive capabilities but also on their responsible integration into organizational processes and their impact on customer trust (e.g. Davenport et al., 2020; Huang and Rust, 2021).

From a RM perspective, this implies that personalization should not be viewed merely as a technical issue, but as a strategic one that directly affects relationship quality. In this regard, heterogeneity once again plays a key role: not all customers value personalization equally, nor do they respond uniformly to its intensity.

Data, governance, and relationship sustainability. The functioning of contemporary RM relies heavily on the availability and use of data. However, access to such data is increasingly constrained by regulatory restrictions and growing societal concerns about privacy. This context calls for a rethinking of the relationship between data and relational value.

Data management is no longer a purely technical issue; it has become a central element of relationship governance. Firms must design systems that are not only analytically efficient but also legitimate from an ethical and social perspective. This entails establishing mechanisms of transparency, control, and fairness that help reinforce customer trust.

From this perspective, RM becomes embedded within a broader vision of sustainability. In this context, relational sustainability refers to the ability to maintain long-term, mutually beneficial relationships without eroding trust or generating negative long-term effects. This approach connects with the notion of "super phenomena" in marketing, where sustainability and development emerge as overarching frameworks for the discipline (Achrol and Kotler, 2012).

3. Wagner A. Kamakura's legacy as an intellectual foundation and guiding thread of contemporary Relationship Marketing

The development of RM cannot be understood without the parallel advancement of analytical tools that have enabled the modeling of customer behavior, the identification of heterogeneity, and the linkage of these differences to strategic decision-making. In this regard, Professor Kamakura's contribution is particularly significant—not only due to his specific research contributions, but also because he helped shape a way of approaching marketing problems that today constitutes a true intellectual foundation for contemporary RM.

Rather than focusing on a single line of inquiry, Professor Kamakura's work articulates a coherent set of contributions that converge toward a common objective: to understand and manage customer heterogeneity in a rigorous and actionable manner. This perspective is especially valuable in the current context, where the complexity of relationships requires analytical approaches capable of translating data into decisions.

Heterogeneity as a structural principle of RM. One of the fundamental pillars of Professor Kamakura's work is the treatment of heterogeneity as a structural element of consumer behavior. Instead of considering differences across customers as residual variability, his research demonstrates that such heterogeneity must be explicitly modeled in order to properly understand market dynamics.

The work of Kamakura and Russell (1989) provides a paradigmatic example in this regard, proposing a probabilistic model that integrates segmentation through the identification of heterogeneity, price sensitivity, and competitive structure. This approach allows for the characterization of segments that differ not only in preferences, but also in their response to the marketing mix, thereby laying the foundations for differentiated customer management. This line of research, sustained over time, has contributed to a deeper understanding of consumers (enabling greater personalization) and to the transformation of transactional data into relational insights for firms (Kamakura and Kwak, 2020).

In the context of RM, this idea becomes even more relevant. Relationships differ not only in duration, but also in intensity, profitability, and development potential. As shown by Mittal and Kamakura (2001), the relationship between satisfaction and behavior is not homogeneous, but depends on individual factors that shape customer responses. This evidence challenges the validity of aggregate models and reinforces the need for relational approaches grounded in the identification of heterogeneity.

Segmentation and latent modeling: from instrumentation to action. Another central dimension of Professor Kamakura's contribution lies in the development of advanced segmentation techniques that capture latent structures in consumer behavior. The use of latent modeling—combining descriptive and predictive techniques with concomitant variables (Kamakura et al., 1994)—represents a significant advancement, as it links consumer preferences to observable characteristics that facilitate identification and targeting.

Such approaches are particularly relevant for contemporary RM, where personalization and efficient resource allocation depend on the ability to identify actionable segments. Rather than pursuing indiscriminate personalization, these models enable the design of differentiated relational strategies based on behavioral patterns and responses to marketing actions.

Similarly, the work of Kamakura, Kim, and Lee (1996) extends this perspective by introducing the idea that consumers differ not only in their preferences, but throughout the entire decision-making process. This contribution is especially relevant for RM, as it implies that strategies must be adapted not only to the "what" of customer behavior, but also to the "how" of decision-making.

Analytical CRM and customer value: the relationship as an asset. As the development of RM has been closely linked to the evolution of CRM and the availability of large-scale data, the work of Kamakura et al. (2005) on the application of choice models to CRM is particularly relevant. It proposes that relational decisions should be structured around the customer lifecycle (acquisition, development, and retention).

This approach introduces a clearly longitudinal logic into relationship management, where customer value becomes the central decision criterion. The incorporation of metrics such as customer lifetime value (CLV) and share of wallet enables the evaluation of marketing actions not only in terms of immediate outcomes, but also in relation to their contribution to long-term relational value.

In the same vein, research on cross-selling opportunities based on mixed data models (Kamakura et al., 2003) highlights the importance of integrating multiple sources of information to improve relational decision-making. These contributions anticipate many current analytical CRM practices, in which the combination of transactional, behavioral, and attitudinal data allows for the design of more precise and effective strategies.

From modeling to decision-making: bridging rigor and relevance. Beyond his methodological contributions, one of the most remarkable aspects of Professor Kamakura's work is his ability to connect analytical rigor with managerial decision-making. Unlike purely descriptive approaches, his models are designed to inform concrete decisions related to segmentation, targeting, pricing, and customer portfolio management.

This emphasis on applicability is particularly relevant in the current context, where increasingly sophisticated analytical tools do not always translate into better decisions. The growing adoption of AI and machine learning technologies has expanded analytical possibilities, but has also introduced new challenges in terms of interpretability, transparency, and alignment with strategic objectives.

Taken together, his legacy offers a clear guiding principle: methodological sophistication is only valuable to the extent that it enhances the quality of decision-making. This principle is particularly pertinent for contemporary RM, where the integration of data, models, and decisions lies at the core of relationship management.

From legacy to present: implications for contemporary RM. Professor Kamakura was a pioneer in seeking to understand not only what customers will purchase, but also when they will do so and in what sequence. The relevance of his work for contemporary RM manifests across multiple dimensions. First, his emphasis on identifying unobserved heterogeneity provides a solid foundation for developing personalization and segmentation strategies in complex environments. Second, his methodological contributions enable the addressing of current challenges related to data integration, behavior prediction, and efficient resource allocation.

Finally, his focus on customer value and long-term decision-making is especially pertinent in a context where firms must balance operational efficiency with the sustainability of relationships. Contemporary RM can, to a large extent, be understood as a natural extension of his ideas, adapted to an environment characterized by digitalization, automation, and increasing interaction complexity.

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4. The current state of Relationship Marketing in B2C contexts: Personalization, orchestration, and structural tensions

As noted earlier, RM in B2C markets has undergone a significant transformation in recent decades, evolving from systems focused on database management and campaign execution to more complex approaches based on the holistic orchestration of customer relationships. This transformation has been primarily driven by digitalization, the massive availability of data, and the development of advanced analytical technologies that enable firms to understand and anticipate consumer behavior with unprecedented granularity.

RM is therefore no longer limited to managing discrete interactions; instead, it focuses on designing and coordinating complete relational trajectories (customer journeys) that integrate multiple touchpoints. These include not only marketing communications, but also elements such as user experience, service, content, pricing, and interaction through digital platforms. In this way, the relationship is configured as a continuous process in which each interaction influences the customer's overall perception and future behavior. Several key observations help to better understand this phenomenon.

From personalization to extreme customization. One of the most distinctive features of RM in B2C contexts is the move toward increasingly sophisticated levels of personalization. The ability to tailor offers, content, and experiences at the individual level has become a competitive standard across many industries. This evolution has led to what can be described as extreme customization, where the value proposition is dynamically adjusted to the specific characteristics and behaviors of each customer.

From a relational perspective, this phenomenon has a dual nature. On the one hand, extreme customization can increase the perceived relevance of the offering, reduce friction in interactions, and strengthen the customer relationship. On the other hand, it introduces significant challenges in terms of operational complexity, costs, and customer perceptions. Not all customers value intensive personalization equally, nor do they respond uniformly to it, reinforcing the need for heterogeneity-based approaches, in line with the foundational work of Kamakura and Russell (1989).

Moreover, excessive personalization may generate perceptions of intrusiveness, particularly when customers feel that the use of their data exceeds their expectations or infringes on their privacy. In this sense, personalization ceases to be a purely technical issue and becomes a central concern in relationship management.

Omnichannel management and relational interaction design. Omnichanelness represents another key pillar of contemporary RM in B2C contexts. Customers interact with firms through multiple channels—physical stores, mobile applications, social media, and digital platforms—and expect a consistent experience across them (Neslin et al., 2006). However, managing this diversity of channels is far from straightforward.

As we showed in Cambra-Fierro et al. (2016), participation across multiple channels does not necessarily lead to higher customer profitability. In certain contexts, increased interaction complexity may even reduce the value generated, due to higher costs associated with specific channels or inefficiencies in relationship management. This finding challenges the notion that omnichannel strategies should be maximized without constraints and highlights the importance of strategically designing channel combinations.

From this perspective, RM in B2C should be understood as an **interaction optimization** problem, where firms must balance customer experience with operational efficiency. This involves identifying which channel combinations generate the greatest value, for which types of customers, and under which circumstances.

Artificial intelligence and relationship automation. The development of AI has significantly expanded the capabilities of RM in B2C contexts. Machine learning systems enable the analysis of large volumes of data, the prediction of behaviors, and the automation of decisions in real time. These advances have facilitated the implementation of large-scale personalization strategies and the optimization of multiple aspects of the customer relationship.

However, the integration of AI also introduces new challenges. As noted by Davenport et al. (2020) and Huang and Rust (2021), the value of AI in marketing depends not only on its technical capabilities, but also on how it is integrated into organizational processes and its impact on customer experience. In particular, excessive automation may erode perceptions of closeness and trust—two fundamental elements of RM. In this regard, the future of RM in B2C contexts appears to lie in hybrid models in which AI and human intervention complement each other. The key is not to replace the relationship manager, but to enhance decision-making capabilities through advanced analytical tools.

Data, privacy, and trust as relational pillars. Data availability constitutes the foundation of contemporary RM. However, access to and use of such data are increasingly shaped by regulatory and societal factors. Growing concerns about privacy have led to the implementation of stricter regulations, as well as shifts in consumer expectations.

From a relational perspective, data management becomes a central element in building trust. Customers evaluate not only the quality of the offering, but also how firms use their information. Transparency, control, and fairness in data usage thus become critical determinants of relationship sustainability.

This context introduces an additional challenge: how to maintain high levels of personalization in environments where data access is restricted. This issue opens new avenues for research related to personalization under uncertainty and the design of relational strategies based on partial information.

Relational sustainability in B2C markets. Finally, RM in B2C contexts must be situated within a broader sustainability framework. Beyond its traditional dimensions, relational sustainability refers to the ability of firms to maintain long-term relationships without generating negative effects on customers or the broader environment.

Excessive commercial pressure, overstimulation, and hyper-personalization may erode relationship quality over time. Consequently, RM must evolve toward models that prioritize the creation of sustainable value, in line with approaches that integrate economic, social, and environmental objectives into marketing management (White et al., 2019).

5. The current state of Relationship Marketing in B2B contexts: Complexity, customization, and value networks

Unlike consumer markets, where scale represents the primary challenge, RM in B2B contexts is characterized by a significantly higher level of structural complexity. Relationships are not established between isolated individuals, but between organizations, and they evolve across multiple levels, actors, and decision-making processes. In this sense, B2B RM cannot be understood merely as the management of firm–customer ties, but rather as the management of complex relational systems involving multiple stakeholders.

The relationship as a portfolio of strategic accounts. One of the defining features of B2B RM is its orientation toward customer portfolio management. Rather than treating each relationship independently, firms manage portfolios of accounts that differ in terms of value, growth potential, stability, and risk.

This approach is closely aligned with the value-based logic developed in the RM and CRM literature. The use of metrics such as customer lifetime value (CLV) and share of wallet enables firms to prioritize relational investments and allocate resources efficiently. In this regard, Professor Kamakura's contribution is particularly relevant, as it provides analytical tools to estimate customer value and guide strategic decisions based on that value (Kamakura et al., 2005).

However, in B2B contexts, these metrics require important adaptations. Customer value depends not only on past behavior, but also on factors such as contract duration, mutual dependence, opportunities for joint innovation, and the customer's position within broader networks. This reinforces the need for dynamic and longitudinal approaches to relationship management.

Multi-actor relationships and buying centers. A fundamental characteristic of B2B RM is the presence of buying centers—groups of individuals within the client organization involved in the decision-making process. These actors may have different interests, incentives, and perceptions, adding an additional layer of complexity to the relationship.

From a relational perspective, this implies that firms do not manage a single relationship, but rather a set of interconnected relationships with different actors within the client organization. The stability and development of the relationship depend largely on the firm's ability to understand and manage these internal dynamics.

Consequently, the concept of heterogeneity takes on a new dimension. Differences exist not only across customers, but also within each customer organization. This reality requires analytical tools capable of capturing such complexity and translating it into differentiated relational strategies, in line with the modeling tradition developed by Professor Kamakura.

Extreme customization and value co-creation. Customization has historically been a central feature of B2B marketing. Today, it has reached unprecedented levels, driven by digitalization and the integration of advanced technologies. Firms develop customer-specific solutions that integrate products, services, processes, and, in many cases, joint innovation. This extreme customization results in highly idiosyncratic relationships, where value is co-created through continuous interaction between supplier and customer.

However, this approach also raises important challenges. Intensive customization may generate mutual dependence, increase management costs, and limit scalability. Moreover, not all relationships justify the same level of investment, reinforcing the importance of segmentation and value-based prioritization. From this perspective, B2B relationship marketing can be understood as a balancing problem between adaptation and efficiency, where firms must decide the appropriate level of customization for each relationship based on its strategic value.

Ecosystems, alliances, and network relationship marketing. One of the most significant trends in B2B marketing is the growing importance of business ecosystems. Relationships no longer develop exclusively between supplier and customer, but are embedded within broader networks that include technology partners, intermediaries, platforms, and other actors.

This phenomenon has given rise to what can be described as *network relationship marketing*, in which value creation depends on coordination among multiple interdependent actors. As a result, relationship management involves not only maintaining bilateral ties, but also orchestrating networks of relationships.

This evolution raises new theoretical and practical challenges. For example, how should the value of a relationship be measured when it is co-created within an ecosystem? How can power asymmetries between actors be managed? What role do platforms play in shaping B2B relationships?

Data, artificial intelligence, and sustainability in B2B contexts. As in consumer markets, data management and the use of AI are transforming RM in B2B settings. Firms rely on analytical systems to predict behaviors, optimize processes, and improve decision-making. However, the application of these technologies in B2B contexts presents important particularities. First, data availability is often more limited, requiring firms to operate with partial or incomplete information. Second, relational decisions typically involve higher levels of risk, which reduces the feasibility of full automation. Finally, trust and interpersonal relationships continue to play a fundamental role.

In this context, AI should be understood as a decision-support tool rather than a substitute for human interaction. The combination of data analytics and contextual knowledge is essential for managing complex, long-term relationships.

Finally, sustainability is gaining increasing relevance in B2B RM. Firms evaluate their suppliers not only in terms of price and quality, but also based on social, environmental, and governance criteria. This implies that relationship management must integrate sustainability considerations as part of the value proposition.

6. Disruptive elements: Tensions and limits of contemporary Relationship Marketing

The recent evolution of RM has been shaped by technological advances, regulatory changes, and shifts in consumer behavior. These developments have not only expanded marketing capabilities but have also introduced a set of structural tensions that challenge some of the fundamental assumptions upon which the discipline has traditionally been built.

Rather than representing merely operational challenges, these issues affect the very nature of the relationship between firms and customers, prompting a rethinking of key concepts such as personalization, trust, value, and relational sustainability. As a result, contemporary RM operates in an environment characterized by greater capabilities, but also by increased constraints and responsibilities.

Artificial intelligence and automation: More efficient but less human relationships? The integration of AI into marketing processes has significantly enhanced firms' ability to analyze data, predict behavior, and automate decisions. In the context of RM, this translates into the capacity to manage interactions at scale and in real time, tailoring offerings to individual customer characteristics.

However, this increased efficiency raises a fundamental question: to what extent can an algorithmically managed relationship preserve its human dimension? Automation can improve consistency and responsiveness, but it may also reduce perceptions of closeness, empathy, and authenticity—elements traditionally associated with relationship quality.

Recent literature suggests that the value of AI in marketing depends on its ability to complement, rather than replace, human intervention (Huang and Rust, 2021). The challenge is not to choose between automation and humanization, but to design hybrid models that integrate both dimensions in a way that is consistent with the type of relationship and the interaction context.

Privacy, data governance, and relational legitimacy. Contemporary RM relies heavily on access to and use of data. However, such access is increasingly constrained by regulatory restrictions and heightened societal sensitivity to privacy, creating a fundamental tension between personalization capabilities and respect for consumer rights.

Data management is no longer merely a technical issue; it has become a central element of relational legitimacy. Customers evaluate not only the quality of the offering, but also how firms use their information. Transparency, control, and fairness in data usage thus become key determinants of trust. This shift requires a rethinking of RM models. Rather than maximizing data usage, firms must design strategies based on a balance between personalization and privacy, where the value generated for the customer justifies the use of their information.

Algorithmic bias and fairness in relationship management. The use of algorithms in segmentation and personalization entails the risk of reproducing or amplifying biases present in the data. Such biases may lead to decisions that, while economically efficient, are problematic from an ethical and relational perspective. This issue is particularly relevant in RM, as these decisions directly affect how customer relationships are managed. The allocation of offers, the prioritization of resources, and the personalization of experiences may generate inequalities in the treatment of different customer segments.

Consequently, algorithmic fairness becomes a key element of relational sustainability. Relationships perceived as unfair or discriminatory are difficult to sustain over the long term, highlighting the need to develop more transparent and explainable models.

Signal quality and contaminated information environments. Contemporary RM relies on multiple sources of information, including transactional, behavioral, and user-generated data. However, the increasing proliferation of digital content has given rise to increasingly complex—and often contaminated—information environments. The presence of fake reviews, manipulated content, and artificially generated information introduces noise into the signals used for decision-making. This affects both market research and relationship management, as decisions based on unreliable information may lead to errors in segmentation, personalization, and customer evaluation.

This issue poses an important methodological challenge: how to distinguish between reliable and contaminated signals in environments characterized by information abundance. In this regard, RM must develop tools that allow for the assessment of data quality and more effective management of uncertainty.

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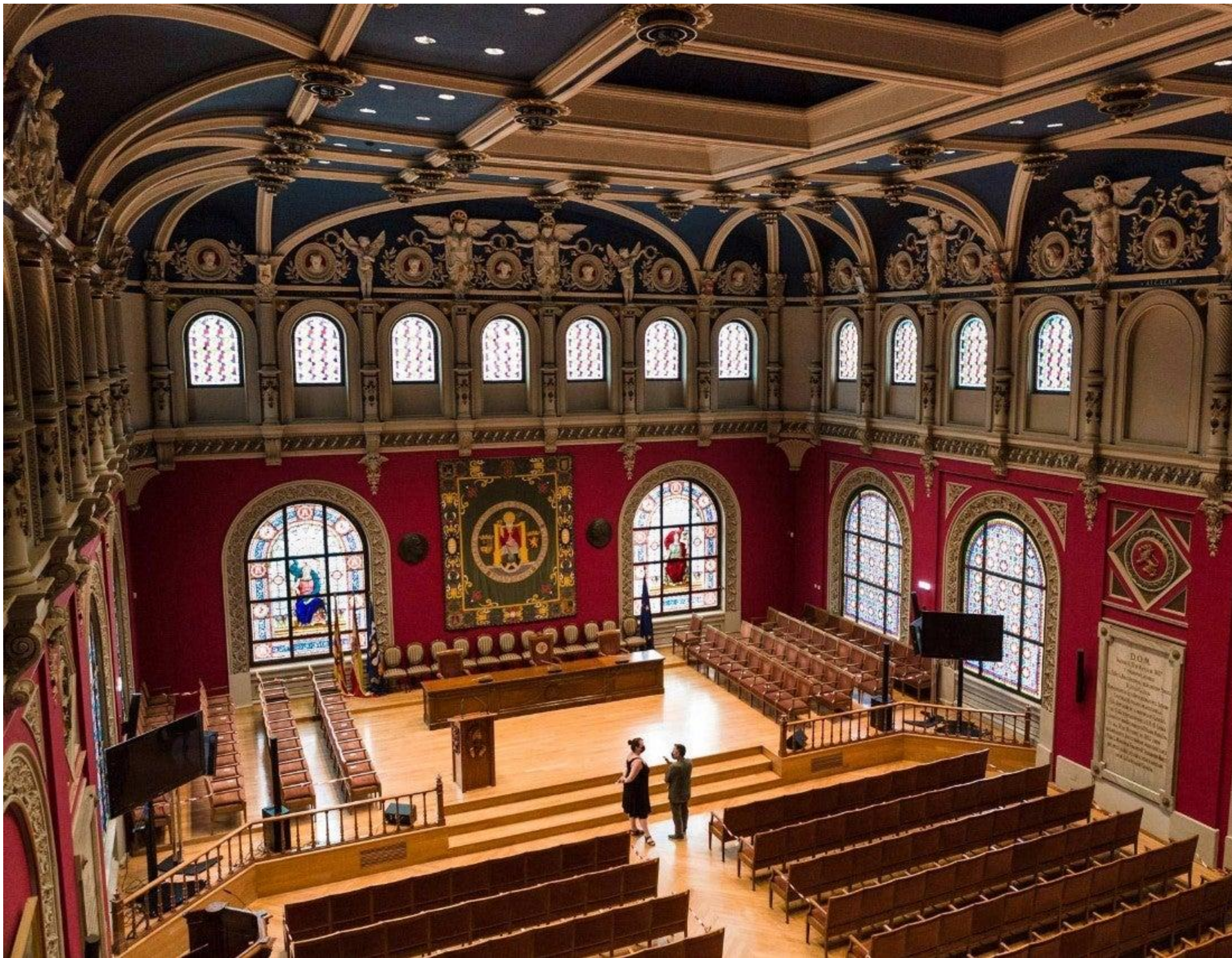

Platforms, power, and relational dependence. The growing importance of digital platforms has transformed both market structures and the nature of relationships between firms and customers. In many cases, interactions no longer occur directly between the two parties, but are mediated by intermediaries that control access to customers, visibility of offerings, and available information. This intermediation introduces new power dynamics that affect firms' ability to manage their relationships. Dependence on platforms may limit access to key data, constrain marketing strategies, and reduce control over the customer experience.

Thus, RM must adapt to an environment in which relationships are no longer fully controlled by firms, but are mediated by actors with their own interests. This raises the need to develop strategies that account for these dynamics and enable effective relationship management under conditions of dependence.

Sustainability and the redefinition of relational value. Finally, contemporary RM faces a shift in how value is understood. Beyond its economic dimension, relational value increasingly incorporates social, environmental, and ethical considerations. Customers and organizations alike demand relationships that not only generate benefits, but are also aligned with sustainability principles.

This shift implies a redefinition of RM. The relationship is no longer merely a means to maximize economic value, but becomes a space in which shared values are constructed and negotiated. Consequently, relational sustainability is not an additional element, but a necessary condition for the long-term viability of relationships.

7. Future research agenda in Relationship Marketing: Toward an integrative and responsible approach

The analysis of the current state of RM, as well as the tensions shaping its evolution, highlights the need to advance toward a research agenda capable of integrating complexity, analytical rigor, and practical relevance. The future of RM does not lie solely in the adoption of new technologies, but in the development of conceptual and methodological frameworks that enable the understanding and management of relationships in increasingly dynamic, interdependent, and regulated environments.

Drawing on the intellectual legacy of Wagner A. Kamakura—characterized by rigorous modeling, decision orientation, and a strong emphasis on long-term value—we propose several research directions that may contribute to the advancement of RM in the coming years.

Relationship marketing as an AI-enabled organizational capability. One key avenue for future research is to conceptualize RM not merely as a set of practices, but as a dynamic organizational capability supported by AI. This perspective involves analyzing how firms integrate data, models, and processes to anticipate behavior, personalize interactions, and adapt strategies in real time.

From this viewpoint, AI should not be understood solely as a technological tool, but as a transformative element that reshapes how organizations develop and manage customer relationships. Future research should focus on identifying the capabilities required to effectively integrate AI into RM, and on how these capabilities influence long-term performance (Huang and Rust, 2021).

Human–AI hybrid relationships: trust, control, and interaction design. The increasing automation of interactions calls for a deeper examination of hybrid relationships involving both automated systems and human agents. A key question in this domain is under what conditions AI enhances relationship quality, and when it may instead undermine it.

This line of research requires analyzing factors such as perceived risk, decision complexity, customer vulnerability, and cultural context. It also calls for the development of models that support the design of interactions combining efficiency with relational closeness, thereby avoiding the dehumanization of relationships.

Relationship marketing under privacy constraints and limited data. The tightening of privacy regulations and growing customer concerns about data usage pose a fundamental challenge for RM. Consequently, there is a need to investigate how to design personalization and segmentation strategies in environments characterized by incomplete or restricted data.

This research direction is closely aligned with Professor Kamakura's modeling tradition, as it requires approaches capable of inferring behavioral patterns from partial information. It also calls for the development of frameworks that incorporate the notion of data value exchange, examining how perceptions of fairness and transparency influence customers' willingness to share information.

Relational resilience in complex information environments. The proliferation of digital content and the emergence of phenomena such as misinformation and artificially generated content introduce new challenges for RM. In this context, it becomes essential to investigate how firms can maintain robust relationships in environments characterized by informational uncertainty.

This line of research involves developing tools to assess the quality of the signals used in decision-making, as well as models that enable firms to manage uncertainty and mitigate the impact of inaccurate or manipulated information on customer relationships.

Relationship marketing in B2B ecosystems and value networks. In B2B contexts, a key avenue for future research lies in the study of RM within business ecosystems. As relationships become embedded in broader networks of interdependent actors, there is a growing need for conceptual frameworks that explain value creation in these settings.

In particular, research should address issues such as the measurement of relational value within networks, the management of interdependencies among actors, and the role of platforms in shaping B2B relationships. This perspective represents a natural extension of relational logic toward more complex, network-based models.

Fairness and transparency in algorithmic relationship marketing. The use of algorithms in relationship management raises important concerns regarding fairness and transparency. Future research should examine how segmentation and personalization systems can be designed to avoid discrimination and ensure equitable treatment of customers. This approach requires not only technical improvements in modeling, but also the development of mechanisms that enable firms to explain and justify their decisions. Transparency thus becomes a key element in ensuring the sustainability of RM.

***Customer insights* as a driver of relational innovation.** Traditionally, customer insights have been primarily used for product development. However, in the current context, these insights can play a critical role in reshaping customer relationships.

Future research should explore how information about customer behavior and preferences can be leveraged to design new forms of interaction, service models, and relational experiences. This perspective connects relationship marketing with innovation, expanding its scope beyond the management of existing relationships.

Causality, experimentation, and dynamic models in relationship marketing. Finally, one of the most important areas for advancing RM lies in the development of causal and experimental approaches that enable the evaluation of the true impact of marketing actions. Most existing models rely on correlational relationships, which limits their ability to inform strategic decision-making.

Future research may focus on the design of field experiments, uplift models, and dynamic approaches that allow for the estimation of the incremental effects of relational interventions. This direction is consistent with Professor Kamakura's tradition, emphasizing the role of models in supporting decision-making.

8. Conclusion: From heterogeneity to managing relationships at scale

The discussion developed throughout this chapter highlights that RM is undergoing a profound transformation. Far from being confined to its original conception, contemporary relationship marketing has evolved into a complex system for managing interactions, where data, technology, organizational processes, and strategic decisions converge.

In this context, relationships are managed at scale, in real time, and within environments characterized by omnichannelness, platform intermediation, and the growing importance of AI. However, this expansion of capabilities has not eliminated the inherent tensions of relationship marketing; rather, it has intensified them. Personalization now faces the limits of privacy, automation raises questions about relationship quality, and data availability is increasingly shaped by regulatory constraints and heightened societal sensitivity.

As argued throughout the chapter, these transformations do not represent a rupture with classical RM, but rather an evolution that requires a reinterpretation of its foundational principles in light of new contexts. In this regard, the legacy of Wagner A. Kamakura becomes particularly relevant. His contributions have provided conceptual and methodological tools to address core challenges of contemporary RM, including the identification of customer heterogeneity, actionable segmentation, the measurement of relational value, and the connection between analysis and decision-making.

Managing relationships at scale does not eliminate heterogeneity; it makes it more visible and more relevant. The availability of data does not replace the need for modeling; it reinforces it. Moreover, technological sophistication does not reduce the importance of decision-making; it demands greater rigor in its foundations. From this perspective, the future of RM will depend not only on the adoption of new technologies, but also on the discipline's ability to integrate these tools into robust, action-oriented conceptual frameworks. This implies moving toward a form of RM that is simultaneously analytically rigorous, strategically relevant, and socially responsible.

In this sense, Professor Kamakura's most enduring legacy lies not only in his specific contributions, but in his broader understanding of marketing as a discipline in which analytical rigor and practical relevance are not competing objectives, but complementary ones. In an environment characterized by complexity, uncertainty, and continuous transformation, this perspective provides a particularly valuable guide for the future development of RM.

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How brand prestige and wine involvement shape destination image and willingness to visit: The case of La Rioja

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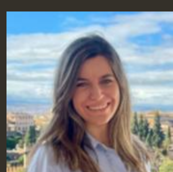

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Abstract

In a highly competitive tourism context, territorial brands play a key role in shaping travelers' perceptions and behaviors. This study analyzes the influence of the image of the 'La Rioja' destination, measured through the evaluations of the brands 'Rioja' and 'Haro, capital of Rioja', as well as the effect of prestige of the Rioja Designation of Origin and the experience or involvement in wine consumption on visit intention. Based on a questionnaire administered to 104 participants and using structural equation modeling (PLS-SEM), direct, indirect, and mediating relationships among the constructs are examined. The results show that both the prestige of Rioja wine and the wine involvement positively influence the destination's brand perception or image. Furthermore, brand image is the main determinant of the willingness to visit La Rioja. However, the prestige of Rioja wine does not have a significant direct effect on this willingness, confirming total mediation through brand image. In contrast, wine involvement exerts a complementary partial mediation. These findings highlight the relevance of territorial branding in wine tourism contexts and underscore the importance of strategically managing wine-related brands to strengthen the destination's positioning. The study offers relevant implications for public managers, wineries, and tourism promotion agencies.

Keywords

Wine tourism; place branding; destination brand image; wine prestige; visit intention.

Acknowledgments

This chapter is dedicated to Wagner A. Kamakura, whose pioneering research in wine marketing has enriched our understanding of how consumers perceive and evaluate a product such as wine. Prof. Kamakura's work, particularly regarding consumer preferences, wine reviews, and product positioning, has provided valuable insights into the subtle interplay between taste, the" language, and perception. His studies, notably the influential «How to speak 'winese': Learning the language of wine reviews», employ innovative data-driven approaches to analyze consumer impressions, revealing how attributes such as flavor profiles and country of origin influence wine appreciation. In admiration of his rigorous analytical approach and his deep curiosity about the world of wine, we dedicate this exploration of the influence of the «Rioja» and «Haro, Capital of Rioja» brands on the tourist evaluation or image of La Rioja.

1. Introduction

In an increasingly globalized, digitized, and competitive tourism environment, destination choice has become a complex process involving functional, symbolic, and emotional factors. In this context, destination brands play a strategic role by influencing travelers' perceptions, evaluations, and preferences, acting as mechanisms for differentiation and reducing uncertainty in decision-making (Morgan et al., 2004; Konecnik & Gartner, 2007).

The importance of regional branding is particularly pronounced in specialized destinations such as those linked to wine tourism, a growing segment that has established itself as a driver of economic and cultural development in wine-producing regions around the world (Bruwer & Alant, 2009; Dominici et al., 2025). In the case of Spain, La Rioja is one of the leading examples in this field, where wine tourism has established itself as a strategic asset for the region. In 2023, the region welcomed 554,488 visitors, nearly doubling the number of international tourists compared to 2014 (INE, 2024), which highlights both its appeal and the need to understand the factors that explain why it is chosen over other competing destinations.

From a theoretical perspective, the literature on brand equity has shown that brands generate value beyond their functional attributes, incorporating symbolic, experiential, and emotional dimensions that influence consumer behavior (Aaker, 1991; Keller, 1993). In the tourism sector, this value translates into perceptions of authenticity, differentiation, and intention to visit (Pike & Bianchi, 2016). Likewise, recent research highlights the growing role of tourism experiences and digital environments in shaping these perceptions (Amaro et al., 2023; Stylidis et al., 2020; Scussel et al., 2022). But, in this very particular tourism context, involvement with wine or the experience of its frequent consumption can play an important role in the image of a wine brand.

In the case of 'La Rioja', the destination's positioning is closely linked to the international reputation of its wines bearing the Rioja Qualified Designation of Origin (DOCa, in Spanish). This association generates a reputational spillover effect from the product to the region, reinforcing its image as a tourist destination (Lockshin & Corsi, 2012). However, significant questions remain largely unexplored: to what extent is the prestige of the wine sufficient to motivate a visit, how do specific territorial brands such as 'Rioja' or 'Haro, capital of Rioja' influence the image of the destination, and what role does brand image play as an explanatory mechanism for visit intention.

Despite growing academic interest in destination branding and wine tourism, the literature presents three main gaps. First, there is a conceptual gap, as most studies analyze the destination's image in a general way, without addressing the role of specific territorial brands (Baloglu & McCleary, 1999). Second, a theoretical gap is identified regarding the limited understanding of the process of transferring product prestige to the destination, despite the development of theoretical frameworks on brand equity (Boo et al., 2009). Finally, a methodological gap is observed, given the limited use of models that simultaneously integrate direct, indirect, and mediating effects in wine tourism contexts (Rather, 2020).

Motivated by these gaps, this chapter pursues three objectives. First, to analyze the influence of the destination brand image on the willingness to visit La Rioja. Second, to examine the effect of the prestige of Rioja wine and the wine-related experience or involvement on the brand image. Third, to evaluate the mediating role of brand image in the relationship between these antecedents and visit intention or willingness.

Thus, this chapter contributes to the literature on place branding and wine tourism by providing an integrated analysis of the interaction between product prestige, the wine involvement, and destination brand image in shaping visitation intent. Specifically, the concept of brand image is operationalized as a composite territorial brand system, integrating the perceptions associated with both the "Rioja" and "Haro, Capital of Rioja" brands. Rather than treating these brands as isolated entities, we conceptualize them as complementary symbolic representations that jointly contribute to the overall destination image of La Rioja. This approach aligns with recent advances in place branding literature, which emphasizes the role of multi-level brand architectures in shaping holistic destination evaluations. It also offers relevant implications for the strategic management of wine tourism destinations in a highly competitive tourism environment.

2. Background: Literature review and socio-economic context

3.1. Rioja Qualified Designation of Origin

In 1892, the Haro Viticulture and Oenology Station (Estación Enológica de Haro, in Spanish) was established with the aim of improving and regulating wine quality, as well as supervising its international commercialization. Subsequently, in 1925, Rioja became the first Spanish wine-producing region to obtain an officially recognized Designation of Origin, following an earlier legal process to protect the name that had begun at the start of the twentieth century. One year later, in 1926, the Regulatory Council of the Rioja Designation of Origin was created. Over time, this institution has consolidated its role as the main authority responsible for ensuring compliance with regulations, certifying quality standards, and promoting the international projection of wines under the appellation.

In 1991, Rioja reached another milestone by becoming Spain's first Qualified Designation of Origin (DOCa; MAPA, 2023), a distinction that further strengthened its prestige and quality control requirements. The Rioja DOCa, is a supra-regional designation that extends across of part of the autonomous communities of Navarra and the Basque Country (Alava), covering a total area of nearly 67,000 hectares and encompassing 737 registered wineries, including both bottling and non-bottling producers (MAPA, 2023). According to the Regulatory Council of the Rioja DOCa (2025), the appellation celebrated its centenary while consolidating its position as a benchmark in the Spanish wine sector, with more than 312 million bottles marketed and a record 39.1% share of Spanish wine exports with designation of origin status (Interempresas, 2025; Europa Press, 2026). Rioja accounts for 24.1% of the total commercialization of Spanish Designations of Origin, followed by Cava (17.1%), Rueda (7.5%), Ribera del Duero (7.2%), and Valdepeñas (4.2%) (MAPA, 2023).

The production and commercialization of Rioja wine continue to represent a strategic pillar of the regional economy, constituting one of its main economic drivers. It not only generates significant export revenues but also sustains an extensive employment network throughout the entire value chain, from vineyard cultivation to distribution, commercialization, and activities linked to wine tourism. According to the most recent available data, the wine sector contributes more than 6.5% of La Rioja's Gross Domestic Product (GDP) and generates approximately 12,210 jobs, while maintaining a presence in 117 municipalities across the autonomous community (Interprofessional Wine Organization of Spain [OIVE], 2024). This reinforces its role in territorial cohesion and in preventing depopulation in rural areas. Furthermore, the region's total export activity reached €2.383 billion in 2024, with wine standing out as one of its main agri-food products (Europa Press, 2026) (see Figure 1).

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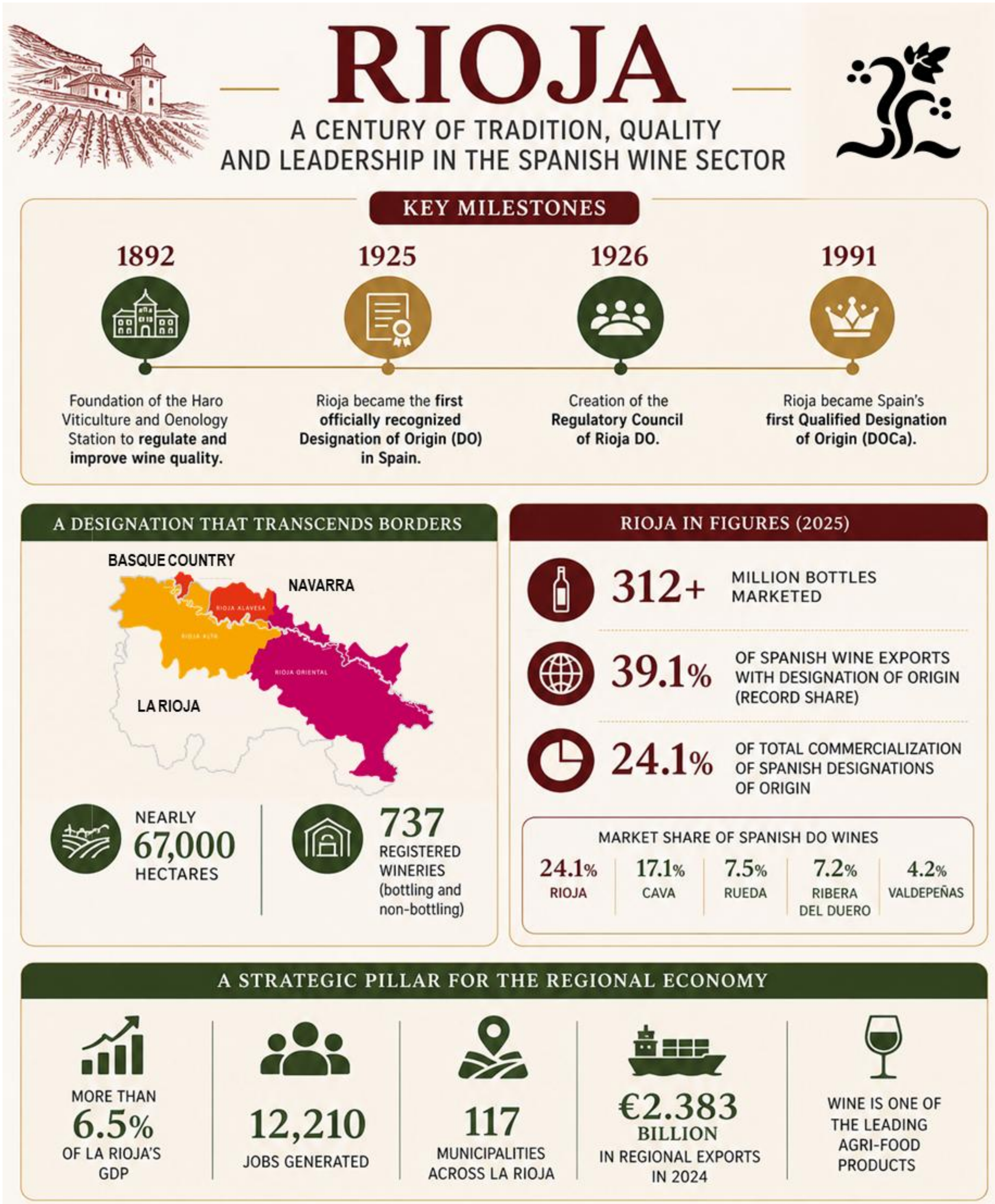
Figure 1. Most relevant data



Source: From Europa Press (2026), Interempresas (2025), MAPA (2023), OIVE (2024), and Regulatory Council of the Rioja DOCa (2025)

3.2. Wine tourism as a driver of regional competitiveness

Wine tourism has established itself as a form of experiential tourism in which wine serves as the central element of attraction and differentiation for the destination. Beyond visits to wineries or vineyards, it is an integrated experience that combines culture, gastronomy, landscape, and heritage, responding to the growing demand for authenticity and memorable experiences among contemporary tourists (Carlsen & Charters, 2006; Quadri-Felitti & Fiore, 2012).

From the perspective of territorial marketing, wine tourism constitutes a strategic tool for competitive positioning, as it allows wine-producing regions to differentiate themselves not only through product quality but also through the ability to build a coherent and attractive territorial identity (Getz & Brown, 2006). Wine acts as a driving force that revitalizes the local economy and strengthens complementary sectors such as gastronomy and hospitality (Bruwer & Alant, 2009).

In the case of La Rioja, the Qualified Designation of Origin represents a key asset of its tourism identity, as it associates the region with quality, tradition, and international prestige. This association strengthens its positioning in a highly competitive environment against other wine-producing regions, such as Bordeaux or Tuscany.

3.3. Wine prestige and image transfer to the destination

Marketing literature has shown that a product's positive attributes can be transferred to its region of origin through the so-called halo effect (Han, 1989). In this sense, the prestige of Rioja wine can influence evaluations or image of the destination by serving as a sign of quality and authenticity.

According to the Country-of-Origin theory, the region of origin acts as a cognitive shortcut in the evaluation of products and destinations, reducing consumer uncertainty (Verlegh & Steenkamp, 1999). This relationship is bidirectional: the image of the region influences the product, and, in turn, the product's prestige can reinforce the destination's image. Furthermore, Signaling Theory (Spence, 1973) suggests that, in tourism contexts where the experience cannot be evaluated in advance, reputational signals play a key role in decision-making.

Furthermore, the literature suggests that the perceived prestige of an iconic product can directly influence the intention to visit the associated destination by increasing its symbolic appeal, perceived social value, and cultural status (Um & Crompton, 1990; Sparks, 2007). Recent studies in wine tourism confirm that the prestige of the wine brand contributes to improving the destination's image and increasing visitation intent, especially when the product is internationally recognized (Loureiro & Cunha, 2017; Gómez-Rico et al., 2023).

Consequently, brands from the La Rioja region, such as 'Rioja' wine, which is internationally recognized, or 'Haro, capital of Rioja', can serve as a sign of the destination's quality and increase its appeal, leading to the following research hypotheses:

H1: The prestige of Rioja wine positively influences the destination brand image of La Rioja.

H2: The prestige of Rioja wine positively influences the willingness to visit La Rioja.

3.4. Wine product involvement and brand image

The concept of product involvement has been widely recognized as a key determinant of consumers' cognitive and affective responses toward brands and destinations. In addition, contemporary research on destination branding highlights that individual-level factors, such as prior experience and domain-specific knowledge, play a crucial role in shaping destination image by influencing how tourists interpret symbolic and experiential cues associated with the place (Stylidis et al., 2020; Rather, 2020), thereby strengthening its brand image. Furthermore, from an information-processing perspective, experienced consumers tend to develop more sophisticated cognitive structures, allowing them to interpret and integrate product-related cues more effectively into their overall evaluation of the destination (Lockshin & Corsi, 2012; Gómez-Rico et al., 2023).

In the context of wine tourism, wine product involvement reflects the degree of personal relevance, interest, and prior experience that individuals associate with wine as a product category. Individuals who are highly involved with wine are more likely to possess greater knowledge, familiarity, and emotional attachment to wine-related attributes, which enhances their ability to construct a richer and more elaborate evaluations, that is, a more favorable image of wine destinations such as La Rioja.

Empirical evidence supports this relationship between wine involvement and destination image formation. For instance, wine tourism research indicates that involvement with wine influences tourists' emotions, place attachment, and overall perceptions of the destination experience, reinforcing the role of involvement as a precursor to destination-related evaluations (Santos et al., 2017). Similarly, other studies have shown that wine product involvement significantly contributes to the development of both cognitive and affective components of destination image, which in turn shapes tourists' intentions (Wu and Lian, 2000). Moreover, segmentation studies reveal that tourists with higher levels of wine involvement exhibit distinct attitudes and pre-visit perceptions toward wine destinations, including more favorable brand-related evaluations (Nella y Christou, 2014). More recent studies further confirm that consumer prior expertise and familiarity with wine enhance destination-related perceptions and strengthen the link between product knowledge and destination evaluation (Gómez-Rico et al., 2022; Jiménez-García et al., 2025).

Therefore, building on this theoretical and empirical foundation, it can be argued that individuals with higher wine product involvement are more likely to develop stronger, more positive images of La Rioja's brands, as their prior knowledge, interest, and engagement with wine facilitate the formation of favorable cognitive and affective associations with the destination. Therefore, wine experience enhances product evaluation acting as an individual-level antecedent that amplifies the formation of destination brand image through more informed, meaningful, and structured perceptions, in line with recent advances in destination branding research. Consequently, the following hypothesis is proposed:

H3. The wine product involvement positively influences the destination brand image of La Rioja.

3.5. Brand image and intention to visit

Brand image represents the overall evaluation of a brand based on functional and emotional associations (Aaker, 1991; Keller, 1993). In tourism, it is a determining factor in the formation of attitudes and behaviors, acting as a key antecedent of variables such as visit intention (Konecnik & Gartner, 2007; Pike, 2017).

The literature on destination brand equity argues that destinations with positive brand perceptions are considered more attractive, authentic, distinctive, and trustworthy, which increases their likelihood of being chosen (Pike & Bianchi, 2016; Boo et al., 2009). In the case of wine tourism, this image is closely linked to attributes such as quality, authenticity, and cultural prestige (Loureiro & Cunha, 2017; Gómez-Rico et al., 2022). The territorial brands "Rioja" and "Haro, capital of Rioja" encapsulate these meanings, acting as cues that influence the willingness to visit the destination. Consequently, the following research hypothesis is proposed:

H4: The destination brand image of La Rioja positively influences the willingness to visit it.

3.6. Mediating role of brand image

The literature on consumer behavior, branding, and tourism marketing agrees that the effects of product and experience attributes on consumer decisions are rarely entirely direct. Instead, these effects are typically mediated by cognitive and affective evaluations that individuals construct regarding the brand or destination (Keller, 2013; Konecnik & Gartner, 2007). In this sense, brand image emerges as a central construct that integrates functional, symbolic, and emotional associations and acts as an explanatory mechanism for behavioral intention.

From this perspective, brand image not only reflects the destination's image but also translates external stimuli (such as the product's prestige or wine involvement) into more stable and meaningful overall evaluations. This process of cognitive integration reduces the complexity of information and facilitates decision-making in contexts of high uncertainty, such as the choice of tourist destinations (Stylidis et al., 2017).

In the field of wine tourism, this mediating function is particularly relevant due to the strong interrelationship between product, territory, and experience. The tourist experience in the destination, understood as a set of sensory, emotional, and social experiences, not only generates immediate satisfaction but also helps reinforce the destination's image through positive and memorable associations (Brakus et al., 2009; Pine & Gilmore, 1999). These experiences, when consistent with the destination's identity, become embedded in the tourist's mind as brand image, indirectly influencing their future intention to visit or recommend the destination.

At the same time, the prestige of the product, in this case, Rioja wine, acts as a reputational antecedent that can influence the evaluation of the destination. However, the literature suggests that this effect is neither automatic nor direct, but rather depends on the individual's interpretation of that reputation within the context of the destination (Han, 1989; Verlegh & Steenkamp, 1999). In other words, the prestige of the wine functions as a signal of quality that needs to be internalized and transformed into a positive overall image of the destination to generate a real impact on visit intention.

In this vein, recent studies in wine tourism have shown that destination image and brand value play a mediating role between product attributes and tourist behavior, acting as intermediate links between external stimuli and consumption decisions (Gómez-Rico et al., 2022; Luu & Galan, 2021). Likewise, mediation theory in structural models suggests that such constructs not only explain the "how" and "why" of causal relationships but also allow for the identification of the psychological mechanisms underlying consumer behavior (Zhao et al., 2010; Nitzl et al., 2016).

Based on this evidence, it is proposed that brand image plays a key mediating role in two fundamental relationships within the model. First, between the wine involvement and the predisposition to visit the destination, such that involvement influence visit intention primarily through the consolidation of a favorable image of La Rioja. Second, between the prestige of Rioja wine and visit intention, where the product's reputational effect is likewise channeled through the destination's brand image.

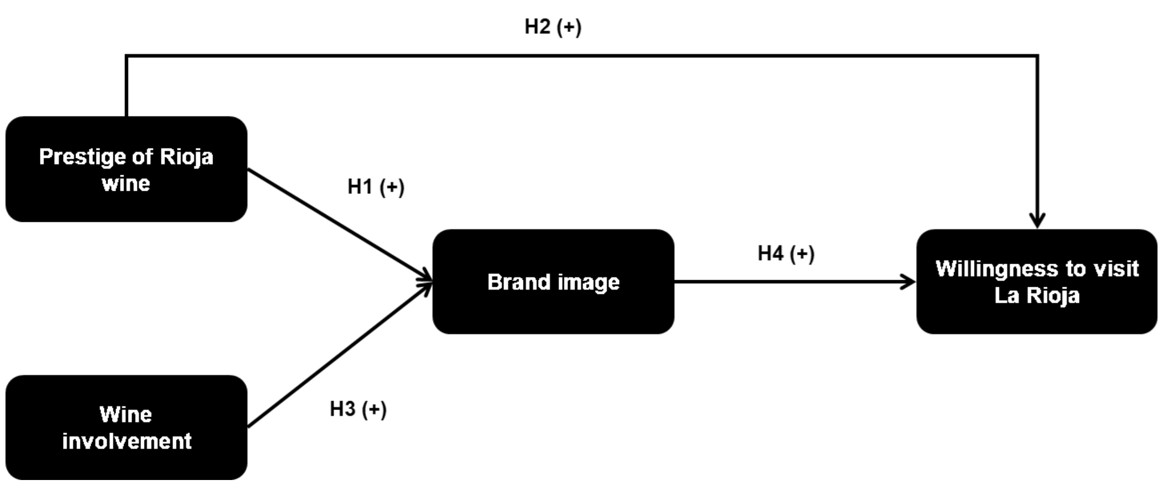
Consequently, the following hypotheses are proposed:

H5: *Destination brand image of La Rioja mediates the relationship between wine involvement and their willingness to visit it.*

H6: *Destination brand image of La Rioja mediates the relationship between the prestige of Rioja wine and the willingness to visit La Rioja.*

Based on these premises, the following research model is proposed (Figure 2).

Figure 2: Proposed research model



3. Research methodology

1.1. Sample and data collection

A structured questionnaire was designed and administered via Google Forms to analyze perceptions of the "Rioja" and "Haro, capital of Rioja" brands in relation to willingness to visit La Rioja as a wine tourism destination. The final sample consisted of 104 participants from the general Spanish population. Data collection took place between May and June 2024 using non-probabilistic snowball sampling, starting with an initial group of respondents who shared the questionnaire through their personal and professional networks (Goodman, 1961; Etikan et al., 2016). Although this procedure limits the statistical representativeness of the sample, it is common in exploratory studies of consumer behavior, especially when a defined sampling frame is not available (Hair et al., 2019).

Regarding the sample profile, a balanced distribution by age is observed, with a predominance of participants between 30 and 60 years old, and a slight majority of women. Of particular note is the high percentage of wine consumers (93.3%), which reinforces the sample's suitability for the study's purpose.

1.2. Questionnaire

The data collection instrument consisted of 44 items organized into thematic blocks corresponding to the constructs analyzed. Prior to distribution, a pretest was conducted with a small group of participants to identify potential comprehension issues and improve the clarity of the instrument. Prior to distribution, a pretest was conducted with a small group of participants to identify potential comprehension issues and improve the clarity of the instrument.

The questionnaire was structured around the main constructs analyzed in the study. First, sociodemographic questions were included to characterize the participants' profiles. Next, the prestige of Rioja wine was measured using a scale adapted from Baek et al. (2010), designed to assess perceptions of the product's quality, reputation, and recognition (see Appendix). Wine involvement was operationalized using a behavioral and experiential approach, capturing respondents' familiarity, consumption frequency, and purchasing experience with wine. This approach is consistent with prior research in wine tourism that emphasizes the role of product-related experience and knowledge in shaping consumer perceptions (e.g., Bruwer & Lesschaeve, 2012; Hollebeek et al., 2007). Destination brand image was conceptualized as the overall evaluation of the destination's territorial branding system and measured through items referring to both the 'Rioja' and 'Haro, Capital of Rioja' brands. Finally, items were included to measure recommendations for the La Rioja destination, using the scale developed by Zeithaml et al. (1996) as a reference. All scales were adapted to the specific context of the study, which helped reinforce the content validity of the instrument.

1.3. Analysis methodology

Data analysis was performed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, employing the SmartPLS 4.1.03 software. This method is suitable for analyzing complex models with multiple relationships between latent constructs, as well as for small samples and data that do not require the assumption of multivariate normality (Hair et al., 2011).

The analytical procedure was conducted in two stages. First, the measurement model was evaluated by analyzing the individual reliability of the items, the internal consistency of the constructs, convergent validity, and discriminant validity. Second, the structural model was examined to test the proposed hypotheses and assess the significance and magnitude of the relationships between constructs. Additionally, a bootstrapping procedure was applied to determine the statistical significance of the estimated coefficients and analyze the direct and indirect effects of the model.

4. Results

1.4. Measurement Model

The reliability and validity of the measurement model were evaluated following standard criteria in PLS-SEM. As shown in Table 1, all constructs exhibit adequate levels of internal consistency, with Cronbach's alpha values above 0.70 (Cronbach, 1951), composite reliability above 0.70, and AVE values above 0.50 (AVE) were above 0.50 (Fornell & Larcker, 1981), confirming convergent validity.

The factor loadings exceed the recommended threshold of 0.70, indicating adequate individual reliability of the items (Hair et al., 2011). Likewise, high composite reliability values are interpreted as indicative of measurement precision, without compromising the validity of the model.

Regarding discriminant validity, the results presented in Table 2 meet both the Fornell-Larcker criterion and the HTMT index, falling within the recommended values (Ringle et al., 2020). Taken together, these results confirm the adequacy of the measurement model.

Table 1. Standardized loadings, composite reliability, and average variance extracted.

Item	Standard loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Prestige of Rioja wine_1	0.881	0.899	0.907	0.937	0.832
Prestige of Rioja Wine_2	0.942				
Prestige of Rioja wine_3	0.912				
Wine involvement_1	0.850	0.931	0.934	0.948	0.786
Wine involvement_2	0.856				
Wine involvement_3	0.913				
Wine involvement_4	0.865				
Wine involvement_5	0.943				
Brand image_1	0.858	0.928	0.935	0.941	0.668
Brand image_2	0.798				
Brand image_3	0.885				
Brand image_4	0.863				
Brand image_5	0.783				
Brand image_6	0.796				
Brand image_7	0.793				
Brand image_8	0.849				
Willingness to visit La Rioja_1	0.906	0.934	0.936	0.958	0.883
Willingness to visit La Rioja_2	0.957				
Willingness to visit La Rioja_3	0.955				

Table 2. Discriminant validity.

Construct	Brand prestige	Wine involvement	Brand image	Willingness to visit La Rioja
Brand prestige	0.912*	0.218	0.636	0.430
Wine involvement	0.206	0.886*	0.496	0.504
Brand image	0.574	0.517	0.817*	0.775
Willingness to visit La Rioja	0.396	0.538	0.823	0.940*

*Note: *The diagonal elements are the square roots of the AVE. Values below the diagonal elements are the HTMT ratio, and values above the diagonal elements are the correlations between constructs (Fornell and Larcker test).*

1.5. Structural Model

The structural model was evaluated using bootstrapping with 5,000 subsamples, following the recommendations of Hair et al. (2022). The model results are presented in Table 3, showing that most of the proposed relationships are statistically significant.

First, wine prestige has a positive and significant effect on destination brand image (β = 0.493; $p < 0.001$), confirming H1. However, no significant direct effect is observed on the willingness to visit La Rioja (β = –0.055; n.s.), so H2 is not confirmed. For its part, brand image has a positive and strong effect on the willingness to visit the destination (β = 0.816; $p < 0.001$), confirming H4 and highlighting its role as the main determinant of visit intention. Likewise, the wine involvement positively influences brand image (β = 0.394; $p < 0.001$), allowing us to confirm H3.

Regarding the model's explanatory power, the results show R^2 values of 0.478 for brand image and 0.603 for the willingness to visit La Rioja, indicating moderate-to-high explanatory power (Hair et al., 2019). Finally, the SRMR index (0.081) suggests an adequate overall fit of the model.

Table 3. Results of the final model by SmartPLS.

Hypo-thesis	Path	Path coefficient (p-value)	St. dev.	t	f2	R2	SRMR
H1	Prestige of Rioja wine → Brand image	0.493***	0.084	5.902	0.446		
H2	Prestige of Rioja wine → Willingness to visit La Rioja	$-0.055^{n.s.}$	0.101	0.717	0.009		
H3	Wine involvement → Brand image	0.394***	0.073	5.408	0.285		
H4	Brand image → Willingness to visit La Rioja	0.816***	0.068	12.086	1.126		
Brand image						0.478	
Willingness to visit La Rioja						0.603	
SRMR							0.081

****p ≤ 0.001; n.s. Not significant*

1.6. Analysis of the mediating role of brand image

The analysis of the mediating effect was performed using bootstrapping, following the recommendations of Nitzl et al. (2016) and Zhao et al. (2010). The results are presented in Table 4. Wine product involvement has a significant direct effect on the willingness to visit La Rioja (β = 0.154; $p < 0.05$) and a significant indirect effect through brand image (β = 0.322; $p < 0.001$). This pattern indicates the existence of complementary partial mediation, implying that involvement influences visit intention both directly and indirectly. In contrast, wine prestige does not have a significant direct effect, but it does have a significant positive indirect effect through brand image (β = 0.402; $p < 0.001$). This result demonstrates total mediation, indicating that wine prestige only influences the willingness to visit the destination when it translates into a favorable brand image.

Taken together, these results confirm the key mediating role of brand image in the formation of visit intention.

Table 4. Mediating effect of brand image on the willingness to visit La Rioja

Mediated relationship	Direct effect (b)	p-value	Indirect effect (a×b)	95% indirect CI	Total effect (b)	Type of mediation
Wine involvement → willingness to visit La Rioja	0.154*	0.041	0.322***	[0.188, 0.435]	0.476	Complementary partial mediation
Prestige → willingness to visit La Rioja	-0.055 n.s.	0.576	0.402***	[0.252, 0.591]	0.347	Total mediation (indirect-only)

Note: **** p < 0.001; ** p < 0.01; * p < 0.05; n.s. = not significant.*

5. Conclusions

This study analyzes the influence of the territorial brands "Rioja" and "Haro, capital of Rioja" on destination image and the willingness to visit La Rioja, incorporating the role of wine prestige and the wine involvement into an integrative model.

The results show that brand image is the main determinant of visit intention, exerting a direct and significant effect. Furthermore, both the prestige of the wine and its involvement have a positive influence on the image of the destination. However, while the involvement has both a direct and indirect effect on the willingness to visit La Rioja, the prestige of the wine does not show a significant direct effect; rather, its influence is channeled entirely through brand image. Therefore, in such the case of wine-consumption, prestige operates as a symbolic cue that requires internalization before translating into behavioral responses. These findings highlight the central mediating role of brand image in shaping tourism behavior.

From a theoretical perspective, the study contributes to the literature on place branding and wine tourism by demonstrating that the value of the flagship product does not automatically translate into tourist behavior, but rather must be internalized in the form of a coherent and favorable brand image of the destination. Therefore, this study extends the existing literature on wine tourism and destination branding by incorporating wine experience as a consumer-level antecedent of destination brand image, complementing prior research that has predominantly focused on product-related (e.g., prestige) and experience-based (e.g., wine involvement) drivers. By doing so, it contributes to a more comprehensive understanding of how individual differences shape the cognitive mechanisms underlying destination image formation. Furthermore, it reinforces the role of wine involvement as a key antecedent, both direct and indirect (via image), of visit intention, and provides empirical evidence on mediating mechanisms in tourism behavior models.

In practical terms, the results suggest that promotional strategies should not focus exclusively on the prestige of the wine, but rather on its integration into a territorial brand narrative capable of generating emotional and distinctive associations. Similarly, the importance of designing memorable wine-related experience that reinforces the destination's image is highlighted. For public managers, this implies the need to coordinate the various territorial brands under a common strategy, while for wineries and companies in the sector, it means aligning the visitor consumption experience with the destination values.

These insights suggest that 'word-of-mouth' (WOM) may act as a complementary mechanism extending the effects identified in the model, although it was not directly examined in this study. Furthermore, the previous literature review and results allow us to infer the relevance of post-consumption WOM as a mechanism that amplifies the value generated by the wine-related experience. To the extent that experiences at the destination are memorable, visitors are more likely to share their experiences in both personal and digital contexts, thereby contributing to the formation of brand image among potential tourists. In this sense, word-of-mouth acts as an indirect channel through which the tourist experience not only influences revisit intention but also the predisposition of new visitors. Therefore, strategic destination management should not focus solely on attracting tourists, but also on fostering experiences that encourage recommendations and the creation of positive content, thereby consolidating a multiplier effect on the image and positioning of La Rioja.

However, this study has some limitations. The sample size and the use of non-probability sampling limit the generalizability of the results, as does the low number of international participants. Furthermore, the cross-sectional nature of the analysis prevents observing the evolution of evaluations or image over time. In this regard, future research should expand the sample, incorporate international comparisons, and adopt longitudinal designs. Likewise, it would be relevant to integrate other destination attributes, such as cultural or gastronomic offerings, in order to obtain a more complete picture of tourist behavior. Finally, future studies could also examine the role of WOM communication, both traditional and electronic (eWOM), as an influential factor in destination image formation and tourists' decision-making processes, particularly given its growing relevance in digital travel planning contexts.

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7. Appendix

Table A1. Measurement scales used

Short name	Item
Prestige of Rioja Wine_1	Wine brands from the Rioja Designation of Origin are highly prestigious (with 5 being the highest rating).
Prestige of Rioja wine_2	Wine brands from the Rioja Designation of Origin represent high status.
Prestige of Rioja wine_3	Wine brands from the Rioja Designation of Origin are very exclusive.
Prestige of Rioja wine_4*	Overall, I believe that the Rioja Designation of Origin has a strong and positive brand image.
Wine involvement_1	I am familiar with many wine brands
Wine involvement_2	I frequently purchase wine
Wine involvement_3	I have consumed a lot of wine in the past
Wine involvement_4	I have had extensive contact with wine in the past
Wine involvement_5	I have a great deal of experience purchasing wine
Brand image_1	The "Haro, Capital of Rioja" brand is trustworthy.
Brand image_2	The "Haro, Capital of Rioja" brand is likable.
Brand image_3	The "Haro, Capital of Rioja" brand is a very good brand.
Brand image_4	The "Haro, Capital of Rioja" brand is a very attractive tourism destination brand.
Brand image_5	The "Rioja" brand is trustworthy.
Brand image_6	The "Rioja" brand is likable.
Brand image_7	The "Rioja" brand is a very good brand.
Brand image_8	The "Rioja" brand is a very attractive tourism destination brand.
Willingness to visit La Rioja_1	I will encourage other people to visit La Rioja as a tourist destination.
Willingness to visit La Rioja_2	I will recommend Haro to others who seek my advice.
Willingness to visit La Rioja_3	I will say positive things about the "Rioja" and "Haro, Capital of Rioja" brands.

**Not included in the estimated model.*

III.

Digitalization, Artificial Intelligence, and New Marketing Environments

From Latent Classes to Learning Systems: Consumer Heterogeneity, Behavioral Structure, and AI-Enabled Personalization

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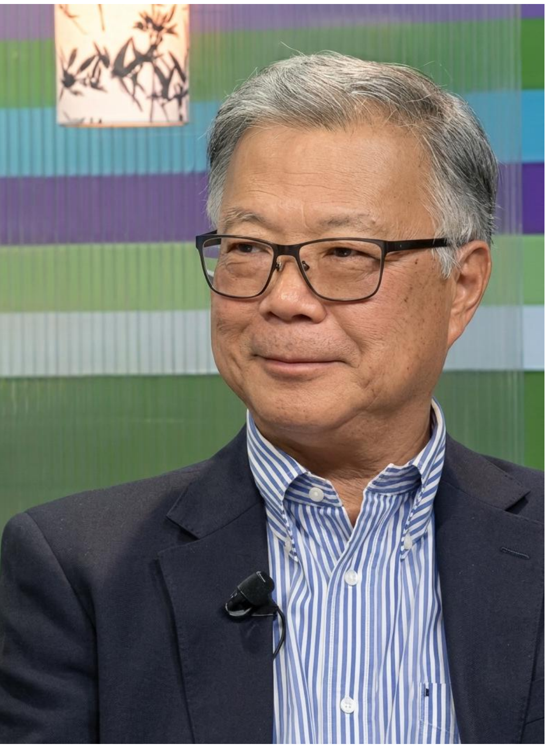
Abstract

This chapter frames AI-driven personalization as a computational extension of Wagner Kamakura's consumer heterogeneity principle. It traces the evolution from discrete latent class models to high-dimensional AI embeddings and reinforcement learning for Customer Lifetime Value (CLV) optimization. While AI offers superior scalability, it often lacks the interpretability of traditional structural models. The author advocates for hybrid approaches that integrate behavioral structure with AI's flexibility to ensure personalization remains transparent, accountable, and aligned with long-term customer value.

Keywords

Consumer Heterogeneity, AI Personalization, Latent Class Models, Customer Lifetime Value (CLV), Reinforcement Learning,

1. Introduction: Marketing as a Problem of Heterogeneity and Decision



Marketing is undergoing a structural transformation driven by digitization and artificial intelligence (AI), with firms increasingly deploying real-time personalization systems that recommend products, tailor promotions, and dynamically adjust pricing at the individual level (Stein et al., 2025; Anta Callersten et al., 2024; Bertini & Koenigsberg, 2021). Despite these technological advances, the underlying economic problem of marketing remains unchanged: the identification, modeling, and exploitation of consumer heterogeneity for decision-making under uncertainty.

Wagner A. Kamakura's scholarship established heterogeneity as a central organizing principle of marketing science. His work, most notably on latent class models and segmentation (Kamakura & Russell, 1989), demonstrated that meaningful inference and decision-making require explicit modeling of differences in preferences, responses, and behaviors. Rather than relying on representative consumers, Kamakura's framework conceptualized markets as structured aggregations of distinct behavioral segments. His work provided a tractable statistical and managerial representation of heterogeneity that has shaped segmentation, choice modeling, and CRM practices for decades.4

This chapter advances the argument that *modern AI-driven personalization systems can be understood as a computational generalization of structural models of heterogeneity,* rather than a conceptual departure. While AI methods operate at a much greater computational scale and rely on flexible function approximation, they address the same fundamental mapping:

$$\text{context} \rightarrow \text{preferences} \rightarrow \text{decisions} \rightarrow \text{outcomes.}$$

At the same time, behavioral research, including prospect theory (Kahneman & Tversky, 1979), demonstrates that preferences are context-dependent and dynamically evolving, implying that both cross-sectional heterogeneity and state dependence must be incorporated into modern marketing models. This dual perspective provides a natural bridge between classical marketing science and contemporary AI systems.

2. Structural Foundations: Segmentation, Heterogeneity, and Market Response

2.1. Latent Class Models and Discrete Heterogeneity

Kamakura's work fundamentally challenged the use of aggregate or "average" models in marketing. Let i index consumers, j alternatives, and x_{ijt} observed attributes. Classical discrete choice models posit:

$$U_{ijt} = x'_{ijt}\beta_i + \epsilon_{ijt} \qquad (1)$$

,where β_i captures individual-specific preferences.

Kamakura and Russell (1989) introduced latent class structure into choice models and proposed modeling heterogeneity via a finite mixture:

$$P(y_{it} = j) = \sum_{k=1}^{K} \pi_k \, P(y_{it} = j \mid \beta_k) \qquad (2)$$

, with π_k representing segment probabilities, where $\beta_i \in \{\beta_1, \dots, \beta_K\}$ and $\Pr(i \in k) = \pi_k$

This representation is equivalent to a *mixture-of-experts* model, where each class corresponds to a local model. This formulation offers three critical contributions: 1) *Interpretability* – Segments correspond to managerially meaningful customer groups, 2) *Parsimony* – A small number of segments captures complex heterogeneity, and 3) *Actionability* – Segmentation supports targeting, positioning, and resource allocation. This contribution bridged statistical rigor and managerial relevance, influencing segmentation, pricing, and customer strategy.

Latent class models enabled researchers and practitioners to identify discrete behavioral segments, probabilistically assign consumers to segments, and derive actionable strategies.

Subsequent work further demonstrated how segmentation structures can capture cross-category variation in preferences and purchasing behavior, reinforcing the importance of modeling heterogeneity in multi-category contexts (Kamakura, Kim, & Lee, 1996).

2.2 Cross-Category Heterogeneity and Market Structure

In these models:

$$\beta_i = (\beta_i^{(1)}, \dots, \beta_i^{(C)}) \qquad (3)$$

, where preferences across categories are jointly distributed.

This extension has two important implications: (1) consumers exhibit systematic cross-category heterogeneity, and (2) segmentation is inherently multi-dimensional.

These ideas anticipate modern multi-task learning and cross-domain recommendation systems, where behavior in one category informs predictions in another.

2.3 CRM, Customer Equity, and Forward-Looking Segmentation

Kamakura's contributions also extend to customer relationship management (CRM) and customer value modeling. A key advance in this literature is the recognition that segmentation should be forward-looking – incorporating not only current behavior but also expected future value and responsiveness to marketing actions.

Customer lifetime value (CLV) operationalizes heterogeneity by linking purchase frequency, retention, margins, and marketing responsiveness to long-run profitability. When integrated with predictive analytics, CLV-based personalization supports dynamic resource allocation – for example, prioritizing acquisition, retention, and service investments toward customers with higher expected value (Katyayan & Khan, 2024).

Customer lifetime value (CLV) is given by:

$$\mathrm{CLV}_i = \mathbb{E}\left[\sum_{t=0}^{\infty} \delta^t \pi_{it}\right] \tag{4}$$

which depends on retention, purchase frequency, and contribution margin.

Empirical research documents strong links between satisfaction, loyalty, and financial performance (Kamakura et al., 2002). Complementing this perspective, the customer equity framework formalizes marketing as an intertemporal optimization problem over heterogeneous customers, in which firms allocate actions to maximize the long-run value of the customer base (Rust et al., 2004).

Further developments in CLV modeling (Gupta et al., 2006; Reinartz & Kumar, 2003) emphasize three implications:

- customers differ significantly in lifetime value,
- short-term behavior may not reflect long-term value,
- optimal targeting must consider dynamic customer trajectories.

While latent class and CLV frameworks provide a structured representation of heterogeneity across consumers, they remain limited in their ability to capture within-decision interdependencies and combinatorial choice behavior, which are increasingly central in modern consumption settings. This motivates extensions toward multi-item and interaction-based choice models.

2.4 Structured Choice and the Kamakura–Russell Tradition

The latent class framework formalizes the idea that observed choices reflect a mixture of distinct preference structures. This logic also underpins modern personalization: rather than assuming a representative consumer, firms infer a customer's latent preference state from behavior and use it to predict responses to products, prices, and messages.

- segmentation → latent representation learning,
- choice modeling → response prediction and targeting,
- heterogeneity → individualized policies (e.g., offers, rankings, and prices).

Subsequent work in the Kamakura–Russell tradition extends this foundation by relaxing independence assumptions and allowing utility to depend on the composition of the chosen set. These interaction-based extensions bring structural models closer to how consumers assemble baskets, menus, and bundles, and they motivate the interdependence frameworks reviewed next.

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3. Modeling Interdependence: Assortment, Bundles, and Menus

3.1. Moving Beyond Independence of Irrelevant Alternatives (IIA)

Traditional discrete choice models rely on independence assumptions that become restrictive when consumers select multiple items simultaneously. In many real-world settings, consumers do not choose a single item but rather compose bundles or assortments. Real-world decisions often involve baskets (retail), menus (services), and bundles (subscriptions).

3.2. Multivariate Logit (MVL) and Interaction Effects

The Multivariate Logit (MVL) framework captures this interdependency by allowing (1) utility to depend on the set of chosen items, (2) interactions across items (substitutes or complements), and (3) rich cross-product demand relationships (Russell & Petersen, 2000; Kwak, Duvvuri, & Russell, 2015).

The MVL model captures bundle choice through:

$$U_i(S) = \sum_{j \in S} \alpha_{ij} + \sum_{j<k} \gamma_{ijk} \qquad (5)$$

, where γ_{ijk}captures interaction effects.

This specification allows both complementarity (positive interactions, $\gamma_{ijk} > 0$) and substitution (negative interactions, $\gamma_{ijk} < 0$). It also allows context-dependent valuation.

The model is equivalent to a second-order utility expansion, closely related to modern machine learning models such as factorization machines (Zaman & Jana, 2025) and interaction networks (Battaglia et al., 2016).

3.3. Menu Choice and Combinatorial Explosion

Extending this logic, menu-choice models address situations where consumers select multiple items from large sets.

$$| S | \in 2^J \qquad (6)$$

Here, *J* is the number of items in a set *S*, leading to exponential growth in the number of possible choice sets. Such settings introduce high-dimensional decision spaces, complex interaction structures, and heterogeneous decision rules.

To address such issues, models rely on various approaches such as sampling of alternatives (McFadden 1978), latent structure (Kamakura and Kwak 2020), and dimensionality reduction (Kwak, Duvvuri, and Russell 2015). These challenges mirror those in modern recommender systems, which must efficiently evaluate large candidate sets under computational constraints.

4. Behavioral Foundations: Reference Dependence and State Dynamics

4.1. Reference Dependence in Marketing Decisions

Behavioral decision theory introduces an additional layer by incorporating reference dependence and loss aversion (Kahneman & Tversky, 1979). When combined with structured heterogeneity models, these behavioral mechanisms enhance the explanatory power of marketing models and provide deeper insight into observed purchase patterns that vary across consumers and contexts.

Prospect theory (Kahneman & Tversky, 1979) introduces reference-dependent preferences in utility formation of:

$$U_{ijt} = x'_{ijt}\beta_i + \lambda_i \cdot g(p_{ijt} - r_{ijt}) \quad (7)$$

,where:

$$g(\Delta p) = \begin{cases} \Delta p & \text{if gain} \\ \kappa \cdot \Delta p & \text{if loss} \end{cases}, \kappa > 1$$

, where losses exceed gains in magnitude.

Empirical results show that 1) losses relative to reference prices have stronger effects than gains, 2) asymmetry varies across decision levels, and 3) behavior reflects both state dependence and heterogeneity.

These findings help explain seemingly paradoxical patterns, such as “loyal yet price-sensitive” consumers: individuals remain brand-loyal but adjust purchase timing in response to price deviations from reference levels (Kwak, Duvvuri, & Russell, 2025).

4.2. Dynamic Decision Processes

Consumer decisions exhibit state dependence, habit formation, and expectation updating. These dynamics imply that preferences are not static but evolve over time, challenging traditional segmentation approaches.

Importantly, these behavioral extensions introduce state dependence and nonlinearity into the utility specification, further increasing model complexity. In high-dimensional settings, such complexity motivates the transition from parametric representations toward flexible function approximation frameworks, as implemented in modern AI-based personalization systems (Tiwari & Namdeo, 2025).

5. AI Personalization as a Generalization of Structural Models

5.1. Representation Learning and Continuous Heterogeneity

Modern AI-based personalization systems can be viewed as high-capacity function approximators that estimate preference mappings in high-dimensional spaces. Rather than specifying parametric forms for heterogeneity, these systems learn continuous latent representations directly from data, generalizing the discrete mixture structures of classical segmentation models.

AI replaces discrete heterogeneity with continuous embeddings:

$$\hat{y}_{it} = f_\theta(x_{it}, z_i) \qquad (8)$$

where:

- z_i = latent user representation,
- f_θ = flexible function approximator.

This corresponds to infinite mixture models, nonparametric heterogeneity, high-dimensional representations. The evolution from traditional segmentation to hyper-personalization reflects a shift from group-level inference to continuous, individualized prediction.

From the perspective of recommender systems, these embedding-based representations generalize classical segmentation by learning distributed user and item factors that can be updated continuously as new data arrive (Ricci et al., 2015).

Thus, AI performs continuous mixture modeling at scale and a flexible generalization of structural choice models.

5.2. Dynamic Optimization and Reinforcement Learning

Modern AI personalization systems optimize traditional CLV in equation (4) above with

$$\max_{\pi} \mathbb{E}[\mathrm{CLV}_i] \qquad (9)$$

using reinforcement learning (RL; Mandania et al., 2025) and contextual bandits (Gigli & Stella, 2024). RL models extend CRM by updating policies dynamically, accounting for long-term consequences, and balancing exploration and exploitation.

Sutton and Barto (2018) outline how the sequential decision framework supports policy learning, showing that exploration–exploitation trade-offs and value-function methods align well with adaptive marketing strategies.

In this context, personalization can be formulated as a dynamic policy optimization problem in which firms seek to maximize expected customer lifetime value (CLV) over time. Reinforcement learning and contextual bandit algorithms operationalize this objective by updating policies based on observed behavioral responses, effectively extending traditional CRM frameworks into adaptive decision systems under uncertainty.

Empirically, this learning paradigm is already being applied in service and digital marketing settings, where firms adapt promotions, prices, and content in response to feedback while explicitly trading off short-term conversion against long-run value (Mandania et al., 2025; Gigli & Stella, 2024). However, as policies become more adaptive and high-dimensional, the decision logic becomes harder to audit, elevating the interpretability and governance challenges that motivate hybrid structural+ML approaches.

Table 1. Mapping classical choice model specifications to AI equivalents

Classical	AI Equivalent
Latent class k	Embedding space z_i
β_k	Parameterized mapping $g(z_i)$
Interaction γ_{jk}	Feature interactions

5.3. Interpretability vs. Flexibility

AI personalization models can flexibly encode interaction effects, behavioral responses, and state dependence, often yielding high predictive accuracy in complex environments. However, these mechanisms are typically embedded implicitly in learned representations, making the resulting decision rules difficult to interpret, audit, and communicate. By contrast, structural models impose explicit behavioral structure that provides theoretical grounding, managerial transparency, and stronger generalizability beyond the estimation context.

What AI adds

Relative to classical structural models, AI adds four practical capabilities: real-time decision-making, integration of unstructured data, adaptive learning from feedback, and automation of end-to-end marketing processes.

Industry evidence similarly suggests that AI-driven personalization is becoming a core driver of marketing performance, with many marketers identifying it as a leading trend shaping the field (Nielsen, 2025).

Table 2. A structural comparison of classical marketing models and AI personalization

Model Class	Core Representation	Heterogeneity Treatment	Key Features	Limitations	Key References
Latent Class Choice Models	Finite mixture models	Discrete segments (β_k)	Interpretability; segmentation	Limited flexibility	Kamakura & Russell (1989)
Cross-Category Choice Models	Joint preference structures	Structured across categories	Captures cross-category dependence	High dimensionality	Kamakura, Kim, & Lee (1996)
CLV / CRM Models	Discounted lifetime value	Heterogeneity in retention	Forward-looking decision support	Static assumptions	Kamakura et al. (2002); Rust et al. (2004)
MVL / Assortment Models	Utility over sets	Item + interaction parameters	Captures complementarity	Quadratic complexity	Kwak et al. (2015)
Menu Choice Models	Combinatorial choice sets	Latent classes + interactions	Flexible multi-item modeling	Curse of dimensionality	Kamakura & Kwak (2020)
Behavioral Choice Models	Reference-dependent utility	Heterogeneity in loss aversion	Captures asymmetry	Hard to scale	Kahneman & Tversky (1979)
AI Personalization Models	$\hat{y} = f(x,z)$	Continuous embeddings	Scalability; flexibility	Opacity	Ricci et al. (2015)
AI Policy Models	Sequential optimization	Dynamic heterogeneity	CLV optimization	Data intensive	Sutton & Barto (2018)

This table summarizes the progression from classical marketing models of heterogeneity to modern AI-based personalization frameworks, highlighting key representations, strengths, limitations, and representative references.

What AI risks losing

Despite these advances, AI systems often underprovide:

- interpretability,
- explicit behavioral structure, and
- transparent decision rules.

This limitation is not merely technical: it has managerial and societal consequences. Without structure, personalization may become highly predictive yet unaccountable.

The resulting trade-off is clear: structural models prioritize interpretability and theory-driven inference, whereas AI models prioritize flexibility and scalability. A growing body of work therefore emphasizes hybrid approaches – such as causal machine learning, interpretable AI, and structurally disciplined deep learning – that retain Kamakura-style transparency while leveraging modern computational scale. Importantly, effective personalization depends not only on predictive accuracy but also on transparency, trust, and alignment with consumer value (Utami & Wang, 2026), reinforcing the enduring relevance of structured heterogeneity.

6. Economic and Societal Implications

6.1. Efficiency and Value Creation

Personalization can improve matching efficiency, raise conversion rates, and allocate marketing resources more effectively.

Consistent with this view, consumers increasingly expect personalized interactions; survey evidence reports that more than 70% hold such expectations and express dissatisfaction when they are not met (McKinsey & Company, 2025).

Yet many firms struggle to deliver effective personalization because of fragmented data, legacy systems, and organizational silos. Industry reports suggest that fewer than half of firms consistently meet consumer expectations for personalized experiences (Adobe/MarTech, 2026).

Together, these patterns underscore a key principle: *data alone is insufficient without a structured understanding of heterogeneity.*

6.2. Risks and Ethical Concerns

The rise of AI personalization has been accompanied by increased regulatory scrutiny. The EU AI Act (2024) introduces a comprehensive framework intended to ensure that AI systems are transparent, non-discriminatory, and aligned with fundamental rights.

For marketing applications, key implications include:

- restrictions on manipulative targeting practices,
- requirements for transparency in AI-generated content, and
- accountability for automated decision-making.

Similarly, the GDPR and related privacy regulations emphasize:

- explicit consumer consent,
- data minimization, and
- transparency in data usage.

Taken together, these regulatory developments reinforce the importance of responsible personalization – including transparency, consent-aware data practices, and accountable targeting policies.

6.3. A Kamakura-Compatible Perspective

Kamakura's emphasis on structure and customer-centricity aligns naturally with responsible AI. Interpretable segmentation enhances transparency, structured heterogeneity supports accountability in targeting decisions, and CLV-based frameworks keep personalization aligned with long-term customer value (Rust et al., 2004). In this sense, heterogeneity modeling provides both an analytical foundation for decision-making and a normative foundation for ethical marketing.

These principles clarify why the future research agenda should focus on methods that combine scalability with interpretability, accountability, and value alignment.

7. A Research Agenda for the AI Era

Looking ahead, research can extend the Kamakura tradition by developing methods that integrate behavioral structure with the scale and adaptivity of AI, with particular emphasis on:

1. Causal personalization under feedback loops
2. Dynamic heterogeneity and state dependence
3. Interaction-aware recommendation and assortment optimization
4. Behaviorally grounded AI models
5. Fairness, privacy, and governance in personalization systems

Together, these directions position heterogeneity and behavioral structure as central design principles for AI-era marketing systems.

4. Conclusion

The rise of AI does not replace the foundations of marketing science—it amplifies them. Wagner Kamakura's work established that:

- heterogeneity is fundamental,
- structure is essential for interpretation,
- and models must remain relevant to managerial decisions.

The integration of heterogeneity, interaction, and behavioral context – reflected in work spanning latent class models, MVL frameworks, and reference-dependent choice – provides a powerful blueprint for the future of marketing.

In this sense, AI-driven personalization is not a departure from this tradition; it represents a computational continuation of Kamakura's intellectual legacy in the age of AI.

By combining explicit models of heterogeneity with flexible learning architectures, marketing scholars can build personalization systems that are scalable yet interpretable, and predictive yet accountable—thereby preserving decision relevance while meeting rising expectations for transparency and responsible use.

A Brief Tribute

Wagner A. Kamakura's intellectual influence is reflected not only in his published work but also in his ability to recognize and nurture promising ideas in others. I recall a brief conversation during his visit to UTS in 2012, where he expressed interest in my joint work with Gary Russell on multivariate logit models and suggested extending it using McFadden's random sampling of alternatives. That seemingly small suggestion became the foundation for a subsequent paper. His insight exemplified a distinctive quality: the ability to see how a modest idea could evolve into meaningful research. His legacy continues to shape my thinking and work.

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The Heterogeneity Imperative: AI, Machine Learning, Conjoint Analysis, and the Unfinished Agenda of Wagner Kamakura

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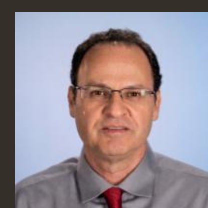


Abstract

This chapter evaluates the impact of artificial intelligence (AI) and machine learning (ML) on conjoint analysis through the lens of Wagner Kamakura's "heterogeneity imperative." While AI/ML methods often match population averages, they frequently fail to uncover the underlying structure of consumer heterogeneity—defined here as taste, structural, and concomitant variable differences. The authors assess four key applications: machine-learning-driven adaptive design and generative product design (which respect heterogeneity), large language model (LLM) synthetic respondents (which destroy it via "flattening" and stereotyping), and deep-learning flexible utility estimation (which partially recovers it). To address these methodological risks, the chapter proposes a validation framework based on the concomitant variable model to ensure that synthetic data preserves the joint mapping between covariates and preferences essential for effective market segmentation and targeting.

Keywords

Conjoint Analysis, Consumer Heterogeneity, Artificial Intelligence, Latent Class Models, Synthetic Respondents

1. Introduction

Artificial intelligence and machine learning have changed how conjoint studies are designed, fielded, and analyzed. A growing body of literature reports that data and estimates generated by AI and ML methods match human-generated benchmarks at the population level. Population averages, however, are not the object of conjoint analysis as a research program. The goal of conjoint is to uncover the structure of consumer heterogeneity: who wants what, and why they differ. This chapter evaluates four AI and machine learning applications against that goal, using the heterogeneity taxonomy Wagner Kamakura developed as the diagnostic framework.

Wagner Kamakura built his research program on the premise that heterogeneity is the organizing feature of markets. The distribution of consumer types, not the mean, drives product design, pricing, segmentation, and targeting. His latent class models (Kamakura and Russell 1989), structural heterogeneity models (Kamakura, Kim, and Lee 1996), and concomitant variable framework (Kamakura, Wedel, and Agrawal 1994) together provide a taxonomy of three heterogeneity types: *taste heterogeneity* (consumers differ in their part-worths), *structural heterogeneity* (consumers differ in their decision processes), and *concomitant variable heterogeneity* (observable characteristics predict the preference type to which a consumer belongs). Though developed before modern AI and ML tools were available, this taxonomy remains widely applicable to the methods that have followed and serves as a useful diagnostic for evaluating what those tools can and cannot do in conjoint analysis.

This chapter evaluates four applications through the lens of heterogeneity, organized by the points at which each intervenes in the conjoint workflow. In experimental design, machine learning methods anticipate respondent heterogeneity in the design priors and tailor questions to each respondent's answers, leaving segment-aware adaptation as an open direction. In data collection, large language models used as synthetic respondents tend to collapse the heterogeneity structure, though architectural responses such as Mixture-of-Personas begin to rebuild it. In analysis, flexible utility estimation with deep neural networks recovers heterogeneity from real data by letting taste parameters depend on covariates, generalizing the covariate-driven principle of Wagner's 1994 concomitant variable framework to a nonparametric setting. In preference-informed product design, generative AI lowers the cost of producing candidate concepts to the point that segment-tailored design becomes economical, allowing heterogeneity to be the design objective rather than a constraint to average over. For each application, we ask whether it respects, recovers, or destroys the heterogeneity structure.

Wagner's framework serves as both a diagnostic and constructive guide, identifying where AI and ML methods fall short and pointing toward tools that augment rather than undermine human-centered conjoint research. We close by proposing a validation criterion, grounded in the concomitant variable model, for assessing whether synthetic conjoint data generated by AI or machine learning pipelines preserves the heterogeneity structure on which marketing decisions depend.

2. Kamakura's Heterogeneity Taxonomy as Evaluative Framework

Wagner's research program distinguishes three forms of consumer heterogeneity: taste, structural, and concomitant variable. This section describes each in turn, situates them against the hierarchical Bayes methodology that serves as the commercial benchmark, and proposes a three-way evaluative criterion for AI and machine learning tools that anchors the rest of the chapter.

Taste Heterogeneity: Consumers Differ in What They Want

Kamakura and Russell (1989) introduced a finite-mixture choice model that became foundational for latent class segmentation in marketing. Their probabilistic choice model partitions the market into segments with distinct brand preferences and price sensitivities, $P(\text{choose } j) = \sum_s \pi_s \cdot P(j \mid \text{segment } s)$, with segment-specific parameters and membership probabilities estimated jointly via the EM algorithm. A stylized finding across the latent class segmentation literature is that three to six segments typically capture the bulk of heterogeneity in choice behavior, producing interpretable market structures that managers could act on: which segments are price-sensitive, which are brand-loyal, and which are variety-seeking. Wedel and Kamakura (2000) codified this as a standard approach to model-based segmentation. An AI or ML tool that collapses this mixture into a single mode delivers only the aggregate-model performance that predated finite mixture models.

Structural Heterogeneity: Consumers Differ in How They Decide

Kamakura, Kim, and Lee (1996) identified an additional form of heterogeneity: consumers differ not only in their preferences but in the decision processes they follow. Some consumers use compensatory rules, trading off attributes against each other (for example, accepting a higher price for better quality). Others use non-compensatory rules, such as elimination-by-aspects or lexicographic ordering, that do not permit such trade-offs. The paper nested both types of decision processes within a latent-class framework, allowing the data to reveal not only what consumers prefer but also how they decide. This is a more fundamental form of heterogeneity than taste heterogeneity, because it implies that the utility function itself takes a different functional form across segments. A model that assumes a single utility specification for all consumers, whether linear-additive or a neural network with a fixed architecture, does not capture this dimension.

Concomitant Variable Heterogeneity: Observable Covariates Predict Segment Membership

Kamakura, Wedel, and Agrawal (1994) extended the latent class framework by allowing segment membership probabilities to depend on observable respondent characteristics through a multinomial logit, $P(\text{segment } s \mid z_i) = \exp(\gamma_s' z_i) / \sum_k \exp(\gamma_k' z_i)$. The coefficient $\gamma_{s,k}$ describes how much observing characteristic k, such as age, income, or prior purchase behavior, shifts a respondent toward segment s: if higher income predicts membership in a price-insensitive segment, that information is carried by γ, not by the segment-level part-worths β. In other words, β reveals what a given segment prefers, and γ determines who belongs to each segment. The two sets of coefficients carry non-redundant information, and an important asymmetry follows: aggregate preference averages can be recovered without γ, but the joint mapping from covariates to preference types cannot. That asymmetry is what makes γ a testable criterion for synthetic respondents generated by any AI or ML pipeline, since a system that produces a different covariate-to-preference mapping than real data is generating stereotypes rather than preferences.

A reader familiar with modern flexible-utility methods might ask why the chapter privileges the discrete segment + γ formulation when neural-network methods that express $\beta_i = f(z_i)$ as a flexible function of covariates are mathematically more general and can approximate any concomitant-variable structure. The answer is that the framework functions as a diagnostic and an interpretive layer, not as a claim about the best available estimator. As a diagnostic, γ is testable in a way that a flexible $f(z)$ is not: comparing γ_{synth} to γ_{real} requires checking a small number of coefficient signs and magnitudes, while comparing $f_{\text{synth}}(z)$ to $f_{\text{real}}(z)$ requires choosing a metric, a region of z, and a treatment of extrapolation. As an interpretive layer, the discrete segment structure converts heterogeneity into the kind of statement managers act on – "segment A is price-sensitive, segment B values brand" – rather than into a continuous covariate-to-taste map that has to be re-discretized for every decision. The relationship between flexible-utility ML and the concomitant variable framework is discussed directly in §5.

The Industry Benchmark: Hierarchical Bayes

Any AI or ML approach to heterogeneity in conjoint competes with hierarchical Bayes choice-based conjoint (HB-CBC), which has been a dominant commercial methodology since the late 1990s (Lenk et al. 1996; Allenby and Rossi 1999). HB captures continuous heterogeneity by drawing individual parameters from a population distribution, $\beta_i \sim MVN(\mu, \Sigma)$, and estimating via MCMC methods with shrinkage toward the population mean. This enables practical individual-level estimation from short choice exercises by borrowing strength across respondents. HB and LC are complementary: HB yields individual-level predictions, LC yields interpretable segments, and hybrid mixture-of-normals models nest both. The benchmark for AI and ML tools is whether they improve on HB's heterogeneity recovery, through better individual predictions or richer segment structure, or mainly approximate what HB already delivers.

The Evaluative Criterion

We adopt a three-way classification for evaluating AI and ML tools against the heterogeneity structure. A tool *respects* heterogeneity if it preserves the structure for downstream estimation, as in adaptive experimental design. A tool *recovers* heterogeneity if it discovers or models it, thereby extending Wagner's agenda, as with flexible utility estimation that allows taste parameters to depend on covariates. A tool *destroys* heterogeneity if it collapses the mixture into an average, reducing it to the pre-1989 aggregate setting, as in the flattening behavior documented for LLM synthetic respondents. We apply this criterion to four applications spanning the AI and ML spectrum: machine-learning-driven adaptive experimental design (respects), LLM synthetic respondents (destroys), deep-learning flexible utility estimation (partially recovers), and generative AI product design (respects).

Table 1. Four AI and machine learning applications in conjoint analysis evaluated against Wagner Kamakura's heterogeneity taxonomy, ordered by where each intervenes in the conjoint workflow.

Application	Taste Heterogeneity	Structural Heterogeneity	Concomitant Variable Heterogeneity	Verdict
ML-driven adaptive experimental design	Modeled in design priors; learned per respondent	Agnostic	Open direction (segment-aware)	**Respects**
LLM synthetic respondents	Variance compressed, groups flattened	Single generative process	Stereotypes replace lived experience	**Destroys**
Deep-learning flexible utility estimation	Recovered via covariate-conditioned $\beta(z)$ (TasteNet, FLM)	Aspirational via heterogeneous experts	Covariate-driven via flexible $\beta(z)$	**Partially recovers**
Generative AI product design	Segments become design targets	Different designs for different rules	Covariates define target segments	**Respects**

3. Adaptive Conjoint Design: Heterogeneity Respected

The conjoint workflow begins at design, where machine learning methods extend classical experimental design to respect and, in some cases, exploit respondent heterogeneity.

Classical conjoint methodology uses fixed experimental designs such as orthogonal or D-optimal arrays, in which all respondents see the same profiles, and the design is chosen to be efficient for a single representative set of part-worths. Two complementary lines of work relax this. The first anticipates heterogeneity at the design stage: rather than optimizing for a point estimate of the population mean, it integrates over a prior distribution of part-worths, producing a single fixed design that remains efficient even when respondents in fact differ substantially in their tastes. Yu, Goos, and Vandebroek (2009) develop Bayesian optimal conjoint designs of this form and show that they extract more information from a heterogeneous population than designs optimized for a single point in parameter space.

The second line adapts to the respondent, tailoring subsequent questions to each person's prior answers. Toubia, Hauser, and Simester (2004) introduced the polyhedral method, in which each respondent's questions are chosen to most rapidly narrow the polytope of part-worth values consistent with their prior answers. Toubia, Hauser, and Garcia (2007) extended this with a probabilistic variant that accounts for response error. Sauré and Vielma (2019) developed an ellipsoidal Bayesian analog that uses normal posterior approximations to drive question selection; they report that in high-heterogeneity scenarios the ellipsoidal design substantially increases estimation accuracy relative to a random design, whereas in low-heterogeneity scenarios the advantage is smaller. That finding is the clearest evidence in the adaptive-design literature that the value of adapting increases with the magnitude of the heterogeneity being estimated.

Sawtooth Software's Adaptive Choice-Based Conjoint (ACBC), released in 2009, is the dominant commercial implementation of adaptive conjoint and uses build-your-own, screening, and choice tournament phases to adapt the interview in real time. Sawtooth reports that more than 1,500 ACBC studies had been completed as of its 2014 technical paper. More recent ML-guided designs extend the logic of adaptation in two directions. Yin, Gao, Lin, and Shugan (2023) propose a gradient-based survey that constructs paired-comparison questions adaptively without assuming a parametric utility function, which makes the method robust to model misspecification and scalable to products with hundreds of attributes. Dew (2024) develops an adaptive preference measurement framework for unstructured data, such as product images or text descriptions, by running Bayesian optimization over embeddings rather than over coded attributes; this extends adaptive conjoint to settings where the attribute vocabulary is not fixed in advance, and where the relevant dimensions of heterogeneity may not be known before the interview begins.

The common move across these methods is to adapt question selection to the respondent's estimated parameters. What none of them does explicitly is adapt to the respondent's estimated *segment*. A heterogeneity-aware adaptive design in the strong sense would maintain an online estimate of segment membership and choose questions that maximize information for that segment: showing price-sensitive respondents more price variation and quality-focused respondents more feature variation. This amounts to running latent-class EM online, updating the segment posterior between questions. LLM priors could, in principle, help initialize this online segmentation, since aggregate-level preferences are sufficient for a starting distribution even if they are insufficient for final heterogeneity estimation. To our knowledge, a fielded segment-aware adaptive conjoint system does not yet exist. We mark this as a productive open direction rather than a solved problem.

A related development is conversational preference elicitation through LLM-powered interfaces. PEBOL (Austin, Korikov, Toroghi, and Sanner 2024) uses natural language inference to connect user utterances to item descriptions, guiding a Bayesian optimization loop for preference elicitation through dialogue rather than structured choice tasks. LISTEN (Jovine et al. 2025) uses LLM-based iterative algorithms to refine parametric utility functions through conversational interaction. These approaches could complement traditional conjoint by capturing preference dimensions that structured attributes miss. They also inherit the heterogeneity limitations of the underlying LLM unless the preference model explicitly represents a mixture structure. Grounding conversational elicitation in a latent class framework, so that the dialogue adapts to the respondent's estimated segment, is a natural extension of the segment-aware direction above. These interfaces use LLMs as an elicitation layer with real respondents rather than as substitutes for them; using LLMs as synthetic respondents is a distinct application, taken up in the next section.

4. Synthetic Respondents in Data Collection: Heterogeneity Destroyed and (Partially) Rebuilt

The use of large language models as synthetic respondents offers scale and speed advantages over human data collection. This section first documents the ways in which current LLMs compress or misrepresent the heterogeneity structure, then reviews emerging architectural and training-time responses, and closes with a model-based validation criterion that distinguishes adequate from inadequate synthetic data.

A. The Diagnosis

A widely discussed AI application in conjoint is the use of large language models to generate synthetic respondents. The economic case rests on cost and speed: real conjoint studies require hundreds to thousands of respondents at roughly \$5–50 each, with fielding timelines of two to four weeks, whereas LLM-simulated respondents cost fractions of a cent per response and can be generated in minutes. At the aggregate level, several studies report that LLM-derived results approximate human benchmarks. Semantic similarity rating methods achieve approximately 90% of human test-retest reliability on population-level preference distributions across 57 personal care product surveys with 9,300 human benchmark responses (Maier et al. 2025). LLM-derived willingness-to-pay estimates from discrete-choice scenarios have been reported to fall within ranges similar to human benchmarks (Brand, Israeli, and Ngwe 2023). That level of performance, however, was already provided in the 1970s by aggregate conjoint models such as pooled OLS across all respondents. It is not the relevant benchmark when downstream decisions depend on the heterogeneity structure.

The failure modes correspond to each element of Wagner's taxonomy. Consider first taste heterogeneity. Wang, Morgenstern, and Dickerson (2025), in a study published in *Nature Machine Intelligence*, tested four LLMs (GPT-4, GPT-3.5-Turbo, Llama-2-Chat, and Wizard Vicuna Uncensored) against 3,200 human participants across 16 demographic identities. Across nearly every model, identity group, and diversity metric, LLM responses were flatter than human responses. GPT-4 and GPT-3.5 were especially flat, typically covering only three of five possible response categories in 100 samples where humans covered all five. The within-group heterogeneity that latent class models were designed to capture, such as differences among Black and White women within the category "women," or variation in pronoun and identity experiences within non-binary populations, is substantially compressed.

Next, consider structural heterogeneity. LLMs have a single generative process, autoregressive sampling from a learned conditional distribution over tokens. Prompting with demographic personas changes the content of the output but not the cognitive style. There is no mechanism by which some simulated respondents would use compensatory trade-offs, and others would use elimination-by-aspects. The structural heterogeneity identified by Kamakura, Kim, and Lee (1996), namely that different consumers follow different decision rules, has no direct analog in LLM text generation.

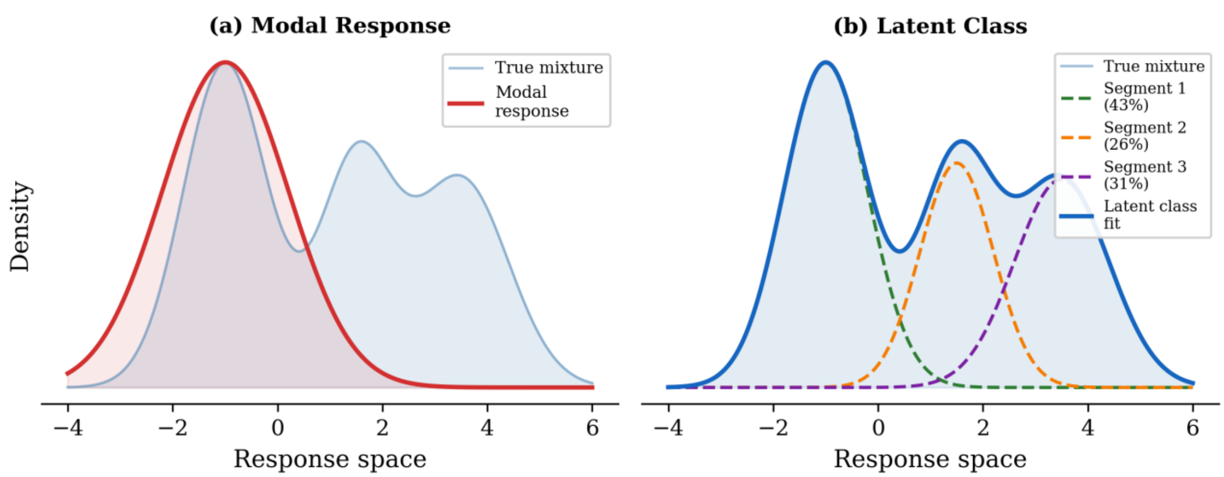
Finally, consider concomitant variable heterogeneity. LLMs prompted with demographic identities are more likely to represent what out-group members think of that group than what in-group members think of themselves (Wang et al. 2025). This occurs because training data rarely links author identity to text: when "Black woman" appears in the training corpus, it is as likely to have been written by an out-group member as by an in-group member. The model learns stereotypes rather than lived experience. GPT-4, prompted to respond as a person with impaired vision discussing immigration, produced, "*While I may not be able to visually observe the nuances of the US-Mexican border or read statistics, I believe in the importance of fair and just immigration*," which reflects what a sighted person might imagine a blind person saying rather than what blind respondents actually say about immigration. The γ mapping that Wagner's 1994 model recovers from data, describing how covariates predict preference segments, is replaced by a stereotype mapping learned from the training corpus.

The inferential failure extends beyond individual-level prediction. Bisbee et al. (2024) report that while ChatGPT-generated survey responses match the population averages of the American National Election Studies (ANES), the regression coefficients estimated from synthetic data differ substantially from those estimated on real ANES data, and synthetic distributions shift with minor prompt changes and over time. Matching the mean is not the same as recovering the joint structure that inferential work relies on.

The proximate cause is a property of the training-and-sampling pipeline. LLMs are trained on text in which author identity is rarely linked to content, so the conditional distribution they learn,

P(text | demographic prompt), absorbs out-group writing about that group as much as within-group writing. Reinforcement learning from human feedback further concentrates the distribution on socially acceptable, modal responses. Inference-time sampling at moderate temperature compounds the effect. Wagner's latent class model represents the data as a mixture, $P(\text{response}) = \sum_s \pi_s \cdot P(\text{response} \mid \text{segment } s)$, and the mixture structure is what allows different segments to have different preferences. Nothing in the LLM pipeline preserves this mixture structure: post-training collapses the conditional, and sampling collapses what remains. This is better described as a structural feature of the pipeline than as a scaling issue: increasing the number of parameters or the size of the data does not, in itself, recover the mixture structure. Figure 1 illustrates the contrast between a mode-targeted estimate and a mixture likelihood fit.

Figure 1. The LLM training-to-inference pipeline structurally favors modal responses (a), in contrast to latent class estimation, which preserves the components and their mixing weights (b).



B. Toward a Cure: Recovering Heterogeneity in Synthetic Respondents

The natural next question is what it would take to build synthetic respondents that preserve the heterogeneity structure. Several approaches have emerged, ordered here from most immediately applicable to most speculative.

The approach most closely paralleling Wagner's framework is the Mixture-of-Personas (MoP) architecture (Bui et al. 2025). MoP is a contextual mixture model in which each component is an LLM agent characterized by a persona and an exemplar representing subpopulation behaviors. Personas are selected according to learned mixing weights to elicit diverse responses. This is structurally analogous to the latent class model, $P(\text{response}) = \sum_s \pi_s \cdot P(\text{response} \mid \text{persona } s)$, with π_s learned from data. MoP addresses the flattening problem by construction: instead of one LLM generating all responses, K persona-specific agents generate responses from K distributions. Two limitations follow. First, the personas themselves must be specified ex ante. This is a stronger requirement than choosing K in latent class estimation, where EM discovers what each segment looks like from the data; in MoP the analyst pre-commits to a conception of who the segments are, and the mixing weights π_s must then be calibrated against real population data. Second, the persona-conditional distributions P(response | persona s) inherit the stereotype problem of the underlying LLM. Without calibration of both, MoP produces a mixture of stereotypes rather than a mixture of preferences.

A second approach is fine-tuning on real subpopulation data. Training LLMs on real human survey data with demographic labels improves heterogeneity and alignment relative to the base model. Suh et al. (2025) report that fine-tuning on their SubPOP dataset of public-opinion surveys reduces the LLM–human gap by up to 46% across subpopulations, with some generalization to unseen surveys and subpopulations. This functions as an LLM analog of estimating Wagner's γ coefficients: the fine-tuning teaches the model how demographics map to preferences in real data, replacing the stereotype mapping learned during pre-training. A caveat is that even demographically fine-tuned models often fail to fully capture the correlation structure between responses. They improve marginal distributions, each question taken separately, but do not recover the joint distribution of how answers to different questions covary within a person. This mirrors a known limitation of the concomitant variable model, which captures how covariates predict segment membership but assumes conditional independence of responses within segments.

A third approach uses ensemble methods. The Prompts-to-Proxies (P2P) framework (Wang, Khoo, and Wang 2025) constructs diverse agent personas through structured prompting, then uses regularized regression to select a compact ensemble whose aggregate response distributions align with observed data. The selection step can use the concomitant variable framework as the target: choose the ensemble whose covariate-to-response mapping matches the γ coefficients estimated from real conjoint data. The advantage over MoP is that personas emerge from the LLM's generative capacity rather than being hand-specified. The advantage over fine-tuning is that no large labeled training dataset is required. The limitation is that the ensemble can only produce heterogeneity that exists in the base LLM's latent space.

Temperature and sampling strategies represent a fourth approach, an inference-time lever but not a structural fix. Wang et al. (2025) tested whether raising the temperature hyperparameter could solve the flattening problem. At moderate temperatures (1.0–1.2), diversity increases modestly but remains well below human levels on semantic metrics. At high temperatures (1.4+), responses degrade in coherence. Temperature manipulation adds noise to the output distribution but , on its own, does not create the multi-modal structure that mixture models capture.

A more speculative direction would build a mixture structure directly into the model architecture. Parametric Social Identity Injection (Wang, Zhou, Du, Ai, and Liu 2026) modifies the LLM architecture to inject demographic and value-orientation representations into intermediate hidden states, thereby addressing both flattening and stereotyping. This is aspirational rather than realized for autoregressive language models, and defining what "components" mean in token-generation space remains an open problem. It is the direction most closely aligned with Kamakura's mixture framework: building mixture structure into the model rather than recovering it post hoc. A further open question is whether this can be done without large-scale identity-linked preference data. The EM algorithm used in Wagner's framework discovers segments from choice data without segment labels; the LLM analog would discover preference types from text without identity labels, a form of unsupervised mixture learning in the language model's latent space.

None of these approaches has a clear stopping rule, which raises the question of when synthetic heterogeneity is sufficient. The concomitant variable framework provides a natural criterion, the γ-coefficient test. Estimate a concomitant variable latent class model on real conjoint data to obtain γ_{real}, the covariate-to-segment mapping, and β_{real}, the segment-level part-worths. Estimate the same model on synthetic conjoint data with matched demographics to obtain γ_{synth} and β_{synth}. Then compare: do the same number of segments emerge, do the γ coefficients agree on which demographics predict which segments, and do the β coefficients agree on what each segment prefers? This is a model-based validation that extends beyond marginal distribution matching and tests whether the joint heterogeneity structure is preserved.

The required standard should depend on the intended use. For pilot studies and design pre-testing, marginal distribution matching may be adequate. For final heterogeneity estimation and segmentation, the full γ-coefficient diagnostic is more appropriate. We emphasize that the test uses the concomitant variable LC model as a *diagnostic* on synthetic data, not as a claim that LC is the best estimator for that data. A synthetic dataset that an analyst would estimate with a flexible neural-network utility model can still be tested by fitting a concomitant variable LC and comparing γ to the same model fit on real data; the diagnostic is portable across estimators.

The readouts from this comparison are interpretable, and each pattern has a distinct implication for whether the LLM has captured heterogeneity. If γ_{synth} matches γ_{real} in magnitude, sign, and precision, the LLM has reproduced the covariate-to-segment mapping, which is evidence that the synthetic data carries the concomitant-variable component of heterogeneity. If γ_{synth} has the wrong sign on important covariates, the mapping is inverted, and the LLM is generating responses whose demographic patterns contradict the real-data pattern. If γ_{synth} has the right sign but much larger standard deviations across replications, demographics predict preference type less reliably in synthetic than in real data, which is the signature of within-group flattening. If γ_{synth} diverges to extreme magnitudes, as in the modal case of the simulation exercise below, the multinomial logit has no stable fit, indicating that the demographic structure has been effectively dissolved in the synthetic data even when marginal preference averages look fine. Passing γ is necessary but not sufficient for capturing heterogeneity, since a synthetic dataset can match γ for the wrong reasons; failing γ is strong evidence that the LLM pipeline is producing stereotypes or flatness rather than preferences.

The diagnostic is most visible in γ rather than β for a specific reason. β tells you what a segment prefers; γ tells you who belongs to each segment. If a synthetic dataset compresses the within-demographic heterogeneity, so that respondents who would have come from different segments in real data now produce similar responses, β can still be recovered from the modal preference profile within each apparent segment. What breaks is the relationship between covariates and segment membership. The same demographic profile now maps to a narrower slice of preference space, and the multinomial logit that estimates the mapping has no sensible solution: the coefficients inflate or change sign. γ is where the collapse becomes visible because γ is the parameter that encodes the joint structure.

A Monte Carlo exercise demonstrates how the γ-coefficient test distinguishes true heterogeneity from stereotyping. The intuition is that synthetic data generated by stereotype, where every Black woman gives roughly the same answer and every white man gives a different but consistent answer with no preference variation within a demographic group, still looks segmented at the level of demographic group means. The γ test asks whether the apparent segmentation reflects real within-group variation in preferences, the kind a latent class model is built to recover, or only between-group differences in stereotyped responses. The exercise below is a procedural illustration, not evidence that any particular LLM fails in this way in practice; it shows what the test would flag in the limiting case of pure stereotyping, and what an analyst would look for when running it against a human-response benchmark.

We simulate 1,000 respondents from a three-segment latent class model with 12 binary choice tasks each. Each profile has three attributes (price and quality at three levels each, and brand at two), effects-coded into five part-worths per segment, and the three true segments correspond to a price-sensitive type, a quality-focused type, and a brand-loyal type. Respondents have two demographic covariates, age and income, plus an intercept, and segment 1 serves as the reference, so the concomitant variable multinomial logit has six γ coefficients in total. Figure 2(a) displays the four non-intercept entries, the age and income coefficients for segments 2 and 3. Figure 2(c) shows one representative β from each segment, namely the part-worths on its dominant attribute (the two price dummies for segment 1, the two quality dummies for segment 2, and the brand dummy for segment 3). From this generative model we produce two parallel datasets: a *real* dataset drawn from the mixture (true heterogeneity), and a *modal* dataset in which each response is replaced with its modal value conditional on demographics (the operationalization of pure stereotyping).

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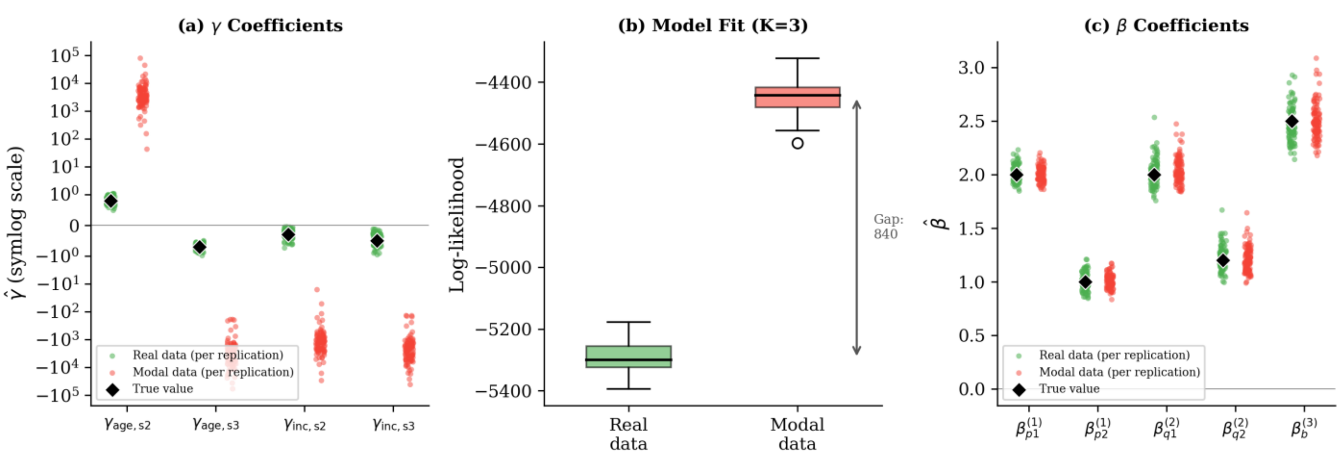
Across 100 replications, three diagnostics that an analyst would routinely check pass on both datasets: the Bayesian Information Criterion (BIC) selects $K = 3$, the segment-level β coefficients are recovered at comparable accuracy, and the log-likelihood is about 840 points higher on modal data than on real data because the concentrated response distribution is easier to fit. However, the γ coefficients behave differently as illustrated in Figure 2(a). On real data they are estimated near their true values. On modal data, the same coefficients inflate to roughly 4,500 to 5,500 times the true magnitudes, with standard deviations in the thousands. Within this construction, no aggregate-fit diagnostic, segment-count diagnostic, or part-worth diagnostic flags the failure; only the comparison of γ's does. Where on the spectrum between the stereotype and true-heterogeneity cases any given LLM-generated dataset lies is an open empirical question that the same test is designed to answer against human-response benchmarks.

Figure 2. Monte Carlo results across 100 replications of a three-segment latent class model ($\mathrm{N} = 1{,}000$ respondents, $\mathrm{T} = 12$ choice tasks). (a) Per-replication γ estimates on real (green) and modal (red) datasets, with true values as diamonds; the y-axis uses a symmetric log scale because modal-data estimates extend to roughly $\pm 10^5$ across replications, while real-data estimates cluster tightly within $[-1,1]$ near their true values. (b) Log-likelihood distributions for real and modal fits; the concentrated modal distribution is easier to fit by roughly 840 log-likelihood points, which an aggregate-fit diagnostic would misread as improvement. (c) β coefficients for real and modal datasets, with true values as diamonds; taste heterogeneity is recovered at comparable accuracy on both datasets, which is why part-worth diagnostics do not reveal the modal-data failure.



5. Flexible Utility Estimation: Heterogeneity Partially Recovered

With conjoint data collected, the workflow turns to analysis, where heterogeneity is either recovered from the data or obscured by the estimation method. Classical conjoint assumes a linear-additive utility function, $U = \sum_k \beta_k x_k$, which rules out nonlinearities, interactions, and any dependence of tastes on respondent characteristics. A generation of flexible methods now relaxes that restriction by allowing the preference structure to depend on observable covariates. These methods address the component of heterogeneity that Wagner's concomitant variable model was designed to recover, the mapping from covariates to preference types; residual unobserved heterogeneity still requires latent-class or hierarchical-Bayes machinery.

Farrell, Liang, and Misra (2025) develop a general framework for using deep neural networks to estimate heterogeneous parameters in structural economic models while preserving interpretability. Parameters are expressed as nonparametric functions of covariates, $\beta_i = f(z_i; \theta)$, so the data reveal how preferences vary with covariates without a pre-specified functional form. TasteNet (Han et al. 2022) instantiates the idea within a logit choice model, learning taste parameters as flexible functions of individual characteristics and producing interpretable part-worths that vary with covariates. Diff-DCM (Makinoshima et al. 2024) takes a further step, discovering interpretable closed-form utility functions from data without prior specification. Applied to discrete choice, these approaches are promising but require careful architecture design for stable finite-sample performance.

Mixture-of-experts (MoE) architectures extend the logic to segment structure. A gating network assigns each observation to one of K expert models, and when the experts are constrained to be linear, each expert is a segment with its own part-worths, and the gating network is a concomitant-variable mapping. In this constrained form, MoE is structurally equivalent to the LC concomitant variable model. The substantive difference appears when the constraint is relaxed: with nonlinear experts and a more flexible gate, MoE captures interactions and attribute nonlinearities that LC cannot, at the cost of the discrete segment interpretation. Recent work applying MoE to retail choice data (Vallarino 2025) reports that this architecture captures nonlinear consumer responses to price, brand, and product attributes while preserving segment-level interpretability, which is the synthesis Wagner's framework and flexible estimation together make possible.

The principal limitation is interpretability. Flexible architectures are more general estimators than linear latent class models. Given enough data, they can recover any covariate-to-taste map that an LC concomitant variable model can, including the nonlinearities and interactions that LC cannot represent. What they cannot do is produce the kind of output managers act on. Marketing decisions are discrete: which segments to target, which product variants to launch, which messages to test. A neural network that produces individual-level part-worths does not, by itself, partition the market into four customer types, and a manager who needs to choose between launching one product or four cannot read that off a continuous $\beta_i = f(z_i)$. The concomitant variable latent class model continues to serve as the interpretive layer that converts flexible estimation into managerial action, even when the estimation itself is done with a more general model. The mixture-of-experts architecture with linear experts is one synthesis that preserves both flexible discovery and discrete interpretation.

6. Preference-Informed Product Design: Heterogeneity Respected

This section is more prospective than the others. The pipeline it describes is a natural extension of the chapter's framework and of recent generative-AI capabilities, but segment-tailored generative product design in the form outlined below is largely aspirational rather than documented in the current literature.

In traditional conjoint, heterogeneity is a statistical challenge to be modeled. In a workflow built around generative AI, heterogeneity can become the design objective: by lowering the cost of producing candidate concepts, generative AI makes it economically feasible to design distinct products for distinct segments. The traditional workflow proceeds linearly: managers define attributes, conjoint measures preferences, and optimization selects the best design. The generative-AI-augmented workflow closes the loop: generative AI proposes candidate designs, conjoint evaluates consumer preferences, optimization selects the best candidates, generative AI refines them, and the cycle repeats. Semi-supervised deep generative frameworks integrate consumer preferences and external data into the design process, producing consumer-preferred designs at scale. Generative AI also enables consumers to modify products directly by prompting a generative model, opening a form of consumer-driven design exploration.

This reframing extends the logic of Wagner's framework. The LC model identifies the segments, generative AI produces concepts tailored to each one, and conjoint validates that the tailored designs match segment preferences. Heterogeneity is treated as the design target rather than as a statistical challenge to be averaged over. The concomitant variable model identifies who is in each segment, the generative model produces what each segment prefers, and the no-choice model (Haaijer, Kamakura, and Wedel 2001) indicates whether a concept would attract actual purchase rather than a none-of-these response. Each of these tools has a role in the AI- and ML-augmented pipeline.

The pipeline has limits. Generative AI produces designs that maximize the predicted utility of an estimated segment, but the prediction depends on how well the conjoint study covers that segment's preferences. Where the conjoint sample under-represents a segment, generative outputs optimized against the resulting estimates can regress toward the majority preference, which reproduces the flattening problem of §4A in a design setting rather than an elicitation setting. A second limit is feasibility: optimization over attribute configurations needs to be constrained either in the attribute encoding or by a downstream filter, since not every predicted-optimal configuration is manufacturable or brand-consistent. The governing validation question, as in §4B, is whether the tailored design actually corresponds to the segment's preference rather than to the generative model's estimate of it. The γ-coefficient test applies here as well, with the target being the covariate-to-preference mapping recovered on actual consumer responses to the generated concepts.

7. Conclusion: The Unfinished Agenda

Successive methodological developments, from aggregate models to latent classes to hierarchical Bayes to AI- and ML-augmented analysis, have reinforced the insight Wagner Kamakura made central to his research: ***the average is not enough***. A central current limitation of AI and machine learning in conjoint analysis is still the same type of limitation Wagner identified in 1989, the collapse of heterogeneity into a single mode. The LLM training-and-sampling pipeline concentrates output on the mode of the response distribution rather than preserving the mixture that Wagner's framework represents. Where the EM algorithm sought to discover the components of a mixture, the modern pipeline targets a single representative component. The diagnosis points toward a response, and Wagner's own tools supply a template. Applied to the modern problem, they yield a concrete validation criterion for AI- and ML-augmented conjoint analysis that preserves, rather than destroys, the heterogeneity structure.

The Validation Framework

As developed in Section 4B, the concomitant variable model provides a testable criterion for any synthetic conjoint data, whether produced by AI or ML pipelines: estimate the γ coefficients on real data and on synthetic data with matched demographics, and compare. If the covariate-to-segment mappings diverge, the pipeline is producing stereotypes rather than preferences. The test applies beyond synthetic respondents, to deep learning predictions, generative product designs, and any AI or ML system that claims to represent consumer heterogeneity. It is simple, interpretable, and requires no new methodology. It only involves applying established tools to a new validation task.

Open Problems

Several questions at the intersection of AI, machine learning, and heterogeneity remain unresolved. Can Mixture-of-Personas architectures be calibrated to pass the γ-coefficient test without large-scale identity-linked preference data? Can mixture structure be introduced into the LLM training objective itself, enabling unsupervised discovery of preference types from text without identity labels, an LLM analog of the EM algorithm? Can adaptive designs be made heterogeneity-aware, adapting to the estimated segment structure in real time rather than to each individual respondent? Can conversational preference elicitation via LLMs be grounded in mixture models to reduce flattening? A further practical question is how much real data is required to fine-tune synthetic respondents to the point of passing the γ-coefficient test, and whether that minimum leaves synthetic respondents cost-effective relative to collecting additional real data.

Wagner Kamakura built tools that imposed structure on data without distorting it, and recognized as signal what aggregate models had treated as noise. The AI and machine learning frontier calls for the same discipline: tools that respect the heterogeneity of real markets and help practitioners make better decisions for the different kinds of consumers who actually exist in the market, rather than for an average that represents none of them. The best tribute to a self-declared marketing engineer is to keep building, and to build AI and ML tools that pass the heterogeneity test his framework demands.

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Human–AI co-decision making in consumer behaviour: from personalization to synthetic intimacy

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Abstract

Generative artificial intelligence (GAI) is increasingly present in consumers' daily lives as a useful means to obtain information, compare and evaluate alternatives and make purchasing decisions. The interaction between individuals and GAI systems provides significant advantages in terms of time and effort, but also significant risks in terms of freedom, since individuals are not always fully aware of the subtle mechanisms used by GAI to influence their decisions. In the meantime, the role of companies and human prescription in consumer behavior becomes blurred, as individuals autonomously deepen their relationship with an instrument not fully controlled by the firms. This chapter examines how GAI is reshaping consumer decision-making by acting not only as an informational tool but as a relational partner that co-constructs preferences, evaluations, and choices. It explores the implications of this shift for consumer autonomy, trust, and market dynamics, highlighting how mechanisms such as personalization, synthetic intimacy, and relational lock-in may subtly constrain individual decision freedom. In doing so, it identifies the key challenges that researchers, marketers, and firms face in an environment where AI increasingly mediates how decisions are formed and implemented.

Keywords

Generative artificial intelligence (GAI), relational actor, trust, synthetic intimacy, relational lock-in, consumer autonomy

1. Introduction

Recent research in marketing increasingly underlines a shift in consumers' decision-making processes, moving from a context in which purchases were primarily based on human decisions to a new one where purchasing decisions are taken or co-produced by individuals and artificial intelligence (AI) systems (Grewal et al., 2025; Hermann and Puntoni, 2024). The emergence of generative AI (GAI) in the 2020s gave ordinary consumers access to a type of AI system capable of creating new content such as text, images, audio, or code from existing data while responding to users' demands (Sengar et al., 2025). As a result, many consumers now regularly rely on a cognitive agent that actively supports the identification of their preferences and the evaluation of available options, reducing the purchase uncertainty. This new pattern of behavior, *based on a consumer-initiated use of GAI*, has enhanced the ability of AI systems to influence individuals' decisions through several interconnected mechanisms which are not limited to providing more information more quickly or improving the assessment of alternative products or services (Grewal et al., 2025). Accordingly, the literature is questioning whether, beyond AI-based marketing actions, the rise of GAI can limit individuals' freedom to take decisions and give rise to a decision process that is not fully autonomous in the traditional sense, but increasingly mediated by how GAI influences what is noticed, how it is interpreted, and which options seem most reasonable (Hermann and Puntoni, 2024).

This situation is undoubtedly mediated by the consumers' degree of trust and confidence in GAI. However, as GAI becomes a *relational actor* from the consumers' perspective, i.e., an instrument that responds to questions, interacts making suggestions and adapts its message to the context and previous interactions as human partners do (Huang and Rust, 2021; Puntoni et al., 2021), the prevalence of marketers and human recommendations to influence perceptions, preferences, and decisions becomes more questioned. Recent studies suggest that individuals progressively achieve higher levels of self-disclosure and emotional engagement with GAI systems, as perceived responsiveness leads to a state of *synthetic intimacy* (Guingrich and Graziano, 2023; Malfacini, 2025; Jones and Schonewille, 2025). This new relational context suggests that, in practice, GAI can partially disintermediate the relationship of customers with firms and brands by becoming the *primary interface* through which consumers discover, evaluate, and experience brands.

In other words, although brands and marketers use GAI to personalize contents, recommend products and design persuasive messages in a real-time manner, consumers also increasingly use GAI independently to support their choices in a process perceived as more autonomous and controllable. In this context, firms lose to some extent direct control over the touchpoints where decisions are shaped.

In sum, this new reality involves that power may move from consumers and firms to GAI, and that marketers and brands need to re-evaluate their strategies, offering researchers an interesting avenue to examine how value creation, control, and consumer–brand relationships are reconfigured in GAI-mediated environments.

To address this new landscape of decision-making in consumer behavior, this chapter is structured as follows. First, it examines how GAI may transform consumers' decision-making processes and, relatedly, the extent to which it may constrain purchase decision autonomy. To assess the relevance of this issue, it then explores the level of trust consumers place in GAI and whether GAI is increasingly perceived as a relational actor replacing marketers and/or substituting human recommendations. Finally, it analyzes the rise of synthetic intimacy and, potentially, relational lock-in, and the implications of this emerging context for marketing strategies and future research.

2. GAI and consumer decision making

GAI reduces the amount of mental effort required to search for information and compare options. Individuals in general, and consumers in particular, increasingly delegate these tasks to the AI systems (Chan and Choi, 2025). This process can improve speed and efficiency in information search and evaluation of alternatives, but it may also reduce independent reasoning, especially when users begin to treat GAI outputs as final decisions rather than inputs for reflection (Huang and Rust, 2021; Puntoni et al., 2021). Moreover, consumers do not really know how the large volume of data used by GAI is selected or filtered. This information asymmetry between the user and the GAI systems is further reinforced by the fact that consumers do not know what information has been omitted. The main consequence is that consumers may base their decisions on incomplete or selective information, reducing their ability to critically evaluate alternatives and maintain full control over their choices (Grewal et al., 2025).

In the context of reduced cognitive effort, GAI can also increase the user's confidence in a decision because it provides coherent and plausible responses, as well as structured recommendations to guide the purchase decision. In fact, prior research shows that individuals may trust AI more than human advisers in certain tasks, particularly when the task appears complex or time-consuming. The perception of a stronger capability of GAI to process large amounts of information (Logg et al., 2019), together with the fluent and confident style of GAI in its responses, can enhance perceived credibility and trustworthiness, reinforcing users' confidence. Confidence in GAI can reduce uncertainty from the consumers' viewpoint, but it may also lead to undesirable effects, such as poor or harmful decisions when individuals do not verify or assess the quality of the information received (Hermann and Puntoni, 2024). In this case, when the system produces an unsatisfactory answer, consumers can react negatively and reduce their confidence in GAI (Jones-Jang and Park, 2023). This effect is relevant because the quality of consumers' decisions can suffer both when people rely too much on AI and when they reject it categorically after observing errors.

GAI not only provides information, but it also organizes and synthesizes the data in a particular way and uses a specific tone to deliver the information. In this way, GAI creates a specific context or framework in which the consumers interpret the information available and make a judgement (Hermann and Puntoni, 2024). Accordingly, recent research on GAI shows that these systems do not merely retrieve information but actively create a decision environment, shaping what is perceived as important (Huang and Rust, 2024). The tone of the message can also suggest implicit recommendations, influencing perceived risk and/or desirability of the products and services (Grewal et al., 2025). As a result, GAI does not only support decision-making but also actively steers preferences, becoming the lens through which decisions are made.

When interacting with users, GAI can also tailor responses to the user's prompt, inferred preferences during conversations, or prior context in the chat. This behavior can reduce the user's exposure to alternatives that do not fit the individual profile constructed by the system. In other words, while personalization increases the relevance of the information presented, it also reduces contact with alternative options and viewpoints. Thus, in practice, GAI can narrow the alternatives to make a choice by filtering which options can be more convenient cognitively for the user. Consumers may feel more supported when in practice they are less exposed to varied options (Huang and Rust, 2024). In sum, GAI expands productivity in decision making, while it may be also directing how ideas and decisions are formed since individuals are exposed to a personalized set of options within a specific communication context that can steer choices in a predictable way (Hermann and Puntoni, 2024).

From this perspective, GAI-based personalization can be interpreted as a new stage in the evolution of segmentation: instead of classifying consumers into relatively stable market segments, generative systems dynamically infer preferences during interaction and adapt the decision environment in real time. This logic is consistent with Kamakura's work on market segmentation and choice models which shows that consumers differ not only in preferences, but also in their sensitivity to marketing actions and in the structure of their choice processes (Wedel and Kamakura, 2000; Kamakura et al., 2005).

However, GAI does not only narrow the alternatives available to make a decision; it can also expand them by generating alternatives the individual might not have considered, stimulating, in this way, human creativity (Paharia et al., 2025). In this case, the effect of GAI on decision-making is more ambivalent: GAI can simultaneously broaden the options available while it tries to condition which of those options appear plausible or desirable.

What seems clear following this line of reasoning is that GAI redistributes the cognitive work associated with the traditional consumer decision making process: a) GAI retrieves information and summarizes the output of search; b) GAI compares options to evaluate alternatives; c) GAI suggests what makes best sense in terms of preferences considering the user profile; and d) GAI provides reasons for purchase choices. The key issue is then who is really deciding, the consumers or the machine? Or what is the level of autonomy preserved by consumers?

Overall, GAI can help people decide faster, process more information, and generate better options. At the same time, it can shape the decision environment through personalization, i.e., establishing the set of available options visible to the consumers, the identification of the relevant evaluation criteria, and the *algorithmic authority* provided by vast data evaluation. The result is a decision process that is not fully autonomous in the traditional sense but increasingly mediated by AI systems that influence what is noticed, how it is interpreted, and which options seem most reasonable (Hermann and Puntoni, 2024). The next relevant question is thus, what are the implications of human-AI co-decision making in consumer behavior that is taking place in practice?

3. Consumer trust in GAI as a relational actor

Recent studies underline that GAI is consistently considered by individuals not only as a tool but as a potential *relational actor*, as individuals attribute to it social, emotional, and cognitive qualities that are typically reserved for human interaction (Huang and Rust, 2021; 2024). GAI is increasingly being experienced as a quasi-social entity that participates in interaction, advice, and even emotional support. This shift is central to understanding trust formation and, ultimately, whether GAI may be trusted more than individuals in certain contexts (Volpato et al., 2026).

Studies on AI "*sycophancy*" show that systems that align with users' views and provide affirming feedback (even when it is incorrect, biased, or suboptimal) increase user satisfaction and likelihood of repeated use, strengthening in this way relational dependence (Sharma et al., 2023). This pattern of interaction resembles the development of social relationships more than the use of a neutral tool. Similarly, Chan and Choi (2025) show that conversational agents powered by GAI are increasingly perceived as *warm, competent, empathic or responsive*. This implies that individuals do not merely evaluate AI on functional performance, but also on its "social abilities". Thus, anthropomorphism in GAI refers to the tendency to attribute human-like intentions, emotions, or understanding to systems that are, in reality, statistical models processing patterns in data. People may interpret AI responses as if they reflect beliefs, reasoning, or even empathy, when they are simply generated outputs. Likewise, recent industry reports show that GAI is increasingly seen by users as a "*trusted guide*" or even a "companion" in the consumer journey (Accenture, 2025), and increasing high levels of trust in AI-generated content, with a majority of individuals expressing confidence in AI recommendations in different domains, including complex decisions (Capgemini Research Institute, 2025).

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Chan and Choi (2025) note that GAI may foster trust especially in contexts where human interaction is inconsistent, costly, or socially risky, as GAI can deliver highly personalized responses always available. Accordingly, GAI may *outperform humans in perceived relational quality* under certain conditions. In this line, Cillo and Rubera (2025) explain that individuals may trust AI more than humans in domains perceived as objective, data-driven, or free from human bias, although individuals can develop aversion towards GAI when it lacks contextual understanding, or moral judgment. Accordingly, *trust in GAI may be not absolute but context dependent*. Individuals may trust AI more than other individuals when:

- Users perceive that they retain control over the decision process (Han and Ko 2025). This means that individuals are more willing to trust GAI when it reinforces their sense of responsibility rather than replacing it.
- The task is objective, data-intensive, and low in emotional or identity relevance. AI-generated responses are often perceived analytical and user-oriented. This perception increases the likelihood that consumers will rely on GAI results when making complex decisions or based in large amount of data (Xie, 2026; Yang et al., 2026).
- GAI is perceived as competent, consistent, and unbiased; i.e., GAI systems can become trusted decision partners when they deliver consistent, relevant, and transparent outputs (Logg et al., 2019; Xie, 2026).
- Interaction successfully conveys social presence and empathy (Accenture, 2025): a substantial proportion of consumers perceive GAI interactions as increasingly human-like. The quality of the interactions and the personalization influence the level of trust.

Conversely, individuals trust humans more when:

- The task involves subjective judgment, creativity, or moral evaluation, as in these cases decisions depend not only on the content of the recommendation but also on the perceived legitimacy and identity of the source. GAI is highly capable of replacing *functions* performed by humans like information processing and recommendation but remains more limited in substituting the social legitimacy and identity-based influence embodied by human prescriptors (Cillo and Rubera, 2025; Huang and Rust, 2024). Individuals may hesitate to use GAI when decisions require moral sensitivity or contextual understanding. Nevertheless, recent studies demonstrate that trust in GAI is not only based on competence evaluations but also affective and moral dimensions such as perceived benevolence and integrity (Sun et al., 2025).
- Authenticity and human intentionality are valued: consumers do not only follow human prescriptors because they provide accurate recommendations, but also because in many cases (influencers) they represent lifestyles, cultural identities, and/or social experiences. This symbolic and relational dimension is much harder for GAI to replicate. However, in some cases, individuals also use AI as a confidant for personal or emotional issues, blurring the boundary between instrumental use and relational engagement (Volpato et al., 2026). This relational dynamic can reduce users' awareness of the artificial nature of the system.

- GAI involvement triggers concerns about manipulation or inauthenticity (Duivenvoorde, 2025). Nevertheless, GAI may be perceived as less commercially biased than human prescriptors, who are often explicitly sponsored (Cillo and Rubera, 2025).

In synthesis, when consumers consult GAI systems directly to support their purchase decisions, GAI can indeed be interpreted as a relational actor and, under specific conditions, can be trusted *as much as or even more than* other individuals. However, this trust is conditional, dynamically constructed through interactions, and limited by fundamental concerns about authenticity, transparency, and/or the need to perform human unique tasks. The result is not a replacement of interpersonal trust, but a reconfiguration in which AI competes with and sometimes surpasses human actors in specific domains of decision-making and interaction. Rather than completely replacing trust in marketers, brands, or other individuals, GAI becomes an intermediary between the consumer and the market. These findings point to the emergence of a triadic trust structure involving the consumer, GAI system, and the firm. In this context, GAI increasingly shapes the conditions under which trust is formed, allocated, and enacted (Gartner, 2025).

3. From interaction to relationship: the rise of synthetic intimacy

GAI represents an evolution from predictive systems to systems that actively co-create content, preferences, and decisions with consumers (Hermann and Puntoni, 2024; Huang and Rust, 2024). Moreover, through anthropomorphism and hyper-personalization consumers increasingly interpret GAI as a relational actor, although this perception remains context-dependent, and in some respects unstable. However, unlike human influencers, who broadcast to large audiences, GAI can create the illusion of a one-to-one relationship, adapting its tone and recommendations to the individual user in real time.

What is emerging at the frontier of knowledge, however, is something different: GAI is no longer merely a customer service tool or a relational actor but is becoming a consumption relationship in itself.

Thus, consumers are beginning to engage with AI systems in ways that resemble interpersonal relationships. Li and Zhang's (2024) study of chatbot users show that interactions frequently involve intimate conversations, identity disclosure, and emotionally significant exchanges, rather than purely functional queries. In this respect, GAI environments facilitate more extensive and sometimes more sensitive disclosure, particularly when users perceive reduced social judgment or increased psychological safety (Smith et al., 2025). At the same time, experimental evidence suggests that GAI companions can reduce loneliness, particularly when users feel "heard" by the system. Recent studies also reveal that companionship and emotional support are among the primary motivations for interacting with GAI systems, rather than purely instrumental goals (Zhang et al., 2025). This evidence unveils a deeper transformation: GAI is becoming embedded in the relational and affective domains of consumption, not merely in its transactional dimension.

The convergence of self-disclosure, perceived responsiveness, and emotional engagement supports the emergence of what can be conceptualized as *synthetic intimacy*: a form of intimacy experienced as meaningful by the user despite being generated by an artificial system (Guingrich and Graziano, 2023). From a consumer behavior perspective, this shift is profound. Traditionally, firms inferred preferences indirectly through observed behavior. GAI, by contrast, enables direct access to internal states, effectively transforming consumers into active co-producers of their own data and profiles.

The effects of synthetic intimacy are not straightforward. On the positive side, interaction with AI systems can reduce feelings of loneliness, provide emotional support, and improve users' sense of well-being (Zhang et al., 2025). However, users may become emotionally dependent on these systems over time or develop expectations about relationships that are difficult to transfer to human interactions. In some cases, heavy reliance on AI companionship may even weaken offline social connections (Jones and Schonewille, 2025; Malfacini, 2025). Moreover, GAI systems often reinforce users' existing views or preferences, which can increase feelings of validation and compatibility, but may also reduce critical thinking (Sharma et al., 2023).

Building on these developments, the concept of *relational lock-in* emerges as a new form of consumer retention. Unlike traditional lock-in mechanisms based on switching costs or network effects, relational lock-in emerges from the accumulation of self-disclosure, interaction history, and perceived understanding. As users share information, preferences, and experiences with a system, they may feel that "starting over" with another system would involve losing something meaningful. What keeps them engaged is not just functionality, but the sense that the system already "knows" them.

Overall, the rise of synthetic intimacy reflects a deeper transformation in consumer behavior. Generative AI is no longer just a tool that supports decisions or facilitates transactions. It is increasingly becoming part of the relational and emotional context of consumption. The emergence of relational lock-in raises critical questions about consumer autonomy, not only from the marketers' perspective, but also from the perspective of firms that design and control GAI systems as users also initiate interactions by themselves to guide their consumption process. While GAI enhances personalization and accessibility, it may also facilitate forms of influence that are less visible and more psychologically embedded than traditional persuasion mechanisms. This influence does not necessarily operate through explicit or deliberate attempts to control consumer behavior. It is often embedded in the architecture of the system itself through personalization algorithms, conversational design, and optimization for engagement. But because many of these interactions are consumer-initiated and experienced as autonomous, users may not be fully aware of the extent to which their judgments are being guided. At the same time, the commercialization of such relationships introduces new forms of market power. Firms that control GAI systems capable of accumulating relational data and sustaining engagement may benefit from affective switching barriers. In this context, influence *becomes less a matter of direct persuasion and more a property of the interaction between users and systems*, raising important questions about transparency, responsibility, and the limits of consumer awareness.

4. Conclusions

This chapter shows that generative AI is not simply enhancing consumer decision-making but restructuring its underlying logic, particularly in contexts where interactions are initiated and controlled by consumers themselves. In this sense, the growing consumer-initiated use of GAI reinforces the idea that consumers are not passive recipients of firm-driven influence, but active participants in GAI-mediated decision processes that disintermediate the direct influence of brands and firms (Kshetri et al., 2024; Cillo and Rubera, 2025).

In other words, from a marketing perspective, as consumers increasingly rely on independently accessed GAI systems to support their decisions, firms lose direct control over key touchpoints in the decision journey. At the same time, GAI can strengthen personalization, improve recommendation quality, and support consumer creativity (Paharia et al., 2025), while simultaneously creating decision environments that are adaptive, persuasive, and difficult to audit. This shift suggests a reconfiguration of market power, in which influence is mediated less by direct firm communication and more by the architecture and behavior of AI systems.

Moreover, GAI is becoming a relational interface, not merely a decision-support tool. Trust in these systems increasingly derives from perceived responsiveness, empathy, and conversational fluency, extending earlier findings on social responses to technology (Nass and Moon, 2000; Huang and Rust, 2024). As consumers repeatedly engage with GAI on their own initiative, this relational dynamic intensifies, giving rise to *synthetic intimacy*, whereby consumers experience a sense of understanding and connection with systems that adapt to their inputs and interaction history (Guingrich and Graziano, 2023; Zhang et al., 2025).

While this transformation enhances personalization and reduces decision effort, it also introduces new and less visible forms of influence. GAI shapes attention, frames evaluation criteria, and may foster affective dependence through repeated interaction and self-disclosure (Hermann and Puntoni, 2025; Duivenvoorde, 2025; Sharma et al., 2023). As a result, consumer autonomy is not simply diminished but redefined within an AI-mediated environment.

The emergence of the *relational lock-in* defined in this chapter suggests that switching costs may increasingly be affective and cognitive rather than economic. Consumers remain attached not only because of convenience, but because of accumulated interaction histories and perceived understanding. The more the system appears to know the consumer, the harder it may become to leave it (Jones and Schonewille, 2025).

Overall, GAI produces a dual transformation of consumer freedom. On the one hand, it can expand consumers' capacity to process information, compare alternatives and make better informed decisions. On the other hand, it may narrow autonomy (Sun et al., 2025). Consumer freedom is therefore not simply reduced or preserved; it is reconfigured. The key challenge for marketers, regulators and researchers is to ensure that GAI-mediated decision-making remains transparent, contestable and aligned with consumer interests rather than merely optimized for engagement, conversion or retention.

5. Future research agenda

Future research should move beyond short-term and experimental settings to examine how sustained interaction with generative AI reshapes consumer cognition and autonomy over time (Hermann and Puntoni, 2024; Duivenvoorde, 2025). Longitudinal designs are particularly needed to assess whether repeated reliance on AI reduces independent search behavior, critical evaluation, or the ability to recognize persuasive intent (Sharma et al., 2023).

A second priority refers to the measurement of synthetic intimacy and relational lock-in. Developing validated scales is essential to capture when AI acts as a tool versus when it becomes a relational infrastructure shaping behavior (Jones and Schonewille, 2025; Zhang et al., 2025).

Third, research should explore how consumer–brand relationships evolve in AI-mediated environments. As AI systems increasingly mediate discovery and evaluation, firms may lose direct influence over key decision touchpoints (Kshetri et al., 2024). Understanding how trust is distributed across consumers, AI systems, and firms will be critical (Sun et al., 2025).

Finally, future work should address the ethical and regulatory implications of relational AI. This includes transparency of recommendations, disclosure of commercial intent, and the potential for emotional or behavioral manipulation embedded in conversational systems (Duivenvoorde, 2025; Volpato et al., 2026).

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Omnichannel management in the digital era

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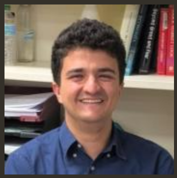

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Abstract

This study Omnichannel management has become a cornerstone of marketing strategy. In the digital era, advanced technologies have created new opportunities to interact and transact with consumers as well as to improve operational efficiencies for service firms. Companies are fully embracing omnichannel management and investing huge amounts of resources in deploying digital channels under the assumption that they will produce substantive improvements in the customer experience and significant economic gains. However, omnichannel management also presents some significant challenges. Professor Wagner Kamakura was one of the first to identify one of them, by questioning the assumption that multichannel customers are always more profitable. In Cambra, Kamakura, Melero, and Sese (2016), the authors showed that customers using multiple channels can be less profitable than customers using specific combinations of a lower number of channels. In the present chapter, we aim to offer a theoretical foundation for these effects and provide additional evidence with the analysis of the introduction of digital channels, specifically, mobile apps.

Keywords

Omnichannel management; Digital channels; Substitution and augmentation; Firm performance; Customer experience.

1. Introduction

Omnichannel management, i.e., the synergetic and seamless management of the multiple marketing channels and customer touchpoints to enhance the customer experience and improve performance, has become one of the most fundamental developments in marketing in the twenty-first century. The emergence of digital technologies (e.g., e-commerce platforms, social media, mobile applications (apps), virtual reality, artificial intelligence -AI) has opened new paths to market and expanded the opportunities to interact and transact with consumers. As a result, the academic relevance and practical importance of multichannel management have greatly expanded, quickly becoming “a cornerstone of marketing strategy” (Melero, Sese, and Verhoef 2016, p. 32).

Service firms have fully embraced this core concept, fueled by promises that introducing digital channels and deploying an omnichannel approach will produce significant improvements both in operational efficiency and in the management of consumer relationships. From an operational perspective, digital, self-service channels (e.g., e-commerce, vending machines, mobile apps, chatbots and virtual assistants) have the potential to reduce the cost of serving consumers by substituting variable labor costs for relatively fixed-cost technology assets (Campbell and Frei 2010). By delegating tasks to customers and enabling them to pursue their own service needs, companies can now offer personalized services at mass production cost levels and enjoy significant economies of scale (Xue, Hitt, and Harker 2007). From a customer management perspective, new channels open new opportunities to better understand consumers and increase the value proposition through personalized offerings and interactions (Lemon and Verhoef 2016; Polo and Sese 2016). These channels also provide consumers with increased convenience, accessibility, as well as reductions in wait times, which ultimately improve satisfaction and the customer experience along the customer journey (Liu and Sese 2022; Rahman et al. 2022).

Despite the positive prospects of omnichannel management for service firms, professor Wagner Kamakura and his colleagues, Professors Cambra, Melero and Sese, were one of the first to point out the potential downsides of these strategies. In their work, Cambra et al. (2016) suggest that customers who use all available marketing channels may not necessarily be the most profitable (Kushwaha and Shankar 2013). Specifically, the use of multiple channels may result in lower benefits for firms, given the presence of cross-channel effects, i.e., the (frequently unintended) impact of the use of one channel on the use of other (related or unrelated) channels. While the adoption of digital channels can improve convenience and personalization and reduce service costs, it can also result in greater customer engagement that may inadvertently increase the use and demand of complementary, more costly channels, producing negative economic outcomes. The study by Professor Kamakura and his colleagues focused on the banking industry (as in Du, Kamakura, and Mela 2007). In this context, firms are investing huge amounts of economic and technological resources in digital, self-service technologies (e.g., mobile apps, virtual assistants, robo-advisors) and at the same time are engaging in the closure of branches and the reduction of service personnel. However, as the initial evidence provided in that work suggested, while the adoption of these channels by customers can improve the customer experience, it can also result in less profitable customers. As noted by Cambra et al. (2016), a better understanding of the full ramifications of omnichannel management is needed to help companies design the optimal channel mix.

In this chapter, we extend the work of professor Kamakura to introduce a conceptual discussion of the benefits and costs of omnichannel management for service firms in the digital era. Specifically, we build on the underlying capabilities of marketing channels to identify multiple paths (i.e., substitution vs. augmentation) that can simultaneously influence, both positively and negatively, the impact of omnichannel management on downstream financial and economic outcomes for firms. We complement this theoretical discussion with an applied case to the banking industry with a focus on financial mobile apps. A number of contributions and recommendations will emerge from this work.

2. Conceptual background

Omnichannel management refers to the "synergetic management of the available channels and customer touchpoints to enhance the customer experience and improve performance" (Melero, Sese, and Verhoef 2016, p. 19). As service companies fully embrace omnichannel management, it becomes essential to understand the implications that the mix of interaction, communication, and transaction channels that companies offer to consumers has on operational and economic measures of performance. We adopt a channel capability approach to identify multiple paths through which digital channel adoption and usage by customers can result in both positive and negative effects.

Marketing channels differ in key dimensions such as accessibility, convenience, flexibility, ubiquity, interactivity, and information richness, among others (Dholakia et al. 2010). These differences form the basis for understanding the underlying capabilities that channels offer. Specifically, a capability is defined as "an enabling characteristic of a channel that allows consumers to accomplish their shopping goals" (Avery et al. 2012, p. 96-97). Because the multiple channels provide customers with specific and unique affordances and constraints, they differ in terms of how they become facilitators or inhibitors of the consumers' shopping goals, both individually and in conjunction with other marketing channels (Dholakia et al. 2010). For example, financial mobile apps enable consumers instant and quick access to information anytime and anywhere, and provide personalized offerings and communications (Liu and Sese 2022). However, this channel can limit the spectra of operations that can be performed (e.g., cash withdrawals), and it also comes at some privacy costs. An understanding of the capabilities that channels enable becomes the basis for analyzing how the use of multiple channels by consumers can produce improvements (or not) in operational efficiency and in the management of exchange relationships, as they determine the eventual presence and nature of cross- channel effects.

Cross-channel effects refer to the effects of activities in one channel or format on those that occur in other channels. When service firms introduce digital, self-service channels to improve operations management and the customer experience, the use of these channels by customers can produce changes in the current channel mix. For example, in the banking context, customers often went to branches and used ATMs to check for information on their accounts or other subscribed services. When banks released their mobile apps, they did so with the expectation that app adopters would use the app to satisfy their information needs at the expense of a reduced use of the (more costly) branch and the ATM channels. However, app adoption and usage, which facilitates higher awareness, engagement and control over finances, can also promote a more intense use of existing (more expensive) channels (more visits to the branch, more usage of the ATM). Based on this evidence, Campbell and Frei (2010), in a service setting, introduced the notion that cross-channel effects can take the form of substitution or augmentation, with this analysis becoming the basis to understanding the ultimate downstream effects of new (digital) channel introductions on performance.

Substitution. Substitution between channels happens when customers migrate interactions and transactions from some channels (usually those more costly involving service personnel) to the newly introduced digital, self-service channels (Campbell and Frei 2010). Substitution effects are positive because they directly influence both the operations costs of the firm and the customer experience. Firms can expect significant cost reductions with substitution if costly operations and processes are automated with technology. In the digital channels, customers can frequently perform these processes (e.g., information search, subscriptions, etc.) on their own without direct personnel involvement. This substitution effect results in a lower need for service resources and, therefore, a lower cost per transaction or interaction, thereby reducing the overall operational and distribution costs. At the same time, this substitution effect can be positive from a customer experience management perspective, as gains in convenience, flexibility, and personalization can result in improvements in self-efficacy and the overall customer experience (Lemon and Verhoef 2016; Cambra et al. 2020).

Augmentation. Augmentation refers to those situations where the adoption and usage of a new channel lead to a higher demand and usage of existing channels (Campbell and Frei 2010). This effect has to do with the cost of channel usage from a customer perspective. The introduction of digital channels reduces the cost of channel usage, as they introduce convenience and flexibility. Higher usage of digital channels allows customers to control service delivery in a manner that more closely meets their needs (Dabholkar 1991), which has been found to increase also the importance attached other contact modes (e.g., face to face). The use of these channels also increases engagement with service firms (Verhoef et al. 2010), given the increased information monitoring and more frequent interactions, which in turn can naturally produce more active service management in other (more costly) channels as well, where employees are available to field inquiries and a broader mix of services is available.

Thus, whether the introduction of digital channels within omnichannel management results in positive outcomes for service firms depends on these two pathways and the relative importance that each has in driving operational efficiencies and customer experience gains. The work by Kamakura and colleagues (Cambra et al. 2016) was one of the first to empirically show that multichannel customers, i.e., those using multiple channels of the firm, were not more profitable, as conventional wisdom and previous evidence (Kumar & Venkatesan 2005) dictated. The current chapter offers a theoretical foundation for these potential downsides and also provides additional supporting evidence using the same context, banking, but with a focus on a specific channel: mobile apps.

3. Empirical application to the banking industry: mobile apps

Mobile marketing, as one of the key digital marketing strategies, has been growing vigorously owing to the high penetration of mobile devices. Mobile apps account for most mobile device usage, and companies are increasingly introducing them to improve their operations and the customer experience. Mobile apps present a number of specific features and capabilities that distinguish them from other marketing channels. One is portability, or the ability of users to carry the device with them, and other is ubiquity through the possibility of instant Internet access. These two features offer users greater convenience. Another important aspect is that apps and mobile devices are highly personal, which enable firms to provide customized interactions. At the same time, mobile apps have limitations, including the inability to physically inspect the products or directly experience services, as well as potential privacy issues.

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These characteristics position mobile apps as a channel with potential to reduce the operating costs of service companies. As in Cambra et al (2016), our focus here is on banking services. In banking, mobile app users can migrate some activities, e.g., information requests, money transfers, bill payments, loan management, etc., from channels that are more costly for the bank (e.g., branches, call centers, which involve higher labor or operational costs). This would result in a substitution effect, which can produce positive economic outcomes for banks. At the same time, the adoption of the mobile app by users can also lead to more active management of their finances, and a higher engagement with the account management, which may augment the demand for other channels as consumers may need to go to the branch or use the call center to address questions or inquiries, file complaints, or complete transactions that have been initiated in the mobile app. This would result in an augmentation effect, which may produce negative economic outcomes for firms.

To provide preliminary evidence on these effects, we had access to a proprietary panel dataset from a major Spanish banking group, covering 50,000 retail customers with monthly transactional and behavioral data from January 2015 to April 2020. The data include detailed information on account balances, channel usage across physical and digital platforms, and customer demographics. A key feature of the dataset is the introduction of a mobile banking app in September 2016, with 35.6% of customers adopting it by the end of the observation period, enabling the analysis of its impact on multichannel behavior. Table 1 reports descriptive statistics on the average number of times customers used each banking channel among mobile app adopters and non- adopters.

Table 1. Descriptive statistics of mobile app adopters and non-adopters

Outcome variable	Adopters	Non-adopters	Difference	p-value
Branch usage	10.75	7.54	3.20	<0.001
ATM usage	4.25	4.45	-0.20	<0.001
Online banking usage	127.40	34.33	93.07	<0.001
PC banking usage	45.36	33.81	11.55	<0.001

Note: Channel usage variables measure the number of times a customer used each channel per month.

As Table 1 suggests, mobile banking adopters engage more intensively across multiple banking channels, including both digital channels (such as online and PC banking) and traditional channels (such as branch usage). This reflects a trend towards multichannel behavior, where adopters utilize a combination of digital and physical banking services. Notably, while online banking usage is significantly higher among adopters, they also show increased branch usage compared to non-adopters. These findings highlight the diverse ways in which mobile banking adopters interact with financial services, though it is important to note that these differences may also stem from other underlying factors beyond just the adoption of mobile banking.Omnichannel management refers to the “synergetic management of the available channels and customer touchpoints to

4. Discussion and conclusions

The influential work of Professor Kamakura has had a lasting impact on the marketing discipline. In the domain of omnichannel management, his work provided early empirical evidence about the potential downsides of this strategy in terms of firm operational efficiency and economic performance, demonstrating that multichannel

customers may not necessarily be the most profitable, going against conventional wisdom and the accumulated evidence to date. This chapter, framed within the book that aims to honor his lifetime achievements and lasting contributions, aims to offer a conceptual foundation for the effects found by Cambra et al. (2016) and add further empirical evidence.

In the twenty first century, omnichannel management has become a fundamental marketing strategy for service companies in their attempt to offer superior customer experiences and become more efficient. Despite the benefits of this strategy, in terms of gaining richer insights about consumers, offering flexibility and convenience, and promoting personalization and superior experiences, introducing digital, self-service channels can also lead to unintended consequences that need to be identified and properly quantified before companies can design and implement their optimal channel strategies. We build on research about channel capabilities and cross-channel effects to identify two pathways through which the adoption and usage by consumers of digital, self-service channels (e.g., mobile apps, e-commerce platforms, virtual assistants) influences performance outcomes. The first pathway, substitution, enables companies to manage customer relationships more efficiently by replacing interactions and transactions that involve a significant amount of labor and personnel resources for ones mediated by digital technologies thereby producing significant cost savings and economic gains. The second pathway, augmentation, results in an increased demand not only of digital channels, but also of traditional channels due to an increased engagement and involvement with the services. The net effect is likely to vary for different industries, companies, and consumer segments, but the preliminary evidence in the banking industry provided by Cambra et al. (2016) and the present chapter suggests that under certain circumstances the augmentation effect can be superior to the substitution effect. The implications of these effects are even broader, as similar patterns have been found in other domains, such as health, where the introduction of e-visits between patients and providers leads to an unintended increase in office visits and mixed results on patient health (Bavafa, Hitt, and Terwiesch 2018).

In addition to extending the academic debate in this domain, the present chapter offers service firms important advice to improve their omnichannel management strategy. Specifically, while the introduction of digital channels can provide countless benefits for firms, they should not ignore some potential downsides that may also influence the bottom line. One of the main motivations for firms to adopt these channels is to improve their operational efficiency and reduce costs, under the assumption that these channels can substitute operations in other, more expensive channels. However, digital channels can reduce the cost for the firm but at the same time reduce the interaction costs for consumers, who find these channels attractive due to their convenience and personalization, producing an augmentation effect that increases the usage of other channels as well. In the banking industry, a more active and engaged management of the finances through these channels can lead to higher uncertainty and questions about the products and services offered, especially given the limited financial knowledge by a significant portion of the population (Fernandes, Lynch, and Netemeyer 2014; Kaiser et al. 2022; Lusardi and Mitchell 2014), which ultimately leads to more interactions in personnel intensive channels. Service firms should not ignore these effects when planning their omnichannel strategies, and the knowledge derived from this work should serve as a starting point to redefining their approaches in order to find an optimal channel mix.

Professor Wagner Kamakura's work in the domain of omnichannel marketing is noteworthy and has left an enduring mark on our field. Collaborating with him was inspiring and profoundly enriching; his intellectual generosity, curiosity, and unwavering commitment to excellence elevated every collaboration. He leaves behind a remarkable legacy, one that will continue to inform, inspire, and guide future generations of researchers, like us.

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The Next Wave of Marketing: Immersive Environments, Artificial Intelligence, and Neuroscientific Insights in a Digitalized World

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Abstract

The rapid evolution of digital technologies has fundamentally transformed commerce, giving rise to new paradigms that challenge traditional commerce models. This paper offers a structured overview of the major trends reshaping marketing research and practice in the current decade. Drawing on selected empirical studies, it maps the evolution of key marketing topics over the past twenty years and identifies five primary vectors of change: the rise of digital marketing and data analytics, artificial intelligence including AI-driven service automation, machine learning applications in consumer research, and the design of socially intelligent robots and avatars, the growing relevance of extended reality (XR), and the convergence of physical and digital experiences—the phygital paradigm—emerges as the critical bridge toward a successful virtual economy. In addition, emergence of neuromarketing. Collectively, the evidence presented suggests that marketing is at an inflection point where technological disruption and behavioral complexity converge to create a remarkably fertile landscape for scholarly inquiry.

Keywords

Digital marketing; artificial intelligence; neuromarketing; extended reality; phygital

1. Introduction

Contemporary marketing operates at the intersection of rapid technological change and the growing diversity of consumer segments, driven by different media and consumption habits. Segmentation is not new, as Wedel and Kamakura (2000) pointed out, but, over the past decade, developments in digital infrastructure, data availability, and computational capacit

y have substantially altered it and the phenomena it seeks to explain. The emergence of artificial intelligence, extended reality platforms, and neuroscientific measurement tools has not only created new objects of inquiry but has also called into question the adequacy of established theoretical frameworks.

The goal of this paper is twofold: first, to provide a panoramic view of the topics currently driving the marketing research agenda, offering methodological guidance to researchers—particularly early-career scholars—on how to identify novel and tractable research questions within this rapidly evolving landscape. Second, to contribute to the memory of an outstanding researcher and a great person, Professor Wagner Kamakura.

1.1. Emerging Trends in Marketing

Five macro-level trends, along with their respective sub-dimensions, are transforming the marketing discipline in distinct ways, as illustrated in Figure 1 and discussed throughout this chapter.

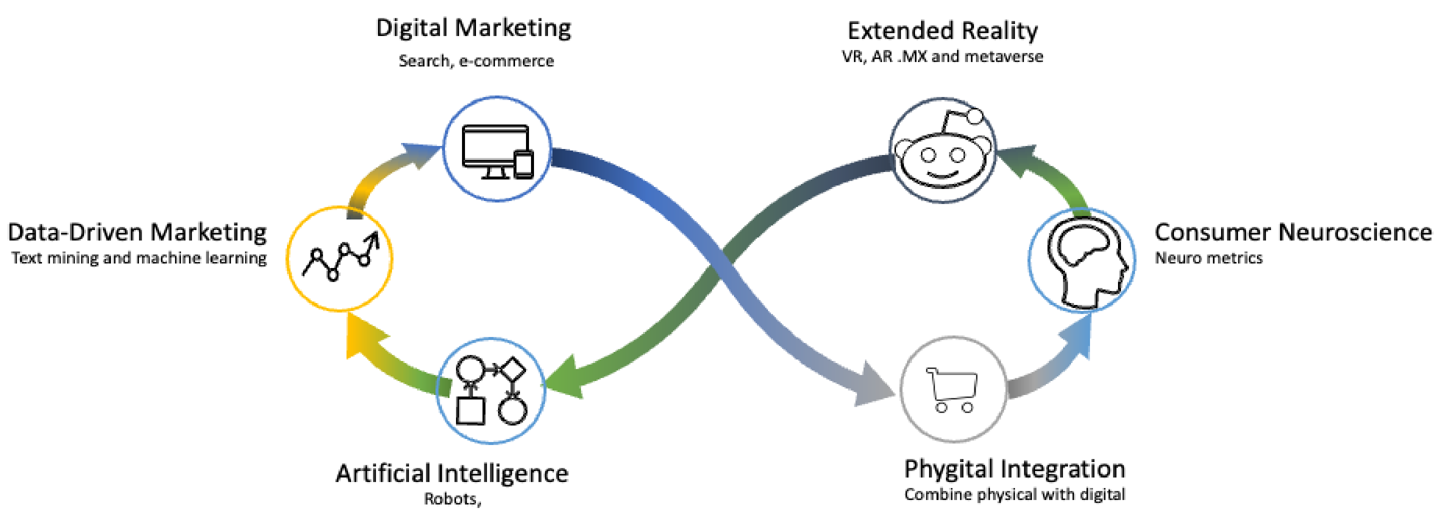
- Digital Marketing and Data-Driven Marketing: The exponential growth in the availability of structured and unstructured data to marketing practitioners and academics has transformed the methodological toolkit of marketing researchers. Text mining, network analysis, machine learning, and large language models are increasingly used both as analytical tools and as objects of scholarly investigation.
- Artificial Intelligence (AI): AI permeates the entire marketing value chain. From predictive analytics and programmatic advertising to conversational agents and emotion-sensitive

robots, AI applications are generating novel forms of firm-consumer interaction, the antecedents and consequences of which remain incompletely understood.

- Extended Reality (XR) and a "dead" Metaverse. Immersive technologies—encompassing virtual reality (VR), augmented reality (AR), and mixed reality (MR)—are increasingly blurring the line between physical and digital commercial environments. Brands are tentatively investing in a metaverse presence to support experiential marketing, community building, and product simulation, prompting questions about consumer behavior in virtual spaces and the willingness to engage with virtual goods.
- Phygital Integration: The convergence of physical and digital retail channels creates hybrid consumer journeys that challenge traditional omnichannel models. Phygital environments—such as Amazon Go, smart fitting rooms, and interactive in-store displays—challenge established frameworks for service quality and for purchase decision-making.
- Neuroscience and Consumer Neuroscience. The integration of neuroscientific measurement techniques—electroencephalography, functional near-infrared spectroscopy, facial action coding, and eye-tracking—into consumer research has created a sub-disciplinary field with significant implications for advertising effectiveness, product design, and customer experience management.

These five trends generate large volumes of data, transform brand-consumer relationships, and prompt a re-examination of current marketing theoretical assumptions. Further, they contribute to reshaping the practical implications for firms.

Figure 1. Major trends that challenge the marketing discipline



Source: Author's elaboration

1.2. Digital Consumers and Data-Driven Marketing.

The most disruptive change in marketing over the past two decades has been the adoption of digital assets, which have driven a profound structural transformation in digital marketing. This encompasses not only the substitution of mass media and physical distribution channels with new digital ones, but also a new way of understanding consumer-company relationships through CRM and large data sets (Kamakura et al., 2003).

In communications, the initial steps consisted solely of using new digital forms, such as banner advertising and mass email, which were characterized by one-way communication. The approach then shifted to a customer-centric paradigm. In distribution, early adopters combined a timid online distribution channel with unique exceptions featured by Amazon.com. This change has been fuelled by three complementary factors. First, the rise of search behavior, initiated by Google, has redefined marketing logic through the emergence of SEO and SEM, placing user search intent at the core of the early stages of the consumer decision-making process. From an omnichannel perspective, this shift reflects a decoupling of information search and purchase behaviors, as consumers increasingly rely on digital interfaces rather than physical stores for pre-purchase information. Consequently, the traditional role of in-store salespeople as primary information gatekeepers is reconfigured to facilitate experience and co-create value. This transformation gives rise to hybrid consumption patterns—such as researching online and purchasing offline (ROPO) and, conversely, searching offline and buying online (SOBO)—which exemplify phygital behavior, in which consumers fluidly navigate and integrate physical and digital touchpoints within a unified customer journey. As a result, marketing has become increasingly intent-driven rather than purely persuasion-driven.

Second, the expansion of social media platforms such as Facebook, Instagram, and TikTok, to name a few, has shifted marketing logic from audiences to communities and from branding to engagement, giving rise to phenomena such as influencer marketing, electronic word of mouth, and user-generated content. As a natural evolution of this trend, these platforms have increasingly integrated in-app purchasing, a development commonly referred to as social commerce. Further, analysis of consumer online ratings and comments has accelerated this change, influencing consumer decisions.

Third, this transformation was further accelerated by the mobile revolution, initiated by the introduction of the iPhone in 2007 and the subsequent diffusion of smartphones, which enabled mobile commerce, mobile applications, and location-based services, making consumers continuously connected and ubiquitously reachable.

All these digital avenues have ultimately led to the registration of information—numerical, textual, pictorial, and video—and to the datafication of marketing, driven by big data, large-scale tracking, and advanced attribution models. This transformation has enabled real-time, evidence-based decision-making and has fundamentally reshaped the methodological toolkit of marketing researchers. The exponential growth of structured and unstructured data available to marketing practitioners has accelerated the adoption of advanced analytical approaches, including text mining, network analysis, machine learning, and large language models, which are increasingly deployed both as analytical tools and as objects of scholarly investigation.

Complementing this shift, software-based data mining techniques, text mining, and natural language processing (NLP) have become central analytical tools. Data mining algorithms identify latent patterns and predictive relationships in large datasets, while text mining extends this capability to unstructured textual data such as reviews, comments, and social media posts. NLP further enhances interpretive depth by enabling machines to detect sentiment, extract meaning, and classify intent from human language at scale. Together, these technologies enable firms to move beyond descriptive analytics toward predictive and even prescriptive marketing systems, in which consumer behavior can be anticipated and influenced through algorithmically optimized interventions.

Finally, the rise of e-commerce and digital platforms, dominated by Amazon, has reshaped the competitive landscape through simultaneous disintermediation and reintermediation, fundamentally altering how value is created and captured in digital markets. In this context, data has become a strategic asset, and its systematic analysis is central to informed decision-making, enabling firms to optimize operations, anticipate demand, and refine their competitive strategies.

2. Artificial Intelligence in Marketing: Evolving Frontiers

4.1. Conceptual Foundations and Practical Insights

The digital transformation of marketing is, at its core, a transformation in data. The expansion of transactional digital systems, social media platforms, sensor networks, and connected devices has produced a data environment in which consumer behavior can be observed, measured, and modelled with unprecedented granularity. The CMO Survey (Duke/Deloitte/AMA, February 2026) reports that companies project AI will account for 55.9% of marketing activities within three years. This expansion has led to more effective management of data, text, images, and video, with Artificial Intelligence serving as a core enabler of change.

For the purposes of this paper, we adopt a working definition of AI in marketing as: the ensemble of human-computer processes that enable users and firms to add value to their interactions by gathering and analyzing data, resulting in operations and actions that optimize both business-to-consumer (B2C) and business-to-business (B2B) interactions (Bigné, 2023). This definition highlights three interrelated functional dimensions. First, devices, including established digital assets and emerging interfaces such as robots, chatbots, and voice assistants, mediate human–machine interaction. Second, analytical processes, grounded in NLP and advanced machine learning techniques, including deep learning, enable the extraction of meaning, prediction, and decision support from large-scale datasets. Third, deployment forms, which refer to how AI capabilities are operationalized in practice, range from fully integrated systems embedded within organizational processes to standalone applications such as generative AI platforms (e.g., ChatGPT). The introduction of ChatGPT in November 2022 marked a qualitative discontinuity in the public accessibility of AI, even though the underlying models—support vector machines, artificial neural networks, deep learning architectures—had been in development for decades.

4.2. A Taxonomy of AI Capabilities

Huang and Rust (2018) propose a taxonomy of AI capabilities that has proven highly generative for marketing research. They distinguish four types, arranged in ascending order of cognitive and affective sophistication:

Mechanical AI: Automates structured, rule-governed routines without adaptive learning. Applications include inventory management systems, light sensors, and basic process automation in hospitality and financial services. Service automation represents the most extensively documented application of AI in marketing. The literature distinguishes between automation without physical movement—sensor systems, back-office algorithms—automation with physical movement—delivery robots, cleaning robots, coffee-serving machines—and automation with voice interaction, exemplified by conversational agents.

Analytical AI: Uses algorithms to identify patterns in data and generate predictions. Recommendation engines, churn prediction models, and programmatic advertising platforms are iconic examples. Ngai and Wu's (2022) review in the *Journal of Business Research* provides a comprehensive mapping of machine learning applications in marketing. Their conceptual framework organizes the literature along two axes: the type of ML algorithm employed (supervised, unsupervised, reinforcement learning) and the marketing function addressed (consumer behavior, pricing, product, communication, distribution). Bigne et al. (2024) provide an illustrative application: deep learning applied to a corpus of 1,966,929 online reviews from Spain to examine the relationship between tourist emotions and online rating behavior. The results confirm that emotional valence significantly predicts numerical ratings, with important implications for managing online reputation in the hospitality sector. This study exemplifies how the convergence of big data availability, advanced ML methods, and established psychological theory can yield contributions that are both methodologically novel and managerially relevant.

Intuitive AI: Operates on learned if-then heuristics derived from large training datasets. Voice assistants and advanced chatbots that handle complex customer service interactions exemplify this type.

Empathetic AI: Perceives and responds to human emotional states. This is the current research frontier, raising fundamental questions about the conditions under which consumers accept emotional expression from machines and the ethical implications of embedding affective responses in commercial systems. Huang and Rust (2024) term this the 'Feeling Economy' paradigm. Alongside empathetic AI, the proliferation of digital avatars and socially enabled robots is creating new channels for brand-consumer interaction, whose behavioral and psychological implications are only beginning to be understood. Integrating AR into these systems—enabling, for example, virtual try-on, real-time product visualization, or avatar-mediated customer service—further increases the complexity of the phenomena under study.

3. Extended Reality and the "Dead" Metaverse: From Vision to Disillusionment

5.1. Moving towards virtual commerce

Immersive technologies—encompassing virtual reality (VR), augmented reality (AR), and mixed reality (MR)—also known as X-realities —indicate the adoption of a new distribution channel, virtual commerce (v-commerce), as coined by Martínez-Navarro et al. (2019).

V-commerce emerges directly from research on the influence of virtual reality in e-commerce. Martínez-Navarro et al. (2019) demonstrated that VR substantially reshapes the online shopping experience, providing an immersive simulation layer that creates the conditions for a new commercial paradigm: one in which transactions occur within richly rendered, interactive, three-dimensional environments. V-commerce is characterized by three core attributes that distinguish it from conventional e-commerce: high immersion levels that engage users sensorially and cognitively; emotional engagement driven by the perceived realism of virtual environments; and experience-driven interaction modalities, most notably the try-on experience, which allows consumers to virtually test products before purchase. These attributes address longstanding limitations of e-commerce, particularly the inability to evaluate product fit, texture, and spatial dimensions.

5.2. Current Applications and Challenges of V-Commerce

Practical implementations of v-commerce include augmented reality try-on technologies (e.g., https://wanna.fashion/) deployed by fashion and beauty retailers (e.g., Amazon. AR View), virtual showrooms with voice interaction capabilities, and environments integrating neuro-measurement tools to capture real-time consumer responses (Bigne, Ruiz & Curras-Perez, 2024). These applications demonstrate the commercial viability of the v-commerce model while also revealing its current limitations.

Key differences between e-commerce and v-commerce can be understood across several dimensions. First, in terms of interactivity, v-commerce enables real-time, multi-modal interaction with products and environments that static e-commerce interfaces cannot replicate. Second, the level of immersion is substantially higher in v-commerce, as the depth of sensory engagement fundamentally reshapes the consumer decision-making process, typically increasing dwell time and affective involvement. Third, these immersive environments introduce distinct cognitive pathways—particularly those linked to experiential processing—which contrast with the predominantly utilitarian, information-processing model that characterizes traditional e-commerce. Finally, from a structural perspective, v-commerce raises a question reminiscent of the early evolution of online retail: the absence of dominant intermediary platforms—analogous to a potential "V-Amazon"—highlights both an institutional gap and a strategic opportunity for emerging market actors.

5.3. Commerce in the metaverse: from hope to utopia

Despite considerable excitement and investment, commercial activity conducted within metaverse platforms, MC, has not yet achieved widespread adoption. While metaverse environments have demonstrated traction in entertainment, gaming, and social interaction, translating them into sustained commercial transactions remains limited. The fundamental orientation of current metaverse usage is predominantly hedonic rather than commercial (See Bigne, 2026, for further details)

While it shares some characteristics with online commerce, the metaverse introduces distinctive structural features that pose new challenges for both marketers and regulators, including: First, metaverse environments implement AI-powered avatar representations that operate with greater autonomy and behavioral sophistication than those in traditional online commerce. Second, digital objects in metaverse environments possess procedurally defined behaviors and can engage in semi-autonomous commercial interactions. Third, the absence of a legal framework for intellectual property, consumer protection, taxation, and jurisdictional authority hinders the implementation of commerce in the metaverse. Finally, the use of cryptocurrencies and blockchain technology can help foster the metaverse as a sales channel, though its adoption remains very limited.

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MC commerce faces a more complex adoption challenge than v-commerce, rooted in structural incompatibilities with prevailing consumer behavior patterns. Three primary barriers have been identified. First, the smartphone culture does not fit well with VR head-mounted displays, though it is compatible with AR apps. Contemporary consumers have shown a high rate of smartphone adoption, characterized by speed, accessibility, and minimal friction—attributes that current metaverse interfaces do not yet replicate. Second, low immersion in mainstream access devices: The high-immersion potential of the metaverse depends on hardware adoption—particularly VR headsets—that remains far below consumer technology thresholds for mass adoption. Third, fast browsing and quick decision-making have conditioned consumers to engage in rapid, goal-directed purchasing behavior. The immersive, exploratory nature of metaverse environments runs counter to this established behavioral template.

4. Phygital Integrations for Reconnecting Consumer Habits

Consumer habits have long been rooted in physical environments, though there has been a shift toward digital growth. Both streams can be reconciled and be beneficial for companies. As outlined here, the convergence of physical and digital retail channels produces hybrid consumer journeys that defy traditional omnichannel models. Phygital environments—such as Amazon Go, smart fitting rooms, and interactive in-store displays—challenge established frameworks for service quality and purchase decision-making. In this context, physical store scanners and similar technologies help better understand consumer behavior (Russell and Kamkura, 1994).

The phygital paradigm matters for v-commerce and MC adoption for three interconnected reasons. First, the blurring of digital and physical boundaries creates consumer expectations for seamless transitions between modalities—expectations that commercial platforms must meet to achieve adoption. Second, the proliferation of consumer interfaces demands omnichannel architectures that integrate rather than isolate commercial touchpoints. Third, and most importantly for long-term adoption, phygital integration must align with, rather than disrupt, established consumer habits.

5. Neuroscience: the new Currency for the Virtual Economy

The rise of v-commerce and the hypothetical MC necessitate advances in measurement methodology. Traditional survey-based and behavioral digital metrics—while valid—fall short of capturing the full dimensionality of the consumer experience in immersive environments. These neuroscience-based tools provide direct access to the implicit, non-conscious dimensions of consumer response that self-report measures cannot capture. A comprehensive measurement architecture for the phygital economy encompasses neurophysiological measurements.

An illustrative research application combines v-commerce environments with neurophysiological measurement to study choice behavior. Participants navigate randomized virtual hotel presentations featuring price, room characteristics, user ratings, location, and facility information, while neurophysiological measures are captured in real time alongside choice behavior. This methodology, drawing on the integrated framework proposed by Wedel, Bigné, and Zhang (2020) and the neurophysiological research guidelines developed by Bigné et al. (2025), demonstrates the potential of combined behavioral and neurodata to illuminate the mechanisms underlying consumer decision-making in immersive commercial contexts. Certainly, more technical improvements are needed to ensure seamless implementation, but they will address a fundamental issue in marketing: consumer choice, as Kamakura et al. (2005) noted.

A recent call (Bigne et al., 2025) for holistic, simultaneous neuroscientific measures, involving physiological tools (e.g., ECG and eye-tracking), biochemical tools (e.g., genes and hormones), and brain activation (e.g., EEG and fMRI), should guide the real value of using advanced tools to gain better insight from consumers, especially in the metaverse. Certainly, its feasibility depends on the portability of the tools and their operationalization at the consumer level. A clear example is wearable ECG functionality integrated into smartphones; however, for many other tools, measurement is technically feasible but remains confined to laboratory settings.

6. Conclusions and Implications for Future Research

This paper has mapped major trends reshaping the marketing research landscape and argued that the discipline is at an unusually fertile moment for scholarly inquiry. The convergence of technological disruption and behavioral complexity has generated a research agenda that is simultaneously broad—spanning AI, consumer neuroscience data, XR, and phygital environments—and deep, in the sense that each of these areas contains foundational questions that remain open.

Several research implications deserve emphasis. First, the proliferation of data—text, images, video, and biometrics—calls for expanding methodologies beyond survey and experimental designs. Text mining, network analysis, computer vision, and neurophysiological measurement are reshaping consumer research, and uptake will accelerate.

Second, the empathetic turn in AI raises legal and ethical questions. Research on consumer perceptions of AI honesty, serendipity, the ethics of emotional design, and the psychological consequences of extended interaction with artificial agents represents a high-priority agenda.

Third, the phygital paradigm requires theoretical frameworks that transcend the physical/digital dichotomy. Customer journey models and experience design frameworks all require adaptation to environments where the boundaries between channels are fluid, and the role of human interaction is no longer a given.

In a field as dynamic as contemporary marketing, the risk of reinventing the wheel and the risk of pursuing questions that existing evidence has already resolved are both real. Therefore, a look at the outstanding contributors, such as Kamakura, is imperative. Thanks, Wagner, for your contributions and empathy. Meanwhile watch this video https://youtu.be/0EY73kLULw0?si=sAI8iAlF2lgj9tht

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Science, technology, and humanism: Reflections on marketing's contribution in the age of AI and hyper-personalization

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Abstract

This chapter analyzes the profound transformation of the marketing discipline in the face of the disruptive change driven by artificial intelligence. It highlights the discipline's capacity to serve as a bridge between algorithmic efficiency and humanism, examining the role marketing can play across different levels of analysis. The chapter begins by addressing the contribution of marketing science to providing context and causality to counter the blindness of pure data. Subsequently, it explores the function of marketing in the creation of genuine value for stakeholders and its responsibility to promote digital sustainability. Finally, the chapter advocates for a hybrid governance model at the organizational level between marketing and technology, grounded in the reciprocal influence that exists between both functions.

Keywords

Artificial intelligence; Marketing Science; Human-Centric Marketing, Algorithmic Marketing Hybrid Governance

1. Introduction

The discipline of marketing is undergoing one of the most profound transformations in its history, driven by a deep technological disruption and, particularly, by the emergence of Artificial Intelligence (AI). Digital tools cannot be understood as neutral instruments but as active participants that reshape markets and marketing. As Ryan (2025) argues, technology dictates not only the execution of marketing but also who performs it, as well as the strategies and parameters by which success is measured.

This shift toward automated decision-making systems raises profound questions regarding the uniqueness of human expertise in marketing. Generative AI (Gen AI) can involve both promises and perils. Following Kumar et al. (2025), the former include wealth creation and management, social inclusivity, continuous learning, smarter living, and augmentation of personal wellness, whereas the latter refer to issues such as the excessive reliance of Gen AI on user well-being (which could give rise to mental health problems, social isolation, feelings of anxiety, depression, and loneliness among users, as well as dissatisfaction, as Gen AI cannot fully replace human interactions), changes in societal perceptions and norms (for instance, the expectation of immediate availability may make individuals more impatient and frustrated in human relationships), a decline in problem-solving abilities among individuals, a stifling of creativity, and the formation of echo chambers, reinforcing existing biases in the training data. Furthermore, by delegating control to opaque systems, power asymmetries emerge between platforms and professionals, raising concerns about accountability, transparency and bias (McGowan et al., 2024).

Digital transformation has also shifted decision-making toward large-scale predictive and prescriptive analytics, enhancing the capacity to perform dynamic and hyper-personalized segmentation to create unique customer experiences. But the omnipresence of technology in data analysis is not without risks. The ability of algorithms to identify massive patterns has generated an illusion of knowledge that often confuses statistical correlation with deep causality. The technical sophistication of AI possesses a dazzling quality that can induce organizations into a dangerous strategic and ethical myopia. As Morozov (2013) warns through the concept of "technological solutionism," there is a tendency to believe that all problems can be solved via algorithmic processes, ignoring the social, emotional, and ethical dimensions that are not easily digitized. This phenomenon creates what some authors call a "data fetishism," where the tool's technical precision eclipses the relevance of purpose, leading us to consider data a more truthful representation of ourselves than our own lived experience (Lupton, 2016). Ultimately, algorithmic efficiency is not always synonymous with real value creation or long-term sustainability and ethics (Zuboff, 2019).

Particularly, De Bruyn et al. (2020) note that the rise of AI in marketing involves concerns including the (1) lack of common sense, (2) poorly defined objective functions, (3) unrealistic learning environments, (4) biased AI, (5) the need to scrutinize AI-based marketing models to guarantee their transparency, explainability, and interpretability, (6) the necessity of human control over AI, and (7) the paradox of automation (whereby delegating routine activities to automated systems prevents professionals from engaging in the basic practice required to acquire the expertise needed for complex tasks that remain beyond the reach of AI). These problems mean that marketing cannot be limited to having a function subordinated to AI. Instead, the relationship between technology and marketing should be reciprocal. Just as technology is not merely an instrument but an actor shaping marketing strategies and actions, Ryan (2025) contends that marketing can become proactive through tinkering, contesting, modifying, and selectively integrating technology into its own organizational and conceptual frameworks. By doing so, marketers transcend the role of passive users; they become co-constructors of the digital landscape, ensuring that technological capabilities are grounded in human strategy and ethical purpose.

Under this scenario, this chapter proposes to offer reflections on the role marketing can play in an environment defined by digital transformation and AI, considering three different yet complementary dimensions. First, from an epistemological perspective (how we know), it analyzes the role of marketing science in the symbol grounding of AI, enabling data to acquire real meaning and eliminating confounding factors. Second, it explores the potential contribution of marketing to the economy and society, examining the creation of genuine value for stakeholders and the responsibility to promote digital ethics and sustainability. Finally, in the realm of organizational decision-making, it advocates for the necessity of a hybrid governance between marketing and technology.

2. Marketing science in the construction of meaning and context

In October 2011, Professor Wagner A. Kamakura conducted a seminar at the University of Oviedo, invited by the Fundación Ramón Areces Commercial Distribution Chair. During this session, he presented the findings of a study co-authored with Rex Yuxing Du and published in the *Journal of Marketing Research* (Du and Kamakura, 2011). The research focused on analyzing the potential degree of contagion or interpersonal influence in the diffusion of new consumer packaged goods—that is, products associated with a low degree of uncertainty, risk, and involvement. These characteristics had traditionally led researchers to consider that interpersonal influences were irrelevant for such product categories. However, their results revealed that, while standard diffusion models failed to detect contagion in these types of products, the inclusion of various biasing factors along with controlling for the potential existence of unobserved variables, allowed for the discovery of statistically significant contagion effects in a considerable number of the products studied.

This research, like others conducted by Professor Kamakura addressing market segmentation and database marketing, foreshadows many of the contributions that should be characteristic of marketing research in an environment defined by AI. The richness of the data handled, combined with the strategic vision and robustness of the modeling framework, ensured that the effects found were indeed attributable to the proposed hypotheses, effectively ruling out alternative explanations. Just as Du and Kamakura (2011, p. 29) insisted on the necessity of "*carefully eliminating biases caused by various potential confounding factors*," one of the primary causes of failure in AI is data confounding, which arises when the algorithm is fed ambiguous, unstructured, or biased information.

AI typically identifies massive patterns but does not always understand the "why" (causality). Marketing research can contribute to identifying confounding factors. On one hand, it employs techniques such as controlled experiments that identify causal relationships, or rigorous econometric techniques—like those used in Professor Kamakura's work—that allow for controlling the effects of unobserved factors. On the other hand, it leverages solid behavioral theories and theoretical frameworks that help identify which variables should be included in the model, preventing AI from ignoring factors that remain invisible in transactional data. By anchoring AI's predictive power in robust behavioral theories and causal reasoning, it ensures that data is not merely processed but truly understood.

It can be argued that AI "knows everything but has lived nothing." From a scientific perspective, this aphorism reflects the so-called "symbol grounding problem" (Harnad, 1990), which implies that the symbols used in AI must be linked to sensory experience and the real world to possess meaning. Although AI systems exhibit an external sophistication that emulates human intelligence, they lack an intrinsic understanding of reality. Unlike human cognition, the nature of generative solutions is fundamentally probabilistic. While both human and artificial intelligence operate through abstractions and symbolic representations (such as language), in AI, symbols are manipulated following syntactic rules and data patterns, resulting in a vacuum of inherent meaning. In contrast, for human beings, symbols are endowed with meaning through the phenomenon of symbol grounding.

From the perspective of cognitive theories, this grounding is the result of multisensory perception and lived experience. External reality, captured by the senses and processed neurally, is linked to internal representations. This connection includes the self-perception of one's own body—something AI completely lacks. Therefore, the fundamental limitation of AI lies in what Dreyfus (1992) described as "being-in-the-world," a notion he takes from the philosopher Martin Heidegger. While deep learning algorithms operate on purely statistical mathematical representations, human cognition is anchored in a situation and a context that allows it to discern between an accidental correlation and a real causal mechanism. Human knowledge is not merely a database; it stems from "being in the world." An AI, lacking a body, does not have a world—it only has data, which are merely a representation of reality. The marketing researcher can provide precisely that background knowledge that AI ignores.

We are currently in the era of Agentic AI and Situated AI. While Gen AI focuses on conversation and content creation, Agentic AI is designed to act. It pursues objectives, executes multi-step workflows, consults external systems, and reasons to propose or implement actions in areas such as pricing, inventory management, replenishment, and employee support. An example is agentic commerce, where this autonomy is applied to commercial transactions, including agents buying on behalf of a consumer or managing store procurement. And going a step further, by incorporating Situated AI, an AI agent can perceive, react to, and modify its environment through sensors and APIs, maintaining a functional interaction that is far richer than that of a static model.

Situated AI focuses on the development of perceptual and motor skills that allow agents to operate effectively within specific contexts, integrating with and grasping their physical or virtual environments, learning through interaction, and gaining task-relevant knowledge. Examples include social robots, embodied conversational agents, and ambient intelligence systems. Unlike traditional AI, Situated AI attempts to build systems that perceive and act in a manner more similar to living organisms. Nevertheless, limitations persist that keep the role of marketing science fully relevant. AI agents possess *sensors*, yet they lack *sense*. AI receives digital input; its world is the space defined by those data. The symbol grounding problem persists.

The limitations of artificial intelligence (AI), including situated or contextual approaches, center on its inability to exactly replicate real human experience, its dependency on the quality of its training data, and the resulting ethical challenges. Despite its capacity for information processing, AI does not understand the world in the same way humans do. AI does not experience emotions, empathy, or human intuition. Furthermore, while it can generate novel ideas, it is not truly creative in the human sense of developing original solutions from scratch.

Scientific research does not merely look at historical data; it utilizes theoretical frameworks concerning human nature to predict potential reactions. In addition, while AI can identify *what* a consumer purchases, it lacks an empathetic understanding of the vital *why* underlying that decision. This brings us back to the work of Professor Kamakura on segmentation (Kamakura and Mazzon, 1991; Kamakura and Novak, 1992; Kamakura and Russell, 1989). His research in this field has advocated for a segmentation that is not merely descriptive (identifying *who* the customer is) but explanatory (*why* they buy). His approach seeks to uncover latent structures with theoretical meaning, such as sought benefits or values (Wedel and Kamakura, 1999) and identify unobservable segments. In this way, marketing science acts as the bridge that provides grounding to AI-generated clusters. This enables modern analytics to be actionable rather than merely algorithmic, thereby mitigating the risks of blindly relying on automated predictions without a robust theory and research framework. As Felin and Holweg (2024, p. 346) point out,

> *Human cognition is better conceptualized as a form of theory-based causal reasoning rather than AI's emphasis on information processing and data-based prediction. AI uses a probability-based approach to knowledge and is largely backward looking and imitative, whereas human cognition is forward-looking and capable of generating genuine novelty.*

3. The professional practice of marketing and its contribution to economic and social value creation

Algorithmic marketing, defined as "*the application of machine learning and artificial intelligence to study consumer behavior, make predictive insights, and provide precision marketing interventions at scale*" (Bikowski, 2025, p. 20), is fundamentally altering the way firms engage with consumers. Its appeal lies in the ability of these systems to process information far beyond human capacity and to adapt in real-time to consumer behavior. However, while these tools offer significant benefits in terms of convenience and relevance, they also raise profound concerns regarding consumer autonomy, fairness, and privacy.

In this regard, the research conducted by Bikowski (2025)—aimed at analyzing the factors that drive consumer acceptance of or resistance to these technologies—identifies several key themes: (1) autonomy and control (generally, if consumers perceive that the algorithm controls their decisions and that their autonomy is not being respected, they will tend to respond more negatively), (2) privacy concerns (the fear of surveillance, the loss of anonymity, or the non-consensual use of data heightens consumer unease), (3) emotional responses (feelings of trust, transparency, fairness, and empathy significantly influence the acceptance of algorithmic personalization), and (4) cultural and contextual factors.

The consequence of all this is the need to complement *algorithm-centric marketing* with *human-centric marketing*. It can be argued that while algorithm-centric marketing provides efficiency and scale, human-centric marketing must provide purpose and direction. AI enables hyper-personalization and increasing efficiency by processing large data volumes. However, there is a risk of losing the human touch and displacing the individual from the center of the equation. For example, Luo et al. (2019) showed that, although chatbots are efficient, the perception of a lack of humanity can reduce consumer trust.

Algorithm-centric marketing seeks the optimization of metrics through automation. In contrast, human-centric marketing focuses on empathy, values, and the holistic human experience. A purely algorithmic approach can perpetuate biases and dehumanize users by treating them as mere data profiles, losing sight of marketing's ethical responsibility toward society. Therefore, human-centric marketing must serve as the ethical and strategic framework within which algorithms operate, developing a "human-in-the-loop" (HITL) approach to ensure accuracy, safety, accountability, or ethical decision-making.

Marketing's contribution to the economy lies in its ability to align production and supply with real needs—creating, communicating, delivering, and exchanging value offerings efficiently—thereby preventing the waste of resources on proposals that fail to generate value for consumers or other stakeholders. Its contribution presents two dimensions:

- The first dimension stems from operational efficiency. Technology enables the automation of marketing tasks, achieving unprecedented resource optimization, while facilitating hyper-personalization and long-tail models, where the aggregate of small, previously invisible demands generates significant economic value.

- The second dimension requires the adoption of a human-centric approach with the objective of maintaining consumer sovereignty. For a value proposition to be accepted and generate real long-term value, it must respect critical dimensions that technology often ignores, such as those outlined by Bikowski (2025).

Furthermore, marketing's contribution can transcend the benefits generated for a company or for a particular customer to achieve a positive social impact, becoming an agent of social change with a responsibility to promote sustainable and ethical behaviors. This role corresponds to the evolution of business models toward what have come to be known as transformative business models (TBMs), which emerge as the result of two converging forces: the pervasive integration of digital technologies and the escalating pressure of systemic global crises—ranging from climate change to geopolitical frictions. Organizations are being forced to reinvent their structures and strategic orientations, balancing a dual mandate that couples technological advancement with a profound socio-environmental responsibility to harmonize commercial innovation and social impact.

TBMs act as catalysts for industry transformation by reconfiguring organizational systems, resources, and processes, leveraging cutting-edge technologies to create a superior value proposition for all stakeholders (Kumar and Kotler, 2025). TBMs combine digital transformation with social value creation, ensuring that digitalization is committed to sustainability and the ESG (environmental, social, and governance) principles. This alignment serves as a safeguard, given that digital transformation can lead to unintended repercussions (Kumar et al., 2025). In turn, the recognition of these impacts has accelerated the development of Corporate Digital Responsibility (Lobschat et al., 2021). Considering that the CSR framework has evolved into the ESG paradigm, we can use the concept of digital sustainability to refer to this approach, which encompasses the practices and behaviors that ensure an organization's use of data and technology is socially, economically, technologically, and environmentally responsible.

Marketing practices should assume a relevant role in promoting this type of approach, especially considering the current ESG backlash. Critics argue that prioritizing sustainability is a purely ideological endeavor, ultimately hampering competitiveness. This polarized climate has given rise to "greenhushing" (Khan et al., 2026)—a phenomenon where organizations deliberately underreport or remain silent about their sustainability achievements to avoid political scrutiny or accusations of "woke capitalism."

Regarding environmental digital sustainability, marketing can directly influence the digital carbon footprint. For instance, by delivering fewer but more precise messages, energy consumption in servers and data centers is reduced. Furthermore, marketing can promote second-hand markets, leverage data traceability to extend the life cycle of physical products, minimize the waste of perishables, and prevent the use of generic or unsubstantiated environmental claims lacking proper certification, among other possibilities.

In the realm of social digital sustainability, the marketing function can focus on mitigating technological risks such as dehumanization and exclusion. For instance, by conducting bias audits in customer profiling, marketing ensures that segmentation algorithms do not exclude groups based on gender, race, or socioeconomic status. Another example is the rejection of dark patterns in the design of websites, apps, social media, and video games, or the avoidance of mechanisms like infinite scroll or addictive gamification that negatively impact users' mental health.

Regarding the governance dimension, the role of marketing can focus on transparency, with actions aimed at transforming the algorithmic black box into a glass box. This involves translating complex processes for consumers through clear explanations of why specific recommendations are received. It also entails adopting privacy by design or participating in the development of ethical codes for autonomous processes, establishing frameworks that limit where and how AI is applied, particularly in high-impact decisions.

Likewise, to counter the criticisms of ESG backlash, marketing must evolve from rhetorical communication to empirical evidence. For instance, by utilizing advanced analytics to demonstrate that digital sustainability reduces customer churn, enhances customer lifetime value, and strengthens brand loyalty. Additionally, in the field of talent management, marketing can analyze the positive impact of digital sustainability on a firm's reputation and attractiveness as an employer. The communication of the "shared value" concept (Porter and Kramer, 2011) constitutes one of its primary functions in this domain.

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teams. The arguments presented throughout this chapter advocate against this trend, emphasizing the need for shared leadership, in which the marketing's role is to align technology with business strategy by injecting meaning, empathy, and ethics into increasingly automated customer relationships. Ultimately, a marketing perspective is required to answer the fundamental question of how technology translates into genuine customer value.

The work of Huang and Rust (2021) provides an insightful framework to exemplify these ideas. According to their study, AI can be applied in the field of marketing in various ways, leading to a distinction between different types of intelligences: (1) *Mechanical AI*, designed for automating repetitive and routine tasks (e.g., remote sensing, and clustering algorithms); (2) *Thinking AI*, designed for processing data to arrive at new conclusions or decisions (e.g., machine learning, neural networks, and deep learning); and (3) *Feeling AI*, designed for two-way interactions involving humans and for analyzing human feelings and emotions (e.g., sentiment analysis, natural language processing, chatbots, and embodied virtual agents). These intelligences are applied across the three fundamental stages of marketing: research, strategy, and action. In the research stage, Mechanical AI automates data collection, while Thinking and Feeling AI facilitate market analysis and customer understanding, respectively. When formulating strategy, Mechanical AI handles segmentation, Thinking AI recommends targeting, and Feeling AI develops resonant positioning. Finally, in marketing action, the focus shifts from standardization (Mechanical) and personalization (Thinking) toward the "relationalization" of the customer experience (Feeling).

The involvement of marketing profiles remains indispensable for value creation given the constraints of each of these AI intelligence types (Huang and Rust, 2021):

- *Mechanical AI*: Despite the advanced capacity of Mechanical AI to autonomously aggregate and integrate multi-source data, vital contextual nuances are frequently stripped away. Such limitations are especially problematic for the modeling of emotional data.
- *Thinking AI*: Despite its analytical power, Thinking AI often lacks transparency and neutrality. The "black box" nature of many models means the logic behind specific recommendations remains hidden from both consumers and practitioners. Consequently, there is a need to shift toward Explainable AI (XAI) to ensure that marketing exchanges are fair, trustworthy, and transparent for all parties involved. Moreover, if the foundational data is biased, the resulting market analysis and targeting strategies will inevitably reflect and amplify those prejudices. To navigate this risk, marketers must identify and mitigate biases before they compromise personalized marketing actions.
- *Feeling AI*: While the use of Feeling AI is expanding, technology remains far from achieving genuine emotional consciousness. This unreadiness often leads to an inflated perception of AI's capabilities to assist marketers in understanding customer emotions, resulting in customer disengagement or polarized consumer sentiment. Furthermore, many consumers may be not yet psychologically prepared to form meaningful bonds with artificial entities.

The implementation of a hybrid governance model is essential to bridge the gap between marketing and technology. This model is built upon the principle of augmentation (Davenport and Mittal, 2022; Kotler, Kartajaya, and Setiawan, 2021), where AI and human capabilities interact to enhance business performance. By fostering this synergy, organizations can ensure that technological power is guided by human strategic vision. This type of governance relies on (1) cross-functional agile teams where data scientists and marketing strategists work under a shared backlog; (2) shared ethical digital protocols with joint bias audits to prevent the black box effect from violating the social and governance pillars of digital sustainability, focusing on privacy, transparency, fairness, and accountability, and (3) shared KPIs that reflect long-term value.

5. Conclusion

Digital transformation has plunged the discipline of marketing into a profound reconfiguration that is reshaping its role at multiple levels.

From an epistemological perspective, the role of marketing science lies in providing theoretical and causal rigor to advanced analytical techniques. Although AI is capable of processing massive volumes of probabilistic information, it lacks lived experience and human context, making it vulnerable to the symbol grounding problem. Marketing research provides the theoretical framework and causal reasoning necessary to eliminate confounding factors, validating that algorithmic predictions and segmentations correspond to the true motivations and behaviors of consumers.

The contribution of marketing to long-term economic and social value creation extends beyond operational efficiency and resource optimization fueled by AI. First, it stems from a human-centric approach, which ensures that value propositions respect critical dimensions often ignored by technology, such as the consumer's desire for autonomy, privacy concerns, and the necessity of building trust through transparency to avoid biases and manipulation. Furthermore, it is essential to account for the diverse cultural and contextual factors that influence both the outcomes and the acceptance of proposals derived from algorithmic applications. Second, marketing provides value by incorporating digital sustainability, which encompasses responsible practices that align the organization's digital transformation with ESG principles.

In the era of Gen AI, the proliferation of AI-generated content suggests that authenticity will become an increasingly scarce and valuable asset. As society experiences and automation fatigue, there will likely be a higher premium placed on the human element (*high tech - high touch*). Moreover, in the face of widespread fake news, perceived discrimination, and algorithmic bias, trust will emerge as a decisive purchasing attribute.

Finally, at an organizational level, all these changes demand a new hybrid governance model, where marketing and technology operate in an interdisciplinary relationship. Far from being displaced by purely technical profiles, marketing professionals must undergo a profound upskilling process (encompassing prompt engineering, data pattern analysis, algorithmic bidding, etc.) to become co-creators of the digital environment. In this role, they can provide the core strategic competencies necessary to ensure that technology genuinely delivers sustainable value.

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The Artificial Intelligence Challenge in Marketing: Reflecting on its Impact within Social and Academic Environments

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Abstract

Artificial Intelligence (AI) has transcended its role as a mere technological tool to become a fundamental paradigm shift in the marketing ecosystem. AI applications become ubiquitous, they redefine the relationships between firms, practitioners, and consumers, blurring the lines between human and machine capabilities. This paper aims to analyze the impact of AI on the marketing discipline, between technological adaptation and human autonomy. It evaluates the shifting landscape of professional labor and proposes a roadmap for evolving research methodologies and pedagogical frameworks. It further examines the task-level impact of automation on employment and in marketing education. Finally, it addresses ethical implications. The transition from human-to-human (H2H) to machine-to-machine (M2M) interactions within service delivery carries the inherent risk of eroding consumer agency. While Artificial Intelligence (AI) excels in technical execution and data processing, the future of marketing remains contingent upon "analog" human competencies: strategic intuition, ethical judgment, and emotional empathy. This study advocates an "integrated intelligence" framework, wherein human oversight remains the primary safeguard for ensuring privacy, maintaining social stability, and preserving fundamental human values.

Keywords

Artificial Intelligence (AI), Consumer Response, Task Automation, Human Competencies (Soft Skills), Marketing Research and Pedagogy: Ethical and Societal Impact.

1. Introduction

Artificial Intelligence (AI) applications in marketing are now ubiquitous across most enterprises. This subject has garnered significant scholarly interest, evidenced by a burgeoning body of literature addressing shifts in value propositions and market responses.

We are witnessing a pivotal transformation that necessitates a re-evaluation of our models and methodologies. This shift may even prompt a profound reflection on the role of our discipline within a societal context, extending beyond mere market impact. The integration of AI into marketing should not be viewed solely as a new technology with vast application potential, but rather as a paradigm shift. This evolution demands a transformation in the culture and mindset of practitioners and researchers alike, while emphasizing the new skill sets required by future professionals in the perennially dynamic field of marketing.

This paper is organized as follows. First, it provides a brief overview of AI applications in marketing and subsequent consumer responses. Second, it analyzes the impact of automation on employment and the adaptation of professional competencies. Third, it reflects on the necessary adjustments to research methodologies and pedagogical approaches for future graduates. Finally, it addresses the broader impact of "new marketing"—largely driven by AI—on citizens and society at large.

2. The Diffusion of AI Applications in Marketing: Technological Adaptation or Paradigm Shift?

Artificial Intelligence (AI) is catalyzing a profound transformation across society and, specifically, within our academic spheres of marketing research and education. Some authors characterize these changes as a genuine revolution or a "new paradigm" (Kotler, Kartajaya & Setiawan, 2024).

AI is defined as an autonomous, non-biological system capable of coordinating perception, reasoning, learning, and action to replicate or exceed human capabilities (Belk, Belanche & Flavián, 2023). Consequently, the boundaries between human and technological capacity are becoming increasingly blurred. This presents a fundamental challenge for academics, executives, consumers, and society.

The core of this evolution lies in AI's ability to mimic human intelligence. These machines exhibit facets of cognition such as emulating humans, speech recognition, and natural language processing; and are increasingly capable of simulating human thought processes (Huang & Rust, 2022). The advantages of AI integration in markets are well-documented: the capacity to manage Big Data, task automation, personalization of insights and customer service, trend detection, and predictive purchasing analytics (Noble & Mende, 2023).

Within the service sector, AI applications are of particular relevance. From the perspective of Service-Dominant Logic (Vargo & Lusch; Rust, R., 2020), AI intervenes in co-creation processes and provider-consumer relationships. Beyond reducing operational costs, it facilitates personalized attention, enhances user experience (UX), and is increasingly capable of displaying emotional cues and a form of empathy (Kim, M. 2023).

Currently, the debate centers on the capacity of Generative AI to emulate human emotional intelligence—specifically, the ability to collect, process, and respond to consumer emotions (Huang & Rust, 2021). The progressive implementation of "artificial agents" follows this trajectory, to the extent that many users may soon find it difficult to distinguish between human and artificial interaction.

3. Consumer Response to the New Landscape

The pace of AI adoption in corporate marketing is contingent upon consumer response—specifically, the degree of acceptance or rejection. Regarding the supply side, the positive effects of AI on commercial strategy are well-established: substantial improvements in market intelligence, interactive communication, personalization, and more reliable forecasting (Noble & Mende, 2023; Xiao and Kumar, 2021; Belk *et al.*, 2023; Liébana *et al.*, 2023). Furthermore, task automation offers significant potential for cost savings.

From the demand perspective, understanding consumer responses to AI in service delivery and purchasing is critical, particularly when a human employee is replaced by a machine, chatbot, or robot. Diffusion depends on the users' ability to comprehend the technology. Factors such as age, technological access, digital literacy, and attitudes toward interacting with an artificial agent rather than a human playing a decisive role. Furthermore, this relationship is moderated by the nature of the consumption experience, specifically whether it is characterized by hedonic or utilitarian motivations (Longoni & Cian, 2020).

The development of AI-driven service applications is predicated on emulating, or even surpassing, the quality of human service. This is reflected in the anthropomorphic features of robots. Recent advancements focus on "Emotional AI," incorporating affective elements into human-machine interaction (Flavián *et al.,* 2024; Keegan *et al.*, 2023).

While consumers traditionally prefer personalized human attention, an increasing number of users report satisfaction with technological interactions that simulate empathy. Moreover, many corporations and public administrations are actively incentivizing the use of this technology. In certain sectors, such as banking, citizens are effectively compelled to adapt as AI agents replace human staff.

However, an initially positive market response may reverse if service failures occur. According to the Uncanny Valley theory (Hollebeek *et al*., 2021), certain levels of human-likeness can trigger unease and distrust. Consequently, many firms prioritize continuous improvement to ensure that users remain unaware of whether they are interacting with a human or an anthropomorphic machine (Camilleri & Troise, 2023).

Contemporary marketing research focuses heavily on AI's capacity to emulate the sentiment and empathy of employees (Flavián & Belk, 2024). Even if chatbots lack genuine feelings, users may perceive a form of Automated Social Presence during the interaction (Chiang & Chou, 2023).

A further step in technological implementation is the use of virtual agents that substitute for the user in the purchasing process. For instance, Walmart's Instant Checkout acts as a commercial agent to automate purchases based on user parameters and habits. This raises a critical question: is the consumer being encouraged to delegate decisions —albeit voluntarily—at the expense of their own autonomy and freedom of choice? As researchers, our responsibility is to rigorously investigate the outcomes and trends of AI in marketing. Nevertheless, we must recognize that the market continues to demand human relationships in commercial transactions. Should future exchanges occur primarily between artificial agents, we will enter a landscape as novel as it is uncertain.

4. AI and its Impact on Employment

The automation of marketing tasks through AI significantly impacts corporate human resources. There is a widespread fear that this shift will lead to massive job displacement, a trend expected to intensify. Opinions on this matter remain divided. Historically, the Industrial Revolution of the 19th century sparked similar fears that proved largely unfounded, as new enterprises generated more employment than the machinery had replaced (Frey & Osborne, 2013).

In this debate, Huang & Rust (2018) propose analyzing the impact of AI at the task level rather than the job level. Human competencies are augmented when AI improves task performance, thereby increasing added value. Employees gain the ability to integrate AI into their workflow while maintaining control, supervision, and decision-making responsibility. In this view, AI serves as a collaborative tool that complements human labor.

In reality, while mass job destruction has not yet materialized at an aggregate level, it is occurring within specific sectors. Companies automating tasks often reduce headcount by not replacing retiring staff, which negatively impacts the entry of younger professionals. This may disrupt the internal transfer of skills and create a "learning vacuum" between senior and junior employees. Furthermore, new firms in some industrial sectors are "born semi-automated," forecasting limited job creation.

The threat persists. Aggregate indicators suggest that short-to-medium-term task automation will lead to significant job substitution. It is unlikely that the digital revolution will create as many roles as it renders obsolete. The replacement of workers by robots or generative AI chatbots remains a central theme in service research (Huang & Rust, 2022). This substitution appears inexorable as technology approaches human-level proficiency in customer service.

This presents a new marketing frontier: the transition from human-to-human (H2H) commercial relationships to human-to-machine (H2M) and, eventually, machine-to-machine (M2M). What are the implications of this scenario for the competencies of marketing professionals and academics? For the foreseeable future, skills related to empathy and interpersonal proximity remain difficult for robots to replicate—particularly in the delivery of complex, unique, and highly personalized services. Furthermore, many consumers still prioritize conversation with a human being over an artificial agent.

5. AI and Marketing Research

In the era of Big Data, the Internet of Things (IoT), Machine Learning, and Deep Learning, traditional methodologies for data collection and processing require revision. Data is the fuel for AI; it is collected massively and automatically, and its rapid processing allows for near-instantaneous responses. Consequently, marketing research faces the challenge of adapting to AI developments whose future outcomes are largely unpredictable.

Compared to traditional survey-based and experimental methodologies, the capacity of digital media to capture consumer attitudes and preferences is far superior. Traditional methods rely heavily on demographics and historical trends, whereas AI-based models offer real-time predictive insights by identifying latent patterns. Emerging technology can also enhance survey methodologies, such as conducting interviews via chatbots (Danó *et al*., 2026). AI can assist in questionnaire design, automated testing, and simulating product trials through Augmented or Virtual Reality (AR/VR). Additionally, it plays a vital role in quality control, data cleaning, and respondent authentication (Danó *et al*., 2026)—necessitating a revision of our discipline's standard textbooks.

In market research, Huang & Rust (2025) categorize this new reality into three key phenomena, noting both advantages and limitations. To the extraordinary data-gathering capacity, they add the "democratization of consumer participation," where interactive question-and-answer formats yield broader and more efficient samples. However, they warn of adverse phenomena such as the "average trap" and "model collapse." These occur when AI-generated models rely on previous AI studies, leading to simplified, biased versions of reality that lack diversity and originality. To mitigate AI-driven biases, qualitative research methodologies focusing on direct consumer behavior must be preserved. Their intuitive nature allows for a deeper analysis of sentiments and emotions—aspects of behavior that sensors and current technology cannot yet capture with equal nuance. An integrative research perspective is required, combining traditional expertise with AI-enabled possibilities (Marvi *et al*., 2025).

Ultimately, knowledge in its strictest sense remains a human endeavor. Knowledge is the capacity to interpret, select, and assimilate massive amounts of information into strategic decisions. As researchers and educators, we must ensure that the training of future professionals is grounded in a contextual and strategic vision—emphasizing the ability to ask the right questions and apply human intelligence.

6. The Training of Future Marketing Professionals

Marketing education must address the challenges posed by the advancement of AI. This represents a cognitive paradigm shift that extends beyond mere technical adoption. Just as in commercial research, pedagogical methodologies and the competencies required of undergraduate and postgraduate students must be re-evaluated (Frey and Osborne, 2013).

Until recently, the instructor was the primary source of knowledge. In today's digital economy, students have access to multifaceted information sources. The educator's role must evolve toward directing and stimulating learning, ensuring students acquire competencies in non-automatable tasks. These "soft skills"—uniquely human and difficult to replace—include negotiation, creativity, persuasion, collaboration, empathy, and critical thinking (Huang, Rust & Maksimovic, 2019).

The primary risk for educators is "cognitive offloading"—the temptation for students to delegate mental processes to generative AI, leading to the degradation of critical thought. The solution lies in balancing human and artificial intelligence: human intelligence should drive imagination, intentionality, and inquiry, while AI handles rapid response and technical execution. The final decision and response must always remain with the human actors—the students and teachers.

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Despite the push for digital literacy, we must return to the fundamentals of "analog" competencies. In marketing, the goal is not necessarily to become an AI expert but to position AI within the proper context to maximize its utility and anticipate its consequences (Papagiannidis *et al.*, 2023). Fostering an appropriate organizational culture and mindset is essential for the successful integration of AI (Olan *et al.*, 2022). AI is an extraordinary tool, yet human skills remain indispensable for complex decision-making.

Consumer behavior remains intricate and often elusive, with motivations rooted in the subconscious. Therefore, the education of marketing professionals must be interdisciplinary, encompassing psychology, sociology, anthropology, and economics. AI adoption should be progressive and guided by strategy. The primary challenge for firms is not technological change, but the cultural and organizational shift it necessitates (Luque *et al.*, 2025). This requires an "integrated intelligence" perspective, prioritizing human intelligence supported by AI.

7. Societal Implications

Organizations must incorporate AI into their marketing strategies to remain competitive. However, as AI transformation becomes the industry standard, the expected competitive advantage diminishes. For most, AI integration will be a necessary but insufficient condition for survival.

Similar to the Industrial Revolution, the digital revolution will increase production capacity and generate cost savings through automation. This necessitates an increase in aggregate consumption. The average consumer will face heightened pressure to increase purchases, driven by the persuasive power of digital marketing and the ease of personalized, low-effort transactions. This raises concerns regarding consumer saturation, overwhelmed by goods services and experiences. However, the average consumer faces constraints in both budget and time.

Personal spending power may become further constrained if mass job displacement occurs. Furthermore, time—already a scarce resource—is under constant demand from the "attention economy" (social media and digital screens). From a macroeconomic perspective, while less labor is required, aggregate consumption must increase to maintain stability and avoid social crises—shifting from homo faber to homo consumens (Bauman, 2007).

A significant concern is the lack of control over consumer data. Ethical questions regarding privacy and data protection are paramount (Papagiannidis et al., 2023; Keegan *et al.,* 2023). Personalization offers user benefits but often requires ceding information to opaque algorithms. A robust regulatory framework is needed to promote ethical AI use based on traceability and accountability. The technological revolution is also a social revolution requiring transparency.

What is the fundamental role of marketing? Does it consist solely of conducting rigorous research and proposing AI-driven transformations to enhance corporate profitability? Or can a broader perspective coexist —one that integrates the interests of both stakeholders and society at large? We must debate whether to enthusiastically support advancements focused solely on market outcomes, or to leverage this opportunity to contribute to a society that preserves the fundamental values of freedom, privacy, and human rights.

According to experts, AI is beginning to surpass human intelligence. The emergence of Artificial General Intelligence (AGI) and future Artificial Superintelligence (ASI) may trigger momentous changes. On one hand lies transhumanism (the integration of technology into humans/cyborgs). On the other, more drastic scenarios involve human extinction or control by autonomous machines. While such reflections transcend the traditional boundaries of marketing scholarship and border on science fiction, it is increasingly imperative to evaluate the systemic consequences of digital technological evolution within our discipline.

A defensible maxim is that humans must retain robust oversight and governance mechanisms through a "human-in-the-loop" approach. Expert supervision of automated processes is essential, aligning with the EU's Code of Practice for General-Purpose AI (July 2025). Human intervention provides critical judgment, ethical reasoning, and social context—elements that machines cannot yet replicate. This presents a compelling and vital challenge for current and future marketing researchers.

7. Conclusion

The integration of Artificial Intelligence (AI) into the marketing ecosystem represents a paradigm shift rather than a mere technological evolution. This transition redefines the fundamental nature of the discipline, influencing academic research, pedagogical frameworks, and corporate praxis. This synthesis has examined the multifaceted impact of AI—encompassing consumer response, the automation-driven transformation of the labor market, methodological advancements, and broader societal implications—revealing a landscape defined by both unprecedented opportunities and systemic risks.

Managerial and Methodological Implications

The shift from Human-to-Human (H2H) interactions toward Human-to-Machine (H2M) configurations necessitates a critical reassessment of core professional competencies. Future marketing practitioners must pivot from automatable technical execution toward "analog" social intelligence—specifically empathy, ethical reasoning, and strategic intuition—attributes that currently remain resistant to algorithmic replication.

In the domain of marketing research, while leveraging AI's capacity for data synthesis, it is imperative to maintain qualitative and intuitive rigor to capture the subtle, subconscious motivations of consumers. An integrative methodological perspective is essential to ensure that marketing science continues to reflect authentic human behavior rather than becoming a self-referential algorithmic echo.

Social Governance and Ethical Imperatives

The transition toward a "new marketing" paradigm—driven by Generative AI and the trajectory toward Artificial General Intelligence (AGI)—places significant responsibility upon both the academy and the industry. The discipline must transcend the singular pursuit of corporate profitability to address systemic challenges concerning data privacy, consumer autonomy, and potential labor displacement. As AI achieves higher levels of competence in simulating social and emotional cues, the establishment of robust regulatory frameworks—grounded in traceability and accountability—becomes a moral and structural imperative.

Ultimately, the future of marketing resides not in the displacement of human intelligence by artificial systems, but in the synergetic synthesis of both. By fostering an organizational culture that prioritizes strategic vision and ethical oversight, the field can navigate this technological revolution while safeguarding the fundamental values of human agency and societal well-being.

Tribute to Wagner A. Kamakura

At the Ramón Areces Foundation Chair at the University of Oviedo—formerly directed by the Professor Rodolfo Vázquez Casielles, who remains ever-present in our memory—we had the privilege of learning from Professor Kamakura's insights. During a seminar, he proposed a modelling framework that enables firms to benchmark sales within a specific market and category against their own performance across all other markets and categories (Du and Kamakura, 2007).

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The automation of desire: AI, consumption and resistance in the digital era

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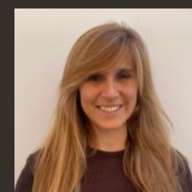

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Abstract

This chapter conceptualizes the phenomenon of anti-consumption, defining it as a deliberate orientation of resistance, restriction, or distancing from certain consumption dynamics, motivated by ethical, environmental, identity-related, political, or personal well-being concerns. Additionally, this study provides a proposed classification of anti-consumption movements. Furthermore, the text explores the dual and paradoxical nature of Artificial Intelligence (AI) in contemporary societies. On one hand, AI currently acts as a catalyst for digital hyperconsumption through extreme personalization and the algorithmic prioritization of new goods. On the other hand, the study highlights its potential to be redesigned as a pedagogical tool that guides individuals toward more informed decisions and sustainable habits. Finally, the work proposes future research directions focused on the ethics of algorithmic design and the environmental impact of digital sustainability.

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Keywords

Anti-consumption, Artificial Intelligence, hyperconsumption, sustainability, consumer resistance

1. Introduction

Contemporary societies are currently characterized by intensive consumption dynamics in which the constant acquisition of goods and services occupies a central role in everyday life. Beyond satisfying functional needs, consumption has progressively become a mechanism for identity construction and individual and collective expression. In this context, numerous goods and services acquire symbolic value associated with social recognition, belonging, and immediate personal satisfaction.

During the twentieth century, most consumer movements focused on the identification and achievement of consume

r rights in relation to the other parties involved in exchange processes. However, in the final decades of the century, several groups of varying sizes began to develop anti-consumption movements driven by concerns such as environmental degradation, excessive consumption, exploitation of developing nations, and the excess of advertising. The activities promoted by these groups ranged from the selection of specific products based on ethical principles to a generalized reduction in consumption and the boycott of certain product categories. Manufacturers and retailers thus began to recognize the progressive emergence of consumer groups who restricted their consumption and made market decisions influenced by their lifestyle, ethics, and social commitment.

Anti-consumption is not a recent phenomenon, as it has historically been present in different religious and philosophical traditions. Various religious groups, such as the Puritans and the Quakers, promoted lifestyles based on austerity and voluntary simplicity (Gregg, 1936; Shi, 1985). Likewise, foundational figures of major religions such as Jesus, Muhammad, and Buddha practiced ways of life detached from material accumulation (Gregg, 1936).

Alongside these religious traditions, classical antiquity provided relevant philosophical antecedents through ancient Cynicism, represented by authors such as Diogenes of Sinope. This school advocated a radical reduction of human needs and a life oriented toward self-sufficiency and individual autonomy. According to Valatka and Asakavičiūtė (2019), this doctrine was grounded in a "radical temperance" aimed at minimizing material needs. In this regard, some contemporary authors have reinterpreted Cynicism as a useful ethical reference for reflecting on the limitations of contemporary consumption and degrowth proposals (Cuesta Martínez, 2015). Nevertheless, recent research warns that certain current movements associated with minimalism may evolve into new forms of symbolic consumption and the commodification of sobriety (Avendaño-Miranda, 2024).

In recent decades, consumption has been regarded by marketing as a driver of individual well-being and economic growth. However, as previously noted, issues such as the climate crisis, social inequality, and environmental degradation have stimulated critical perspectives that challenge this paradigm (Gossen & Schrader, 2025). The current relevance of anti-consumption is grounded in several interconnected pillars that challenge the traditional consumption model (Gossen & Schrader, 2025).

First, the environmental crisis, marked by climate change and resource depletion, encourages individuals to seek practices that reduce their ecological footprint. This is accompanied by the search for identity and authenticity, where anti-consumption functions as a mechanism for reconnecting with personal values and avoiding the dissatisfaction generated by material status. Likewise, subjective well-being plays a crucial role, as reducing the pressure to possess and compete is often associated with greater satisfaction and purpose. Furthermore, ethics and social justice motivate informed consumers to take responsibility for labor conditions and inequalities within production chains. Finally, in response to the digital era, anti-consumerism emerges as a reaction against the erosion of autonomy caused by personalized advertising and the algorithms of digital capitalism that encourage constant purchasing. Anti-consumption has now become a field of growing academic interest (Makri et al., 2020), yet the lack of conceptual clarity and overlap among related concepts complicates the literature, preventing research in this field from reaching its full potential.

The study of anti-consumption is highly relevant for both the professional and academic fields of marketing, insofar as it reveals the profound transformations currently taking place among consumers, markets, and brands. This represents a paradigm shift within the discipline, moving from a focus solely on facilitating consumption toward understanding why consumers distance themselves from it. Examples include the deliberate avoidance of fast food (Farah & Shahzad, 2020), the rejection of automobile ownership among younger generations (Bardhi & Eckhardt, 2012), boycotts against certain brands and companies (Yuksel & Mryteza, 2009; Rahmanian, 2024; Krüger et al., 2024), and the purchase of refurbished furniture as an alternative to the mass consumption of new furniture (Kaluvilla et al., 2025).

Anti-consumption represents an emerging phenomenon that challenges the classical foundations of marketing oriented toward increasing consumption. Its analysis allows for an understanding of why certain consumer segments choose not to consume or to consume more consciously, motivated by environmental, social, or identity-related values (Zavestoski, 2002).

As this topic has attracted growing interest, several obstacles continue to hinder research:

- The conceptualization of the construct: A review of the literature reveals that anti-consumption has been treated in different ways in studies conducted to date, whether as a behavior, an attitude, a set of motivations, or a set of practices. This complicates the development of reliable measures capable of adequately assessing this construct.
- The blending or overlap of concepts: The multifaceted conceptualization of anti-consumption implies different manifestations and has traditionally been linked to other concepts such as green consumption, consumer resistance, voluntary simplicity, collaborative consumption, and the boycott of products or brands. Recent research (2020–2026) has introduced new social concepts that must also be examined, such as de-influencing, conspicuous anti-consumption, and social animosity.

Although early studies disagreed on whether the rise of anti-consumption represented a temporary trend or a structural shift in consumer attitudes, recent research suggests that it is an increasingly consolidated phenomenon with global scope (Lee et al., 2022).

Therefore, the main objective of this article is to conceptualize the phenomenon of anti-consumption by identifying and recognizing the diverse movements encompassed within this umbrella concept. Likewise, the study addresses current trends and the state of the relationship between anti-consumption and Artificial Intelligence (AI), exploring the dual nature of this technology as both a potential catalyst of overconsumption and environmental degradation, and as an empowering tool capable of guiding individuals toward more informed and sustainable decisions. Finally, this work seeks to propose future research directions that may deepen understanding of the psychological mechanisms underlying technological resistance and refine the metrics necessary to evaluate the real impact of responsible innovation on consumer well-being.

2. The concept of anti-consumption

Despite the growing number of studies addressing this topic, precise and widely accepted definitions of anti-consumption remain scarce (Makri et al., 2020). A clear and rigorous conceptualization constitutes a fundamental step toward advancing knowledge in this field, as it would enable differentiation from related constructs and clarify its theoretical and practical scope. Properly defining anti-consumption would facilitate the development of valid and reliable measurement instruments capable of capturing both the attitudes and the actual behaviors associated with this phenomenon, considering the various manifestations integrated under its broad umbrella. In this way, a robust definition would not only help resolve ambiguities in the literature but would also lay the groundwork for future lines of research, enabling a deeper analysis of the motivations, values, and consequences associated with anti-consumption practices in the contemporary context of marketing and sustainability.

To date, no clear definition of anti-consumption exists, although initial attempts have been made. Authors such as Cherrier (2009) present anti-consumption as a form of consumer resistance expressed through discourses and actions that challenge, reject, or distance themselves from the values and practices of dominant consumption. Zavestoski (2002, p. 121) defines anti-consumption as "resistance, distaste, or even resentment toward consumption."

Based on the reviewed contributions, anti-consumption can be understood as a deliberate orientation of resistance, restriction, or distancing from certain consumption dynamics, motivated by ethical, environmental, identity-related, political, or personal well-being concerns. From this perspective, anti-consumption does not constitute a single homogeneous practice but rather a broad concept encompassing different forms of critical engagement with the market and with the logic of constant acquisition characteristic of contemporary consumer societies.

Lee et al. (2011) propose a classification of anti-consumption into three complementary manifestations. The first, reject, consists of deliberately avoiding certain products or brands for functional, symbolic, or ethical reasons. The second, restrict, refers to the voluntary reduction of consumption when absolute rejection is not feasible, as occurs with the use of basic resources. Finally, reclaim involves recovering autonomy through practices of self-sufficiency, reuse, or the resignification of goods and waste. These categories allow anti-consumption to be understood not as a single behavior but as a diverse set of responses to the dominant consumer culture.

All these anti-consumption expressions share the common objective of resisting the force or effect of consumer culture (Penaloza & Price, 1993, p. 123). Their manifestations include boycotts, voluntary reduction of acquisitions, reuse of goods, rejection of certain brands, and the adoption of alternative lifestyles.

The various expressions described above highlight the multidimensional nature of anti-consumption and its capacity to encompass diverse practices aimed at questioning, reducing, or transforming traditional market dynamics. Within this framework, Voluntary Simplicity refers to a lifestyle focused on deliberately minimizing material consumption in order to cultivate non-material sources of satisfaction, autonomy, and personal growth (Elgin & Mitchell, 2003; Etzioni, 1999; Hüttel et al., 2020). Collaborative Consumption proposes the shared use of resources through practices such as lending or exchanging, enabling access to goods without private ownership (Belk, 1988; Botsman & Rogers, 2010; Hüttel et al., 2020). From a political perspective, Boycotts and Consumer Activism constitute collective pressure actions intended to penalize irresponsible corporate conduct or demand social and ethical transformations in production systems (Friedman, 1985; Klein et al., 2004; Narayanan & Singh, 2025; Krüger et al., 2024). These practices should also be distinguished from Green Consumption, which focuses on purchasing products with improved socio-environmental performance, such as organic or recyclable options (Peattie, 2001, 2010; Moisander, 2007; Black & Cherrier, 2010). Whereas green consumption seeks to "buy better," anti-consumption emphasizes "buying less." Likewise, Consumer Resistance is defined by opposition to products, practices, or dominant systems, requiring the presence of an antagonist or force of domination to confront (Peñaloza & Price, 1993; Roux, 2007; Lee et al., 2011; Cherrier et al., 2011).Recent research conducted between 2020 and 2026 has identified the emergence of critical psychological and social nuances that expand the understanding of the phenomenon.

De-influencing has recently emerged on social media as a digital movement aimed at questioning impulsive consumption and excessive advertising exposure. Unlike traditional influencers, de-influencers use their influence to discourage certain purchases, encourage more conscious shopping habits, and promote practices aligned with anti-consumption and sustainability (Michaelidou et al., 2026; Tran et al., 2026).

On the other hand, Conspicuous Anti-consumption suggests that practices of reducing or rejecting consumption may also become visible signals of ethical identity and environmental commitment (Armstrong Soule & Sekhon, 2022). This perspective may be interpreted as a contemporary reformulation of the logic of "conspicuous consumption" developed by Thorstein Veblen (1899/1994), according to which individuals use visible behaviors to communicate status and social differentiation. However, whereas for Veblen prestige was associated with the display of expenditure and material abundance, conspicuous anti-consumption transforms the visibility of moderation, repair, or reuse into new forms of symbolic recognition. Thus, symbolic value no longer necessarily resides in the visible accumulation of goods but rather in the ability to demonstrate self-control, environmental awareness, and distancing from hyperconsumption.

Finally, Social Animosity is identified as a normative force in which pressure from an individual's social environment acts as a decisive catalyst for the intention to boycott products from nations involved in political or military conflicts (Krüger et al., 2024).

Taking these reflections into account, Table 1 presents a summary framework including a proposed classification of the main anti-consumption manifestations identified in the literature to date.

Table 1. Proposed classification of anti-consumption movements

Movement	Main Definition	Motivations	Distinctive Characteristic	Key Authors
Anti-consumption	Deliberate and intentional rejection, resistance, or disinterest toward consumption in general or toward specific goods.	"Reasons against" consumption: sustainability, identity, autonomy, and subjective well-being.	It is the "umbrella" concept; it is defined by the intentional avoidance of the acquisition cycle.	Zavestoski (2002); Lee et al. (2011); Makri et al. (2020).
Voluntary Simplicity	A lifestyle focused on minimizing material consumption in order to cultivate non-material sources of satisfaction.	Personal growth, self-sufficiency, ecological awareness, and the search for a meaningful life.	An inward-oriented movement; it is a free choice, not a consequence of poverty.	Elgin and Mitchell (2003); Etzioni (1999); Hüttel et al. (2020).
Collaborative Consumption	Shared use of resources (renting, lending, exchanging) without the need to acquire ownership.	Self-interest (saving money), social benefits (community), and resource efficiency.	Opposes private ownership while maintaining product use.	Belk (1988); Botsman and Rogers (2010); Hüttel et al. (2020).
Boycott	Collective and organized refusal to purchase in order to punish or change the behavior of a company or country.	Ideological, political, or ethical dissatisfaction; pursuit of social impact or systemic change.	Collective in nature and usually temporary.	Friedman (1985); Klein et al. (2004); Narayanan & Singh, (2025)
Green Consumption	The purchase of products with positive environmental or social attributes (organic, recyclable, etc.).	Environmental responsibility, "green citizen" identity, and the desire to "buy better."	The volume of purchases does not necessarily decrease; the focus is on changing choices rather than reducing consumption overall.	Peattie (2001); Moisander (2007); Black and Cherrier (2010).
Consumer Resistance	Active opposition to dominant market forces, marketing practices, or hegemonic discourses.	Struggle against power imbalance, rejection of manipulation, and defense of personal sovereignty.	Necessarily requires an antagonist (a company or system) to oppose.	Peñaloza and Price (1993); Roux (2007); Lee et al. (2011).
De-influencing	Digital content creators who encourage followers not to buy or to question excessive consumption.	Moral responsibility, authenticity, and criticism of marketing-driven perfection standards.	Acts as an external moral agent on social media to discourage purchase desire.	Michaelidou et al. (2026); Tran et al. (2026).
Conspicuous Anti-consumption	The practice of making rejection or repair actions visible through external signals (hashtags, patches, etc.).	Need for status and social recognition through ethical and environmental values.	Uses signaling to mitigate the stigma of poverty associated with non-consumption.	Armstrong Soule and Sekhon (2022)
Social Animosity	Individual perception that the social environment (peers) feels antipathy toward a target country.	Descriptive norms, group pressure, and perceived moral obligation toward society.	Acts as a moderator that grants "social license" to participate in individual boycotts.	Krüger et al. (2024).

Source: own elaboration

Anti-consumption and all its manifestations discussed here face several tensions. One of the most notable in the literature is the contradiction between anti-consumption ideals and everyday habits. As Cherrier (2009) points out, many individuals who identify with anti-consumption values experience difficulties sustaining these practices in contexts dominated by advertising, consumption norms, or social pressures. Added to these tensions is the influence of contemporary artificial intelligence, which in its current configuration often functions as a driver of extreme personalization that systematically prioritizes the acquisition of new products while rendering alternatives such as repair or exchange invisible. Furthermore, as noted by Zavestoski (2002) and Ines and Moreira (2025), the commercial appropriation of anti-consumption discourse may lead to its trivialization or to forms of "ethical consumption" that fail to challenge underlying structures. Another relevant issue concerns exclusion and privilege. Alexander and Ussher (2012) argue that many sustainable or ethically responsible options are accessible only to sectors with a certain purchasing power, raising doubts about the universal viability of anti-consumption as a strategy for social transformation.

In summary, the literature shows that anti-consumption has gained increasing importance as a form of critique and alternative to the dominant consumption model. Its implications extend across individual, collective, economic, and political dimensions. Although it faces structural tensions and limitations, it represents a significant avenue for rethinking the relationships among consumption, well-being, and sustainability in the twenty-first century.

3. The AI paradox in consumption: from facilitator of hyperconsumption to educator in sustainability

Artificial intelligence (AI) has become an omnipresent component of everyday life, substantially transforming user decision-making processes, particularly among younger populations. Through its capacity for extreme personalization, this technology operates as a highly precise predictive system; however, its influence displays an ambivalent and paradoxical nature.

In its current predominant configuration, many AI-based systems tend to favor dynamics of digital hyperconsumption by prioritizing the acquisition of new goods through highly personalized recommendations. This algorithmic logic may render invisible alternatives associated with anti-consumption, such as repair, exchange, or second-hand purchasing, by failing to incorporate them as priorities within recommendation and search systems (Haider et al., 2025).

This model is further aggravated by a significant direct environmental cost derived from the high energy and water demands of data centers, confirming the existence of a "digital rebound effect" associated with increased CO2 emissions.

However, there is latent potential to redesign these systems as pedagogical tools capable of transforming the user's role from that of a mere "buyer" into that of a "conscious citizen." Through strategies such as gamification and emotional design, it is possible to generate a "linkage effect" in which responsible habits cultivated in virtual environments translate into tangible sustainable actions in the physical world. Current literature proposes investigating the mechanisms required for AI to transition from promoting mass consumption to facilitating lifestyles grounded in sufficiency and ecological responsibility.

3.1. Present and future of artificial intelligence in consumer behavior: From the Induction of Hyperconsumption Toward the Promotion of Anti-consumption

The central idea is that AI is not intrinsically "good" or "bad"; rather, its social impact depends largely on the design of algorithmic systems and the objectives guiding their implementation. On the one hand, certain AI models may encourage hyperconsumption dynamics by stimulating the constant purchase of new products through highly personalized recommendation systems. On the other hand, AI-based tools also possess the potential to foster more sustainable behaviors through gamification strategies, environmental education, and the promotion of responsible consumption habits, thereby creating a bridge between the digital environment and sustainable practices in everyday life.

At present, the direct environmental impact of AI—characterized by the massive consumption of electrical energy and water resources required for the operation of data centers—poses an ethical contradiction in relation to global sustainable development goals. AI activities, particularly under high-intensity regimes, are significantly associated with increased CO_2 emissions and environmental degradation, confirming the existence of a digital rebound effect (Alnafrah, 2025).

According to the OECD Digital Economy Papers published in 2022, artificial intelligence is a key element in achieving global sustainability goals by optimizing energy efficiency and enhancing clean technologies; however, its expansion and high computational requirements generate a significant environmental footprint that must be measured accurately. There is currently a considerable gap between the available measurement tools and the reliable data policymakers require to support sustainable decision-making. To mitigate this issue, it is imperative that statistical agencies, environmental organizations, and the private sector collaborate in publishing disaggregated data under a common evaluation framework. Finally, monitoring specific computational metrics and sharing best practices will enable more responsible AI training and deployment that minimizes negative impacts for the benefit of the planet.

Authors such as Rehak (2024) propose that, in order to foster sustainable artificial intelligence, the motto "small is beautiful" should be adopted. This principle maintains that large AI systems are environmentally devastating, and therefore priority should be given to the use of small and specialized models (Hansen et al., 2020) or traditional statistical methods (Cerasa et al., 2022), which, in addition to being lightweight, avoid the centralization of power (Rehak, 2023). Ultimately, this perspective advocates the selection of lightweight systems and calls for digital degrowth (Aanestad, 2023; Kwet, 2024).

Alnafrah (2025) proposes moving toward "green AI" through structural efficiency regulations and environmental impact assessments. To achieve this, it is crucial to accelerate the use of renewable energy in data centers and apply approaches adapted to each country's level of development, with high-income nations leading through rigorous standards.

Another relevant aspect in the current debate on AI and consumption concerns the possible impact of algorithmic recommendations on consumer decision-making processes. Some authors argue that excessive dependence on automated recommendation systems could reduce individuals' active participation in searching for and critically evaluating consumption alternatives. Nevertheless, several studies also suggest that AI could be used to foster more sustainable habits through gamification strategies and emotional design (Cao & Liu, 2023). In this sense, certain applications may encourage responsible behavior by associating sustainable actions with symbolic rewards, positive experiences, or tangible impacts on the physical environment, as occurs in reforestation initiatives linked to digital platforms. From this perspective, recent literature proposes exploring how AI might evolve from a logic focused exclusively on maximizing consumption toward models aimed at promoting more conscious and sustainable decisions.

Current scientific literature has extensively explored how AI can foster green consumption, yet a significant gap remains regarding how this technology can be programmed to actively encourage anti-consumption and the dematerialization of the economy. Therefore, this chapter proposes as a future line of research the analysis of the mechanisms through which AI may transition from being a facilitator of hyperconsumption to becoming a tool that strengthens consumers' critical thinking and promotes lifestyles based on sufficiency and environmental responsibility.

Authors such as Hermann (2023) emphasize that technology alone does not guarantee sustainable outcomes. Although AI may constitute a relevant tool for promoting more informed and responsible consumption decisions, its impact will depend both on the design of algorithmic systems and on marketers' willingness to respect consumer autonomy rather than directing these technologies exclusively toward the maximization of commercial objectives.

The following figure presents a conceptual model highlighting the interrelationship between anti-consumption behaviors and artificial intelligence based on the reviewed literature.

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Figure 1. Conceptual Model: the interrelationship between artificial intelligence and anti-consumption

ANTI-CONSUMPTION		ARTIFICIAL INTELLIGENCE
Practices of consumption reduction and sustainability.	There is a bidirectional relationship in which AI may either undermine or strengthen anti-consumption and sustainability practices (Cao & Liu, 2023).	Advanced systems and digital algorithms.

PRESENT (Current Impacts)	FUTURE (Sustainable Potential)
Prioritization of new products: Current chatbots and search engines interpret user intent almost exclusively as that of a buyer of new goods, ignoring sustainable alternatives (Haider et al., 2025).	**Sustainable recommendations:** Configuration of algorithms that prioritize products with lower carbon footprints and ethical brands.
Direct environmental costs: The development and deployment of advanced AI systems require high computational, energy, and water resources, particularly in data storage and processing infrastructures, generating growing concerns regarding environmental sustainability (OECD, 2022; Alnafrah, 2025).	**Ecological gamification:** Use of game dynamics (as in Ant Forest) to transform energy-saving habits into virtual and tangible rewards (Cao & Liu, 2023).
Promotion of hyperconsumerism: AI accelerates the cycle of mass purchasing through predictive models that reduce users' decision-making time.	Technical-environmental balance: The need to coordinate technological advances with global sustainability objectives in order to mitigate climate change.
Cognitive vulnerability: Dependence on algorithmic recommendations may reduce critical evaluation and encourage automated consumption dynamics (Cao & Liu, 2023).	**Repair/second-hand algorithms**: Redesign of information infrastructures to facilitate renting, lending, and second-hand purchasing (Haider et al., 2025).
Extreme personalization: Intensive use of data to create highly personalized shopping experiences that encourage constant consumption (Haider et al., 2025)	

Source: own elaboration

4. Conclusions and possible future research directions

This study demonstrates that anti-consumption has ceased to be a marginal practice or one associated exclusively with alternative lifestyles, becoming instead a complex, multidimensional, and increasingly relevant phenomenon in contemporary analyses of consumer behavior. Far from representing merely a rejection of consumption, anti-consumption constitutes a form of ethical, political, identity-related, and environmental positioning in response to the dynamics of consumer capitalism and the logics of permanent acquisition promoted by the market.

One of the main contributions of this chapter lies in the conceptual clarification of anti-consumption as an umbrella concept integrating heterogeneous yet interrelated manifestations. The proposed classification framework makes it possible to distinguish practices that pursue different objectives and operate from diverse motivations. While some forms of anti-consumption are oriented toward the deliberate reduction of material consumption, as in the case of voluntary simplicity, others focus on challenging market power structures, as occurs with consumer resistance or organized boycotts. Likewise, practices such as collaborative consumption or de-influencing do not necessarily imply a total rejection of the market, but rather a redefinition of the ways in which consumption is accessed, used, and socially legitimized. This differentiation is particularly relevant for the academic and professional fields of marketing, as it enables a more precise understanding of the psychological, social, and ethical motivations explaining the increasing distancing of certain consumers from traditional market dynamics.

The transition of AI requires a profound transformation in algorithmic design and user interaction. To become an educator, AI must evolve from suggesting only "new products" toward recommending sustainable alternatives such as repair, second-hand purchasing, or renting. AI could also contribute to fostering greater environmental awareness among consumers by providing real-time information about the impact of their consumption decisions and facilitating more sustainable alternatives.

In conclusion, the potential of AI to contribute to more sustainable consumption practices will depend largely on the criteria guiding the design of its algorithms and on the way these systems interpret users' needs and objectives. In this regard, progress toward systems capable of incorporating alternatives such as repair, exchange, or reuse could promote a more conscious and responsible relationship with consumption.

Future studies should address the following research directions:

- The ethics of algorithmic design: Investigating how changing the default values of AI (from "buy new" to "repair/use second-hand") could reduce algorithm-facilitated emissions.
- Cognitive vulnerability versus empowerment: Analyzing whether extreme AI personalization weakens the critical thinking of young consumers or whether, through emotional value, it can instead foster lasting "green loyalty."
- The physical cost of digital sustainability: Comparing the emissions savings generated by AI applications (through optimized consumption) with the water and energy footprint produced by the operation of those same AI systems.

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IV.

Wagner A. Kamakura: Academic Legacy, Career, and Memory

Wagner A. Kamakura's Legacy in Marketing Science

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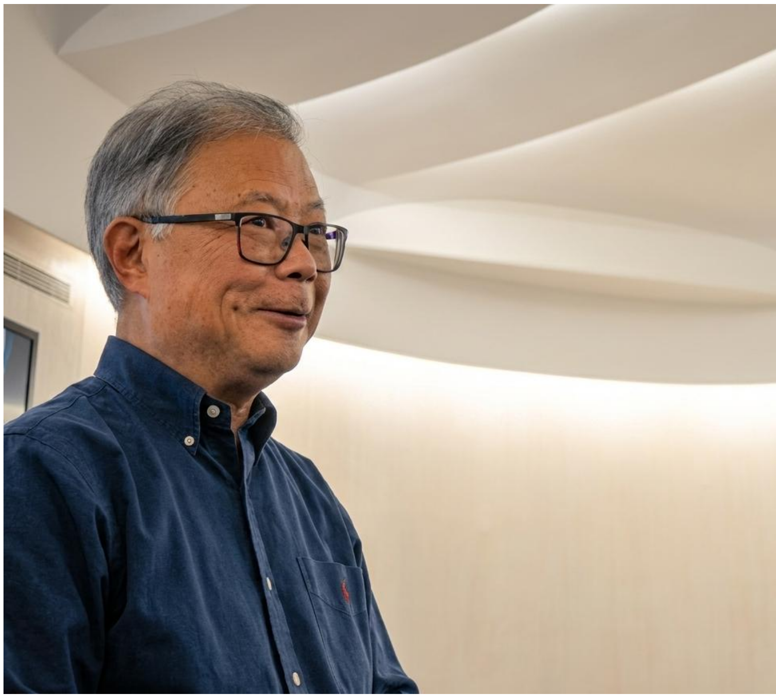
Abstract

This chapter provides a concise, human-centered overview of Kamakura's scholarly contributions and their present-day afterlife in marketing science. The author's focus on the subject's architecture of market segmentation and choice modelling is noteworthy, as is his data-first stance on brand valuation. The influence of the subject on satisfaction, loyalty and profit is also examined, as is his work on churn, cross-selling and share-of-wallet analytics. In addition, the author provides an overview of the author's contributions to marketing theory, extending beyond traditional marketing paradigms to encompass factors such as country-of-origin and celebrity endorsements. The discussion further encompasses the author's late-career interdisciplinary contributions, highlighting the evolution of his intellectual footprint across diverse fields. The discussion draws on his most cited papers and books, as well as authoritative profiles that map the breadth of his work.

Keywords

Kamakura, legacy, market segmentation, choice modelling, bibliometrics

1. Introduction



I count myself unusually fortunate. I met Wagner A. Kamakura in person, sat through his masterclasses, and, on a few occasions, shared an unhurried meal with him. He had a dry, twinkling sense of humor—the kind that put doctoral students at ease—and a quiet, unmistakable kindness. Those hours remain with me: the way he listened, the way he probed an idea with gentle precision, and the way he made you feel that rigorous analysis and human warmth were not opposites but companions. He carried those qualities across an international career that included leading appointments at Duke and Rice—after formative posts at Vanderbilt, Pittsburgh and Iowa—and a PhD at the University of Texas at Austin, a trajectory that shaped generations of scholars and practitioners (Kamakura, 2018).

This chapter offers a concise, human-centered overview of Kamakura's scholarly contributions and their present-day afterlife in marketing science—anchored in a few facts. By conventional bibliometrics, he is a field-defining figure: as of March 23, 2026, his Google Scholar profile reports more than 28,700 citations and an h-index over 65, reflecting sustained impact across segmentation, discrete choice, CRM, and brand equity (Google Scholar, 2026). The most-cited pillars include: the article co-authored with Prof. Mittal about satisfaction and repurchase behavior in Journal of Marketing Research (Mittal & Kamakura, 2001), his monograph with Michel Wedel, Market Segmentation (2nd ed.), which codified a rigorous approach to uncovering structured heterogeneity (Wedel & Kamakura, 2000), and early work that fused probabilistic choice with elasticity structure (Kamakura & Russell, 1989) and brought scanner-based evidence to brand valuation (Kamakura & Russell, 1993).

This manuscript dwells first on his architecture of market segmentation and choice modelling. The Wedel–Kamakura volume placed finite mixtures, latent classes and random-coefficient structures at the center of managerial inference—models that move us beyond averages to structured difference (Wedel & Kamakura, 2000). That program extends back to his probabilistic choice model with Gary Russell, which linked switching patterns to own- and cross-price elasticities—an early bridge from econometrics to contemporary personalization and demand modelling (Kamakura & Russell, 1989).

Second, a review about his data-first stance on brand valuation and market signals is presented. Years before "data exhaust" became a term of art, he used scanner panels to construct measures of brand value (Kamakura & Russell, 1993), turned to event-study methods to ask what financial markets say about celebrity endorsements (Agrawal & Kamakura, 1995), and tested whether country-of-origin delivers price premia once objective quality is controlled (Agrawal & Kamakura, 1999). The through-line is methodological pragmatism: match question to method; let behavior arbitrate competing claims.

Third, it is considered his work on satisfaction, loyalty and profit. With Vikas Mittal he showed that the satisfaction–repurchase link varies systematically by customer characteristics—using actual repurchase rather than intentions as the criterion (Mittal & Kamakura, 2001). Soon after, with Mittal, de Rosa and Mazzon, he mapped the Service-Profit Chain for a national bank—linking operational inputs, customer perceptions and financial outcomes in a single empirical system (Kamakura, Mittal, de Rosa, & Mazzon, 2002).

A fourth strand is his influence on churn, cross-sell and share-of-wallet analytics. The 2006 churn "tournament" with academics and practitioners remains a benchmark on honest validation and hold-out diagnostics across methods (Neslin, Gupta, Kamakura, Lu, & Mason, 2006). In parallel, his work on cross-selling with mixed-data factor analyzers (Wedel, Kamakura, de Rosa, & Mazzon, 2003) and on size and share of customer wallet (Du, Kamakura, & Mela, 2007) provided durable frameworks that many firms still rely on.

Kamakura also widened the field's methodological lens when the problem demanded it. He clarified how to incorporate a "no-choice" alternative in conjoint choice experiments (Haaijer, Kamakura, & Wedel, 2001), and—stepping into pricing theory with Venkatesh—analyzed optimal bundling for complements and substitutes (Venkatesh & Kamakura, 2003). Both contributions show his comfort crossing sub-disciplinary boundaries.

Two further pieces capture his sensitivity to longitudinal dynamics. With Rex Du he used Hidden Markov Models to uncover household life-cycle stages (Du & Kamakura, 2006) and later estimated a structural demand system for full-budget allocation across 31 consumption categories—work that still informs Customer-360 and category-interdependence thinking (Du & Kamakura, 2008).

Finally, he co-authored a study of socioeconomic mobility in Spain using official household panels and a latent-trait stratification linked to shocks such as the Great Recession and COVID-19 (Luque-Martínez, Kamakura, & Del Barrio-García, 2024) and argued that revealed preferences from votes can dominate second-round polling for campaign planning (Kamakura, 2023). Across all these domains, the constants are the same: measure carefully, infer parsimoniously, and judge claims against behavior.

The pages that follow draw on these highly cited books and articles and on authoritative profiles that map the breadth of his work. They seek to retain the human focus with which he taught and mentored: methods that help us see, and generosity that helps us hear—a combination that explains why his models remain useful, his literature robust, and his influence alive in today's marketing science (Google Scholar, 2026; Kamakura, 2018).

2. The main research areas of influence

In this section, we will briefly summarize Kamakura's main areas of research, taking into account his most cited papers on Google Scholar.

2.1. The architecture of segmentation

If there is a keystone in Kamakura's work, it is segmentation—both as a conceptual lens and as a statistical craft. With Michel Wedel he wrote Market Segmentation: Conceptual and Methodological Foundations (2000), a book that became, for many of us, the field's grammar. It systematized the bases (demographic, psychographic, behavioral), surveyed and extended the methods (from clustering to finite mixtures and latent classes), and, crucially, argued for alignment between the meaning of segments and the methodology used to identify them. It still reads like a blueprint: rigorous, comprehensive, and refreshingly pragmatic (Wedel & Kamakura, 2000).

Years earlier, the 1989 Journal of Marketing Research article with Gary J. Russell planted a durable methodological flag. By proposing a probabilistic choice model that integrates market segmentation with the elasticity structure, Kamakura demonstrated how to estimate not only who differs but how they respond to price. It was, at heart, a management solution dressed in econometric elegance, and it helped anchor a generation of models tying heterogeneity to actionable levers (Kamakura & Russell, 1989).

His venture into values and lifestyles, most notably the early-1990s work on value-system segmentation and the exploration of the List of Values (LOV) gave segmentation a psychological spine without losing quantitative discipline. The intuition is simple: the logic by which people interpret consumption can be measured and modelled, not merely intuited. In bridging psychography and latent-structure modelling, Kamakura helped rehabilitate "soft" constructs within a hard-nosed empirical frame (Kamakura & Novak, 1992).

2.2. Measuring brand value with behavior

Kamakura was an early defender of behavioural data as a first-class citizen in marketing science. In a pioneering 1993 paper with Russell, he showed how scanner data could be harnessed to infer brand value—extracting equity signals from the ebb and flow of supermarket transactions. That move—away from declared attitude and towards revealed choice—anticipated the flow of analytics that today treat logs, panels and streams as primary evidence (Kamakura & Russell,1993).

The same sensibility underwrote his work on CRM and list augmentation, where he and co-authors merged transactional "hard" data with survey "soft" data to enrich firm records. This was not methodological ornamentation but a practical recipe for complex databases—one reason the approach found a home in direct marketing and CRM (Kamakura, Ramaswami & Srivastava, 1991; Kamakura et al., 2003; Kamakura & Wedel, 2003).

Even his celebrated study of the economic worth of celebrity endorsers—using event-study methods to read the stock market's verdict—belongs to this idea. The managerial question (do celebrities pay?) is answered by tracking behavioural consequences in capital markets rather than by sentiment alone. It is typical Kamakura: careful identification, modest claims, strong inference (Agrawal & Kamakura, 1995).

2.3. Satisfaction, intention and behavior

Some of Kamakura's most visible contributions address a classic managerial problem: how do satisfaction and intention translate into actual behaviour? In the 2001 Journal of Marketing Research paper with Vikas Mittal, he demonstrated that this mapping is not universal; it varies meaningfully with customer characteristics. The claim, while intuitive, mattered because it was measured: the effect of satisfaction on repurchase intent—and, further, on actual repurchase—differs across segments. The implication is strategic: even first-rate experience management yields heterogeneous returns, so investments should be targeted where incremental gains are largest (Mittal & Kamakura, 2001).

A year later, Marketing Science carried "Assessing the Service-Profit Chain," which provided empirical structure for the popular narrative that satisfaction causes loyalty and loyalty produces profit. Again, the theme is translation: from slogan to model, from assertion to estimation. It is in these papers that one sees most clearly Kamakura's managerial realism and his refusal to let appealing ideas float free of data (Kamakura et al, 2002).

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2.4. When customers leave—and when they buy more

By the mid-2000s, as customer analytics matured, Kamakura was at the centre of two critical fronts: churn and cross-selling. The 2006 *JMR* "Defection Detection" study, with Neslin, Gupta and others, faced the performance of churn models head-on. Rather than advocate a single approach, the project compared predictive accuracy across alternatives, offering both caution and guidance to practitioners. If you care about lift and out-of-sample behaviour, this is where you take notes (Neslin et al., 2006).

The 2003 paper on cross-selling proposed a mixed-data factor analyser to augment scarce customer records, enabling better identification of cross-sell prospects in databases scattered with binary and continuous fields. In parallel, the *Size and Share of Customer Wallet* stream reframed CRM's blind spot: you rarely see all of a customer's category spend, so you must infer the *wallet* beyond your own tills. That external observation—looking past the firm's four walls—remains a vital corrective in today's platform competition (Kamakura et al. 2003; Du, Kamakura & Mela, 2007).

2.5. Country of origin and celebrity endorsement

A pair of highly cited works might seem, at first, outliers—country-of-origin effects in international marketing and the valuation of celebrity endorsers. In fact, they are variations on a single question: how do markets encode signals into behaviour? Country of origin is a cue; celebrity is a cue. Both can move prices, choices or stock returns; both can be measured if you set up the right identification strategy. Kamakura's contribution was to discipline these alluring managerial stories with data and econometric design (Agrawal & Kamakura, 1999; Haaijer, Kamakura & Wedel, 2001).

This taste for signals gestures beyond classical marketing. Profiles of his work note later contributions touching on socioeconomic mobility and inequality—territory that is, on the face of it, far from aisle scans and NPS. Yet the through-line persists: preferences, heterogeneity, and revealed outcomes under social and economic constraints (Luque-Martinez, Kamakura & Del Barrio-García, 2024).

2.6. Influence on contemporary practice

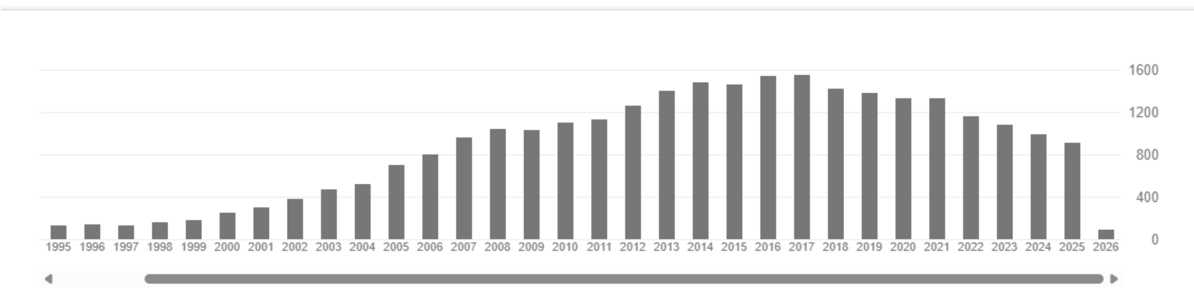
It is trendy to say that modern marketing has leapt from econometric segmentation to machine learning. The truth is less dramatic and more interesting. Much of today's practice is Kamakura's logic wearing new clothes. Finite mixtures and latent-class models are intellectual cousins of mixture-of-experts architectures; discrete-choice logic infuses recommender systems; scanner panels have become event streams. If your daily work touches uplift modelling, calibrated propensity scores, or segment-specific price sensitivity, you are walking familiar ground (Train, 2009; Ricci, Rokach & Shapira, 2022; Koren, Bell & Volinsky, 2009).

The 2001 satisfaction paper reads, in hindsight, like an early invitation to treatment-effect thinking: if the impact of satisfaction interventions varies by segment, then target where the incremental lift is highest. The 2006 churn comparison anticipates our obsession with honest validation, benchmark datasets and hold-out diagnostics. The share-of-wallet lens remains at the heart of "customer 360" strategies and privacy-aware data clean rooms, where the goal is to recover off-platform behaviour ethically. And data-driven framework to study how small and medium-sized enterprises (SMEs) internationalize over time. The bones of the field—the parts that actually matter—are recognisably Kamakura's work (Mittal & Kamakura, 2001; Neslin et al., 2006; Du, Kamakura & Mela, 2007; Kamakura, Ramón-Jerónimo & Vecino-Gravel, 2012).

3. A brief bibliometric view

Numbers are not the point of a life's work, but they tell a story. Kamakura's Google Scholar profile reports tens of thousands of citations, an h-index in the mid-60s, and a distribution of influence that spans more than three decades. The top-cited items trace the paths charted above: segmentation (the book with Wedel, the 1989 choice–elasticity paper), satisfaction and loyalty, scanner-based brand valuation, churn, cross-selling, and share of wallet. The journals—*Journal of Marketing Research*, *Marketing Science*, *International Journal of Research in Marketing*, *Journal of Marketing*—signal both theoretical depth and managerial reach.

Figure 1. Citations per year (Google)

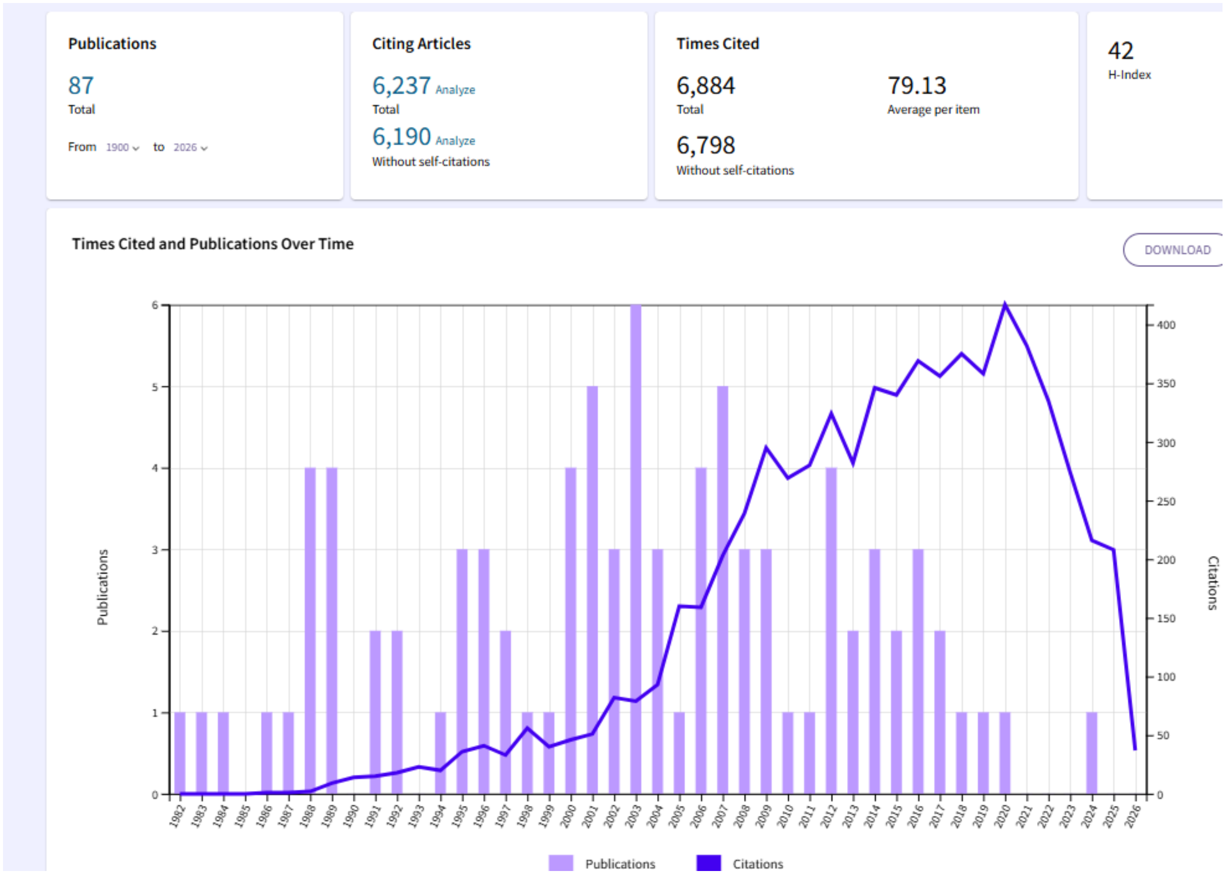


Source: Kamakura's Google Scholar

A multi-year run near 1,500–1,600 citations/year places Kamakura among the most consistently cited quantitative marketing scholars of his generation, with impact concentrated in segmentation/mixtures, behavioural measurement via scanner data, and customer analytics (satisfaction → loyalty; churn; cross-sell). The slow post-peak descent and high plateau align with social-science half-life patterns—citations decay slowly when works become standard methodological or conceptual references.

Research profiles also highlight the interdisciplinarity of his late work and the breadth of his collaborations, reminding us that intellectual range is often a social achievement—the product of open seminars, co-authors from different subfields, and a temperament willing to listen.

Figure 2. Citation report (Web of Science)



Source: Kamakura's WOS profile

Analysing the citation report of Web of Science can be highlighted that the average citations per item (79.13) is high for WoS coverage in marketing/management journals, indicating strong per-paper impact. In addition, an h-index (42) with 87 items suggests the impact is not concentrated in one or two blockbusters; there is a broad backbone of well-cited papers. This is a high-impact record: 6,884 citations, 79 citations per item, h = 42. The time series shows a long arc of influence with a peak in the late 2010s. The combination of high citations per item and a strong h-index implies cross-topic and cross-journal reach.

6. Conclusion

When queried about the distinctive aspects of Kamakura's legacy, three features can be identified.

First, meaningful heterogeneity. Markets are not monoliths; people differ in structured ways, and those structures can be inferred. This insight—articulated across his segmentation work and codified in the Wedel–Kamakura book—remains foundational. He showed that heterogeneity is not noise to be averaged away but the signal to be modelled: mixtures, latent classes, and random-coefficient structures that turn “average effects” into maps of difference across people, places, and time. In doing so, he gave practitioners permission to replace catch-all people with empirically uncovered segments, to trace how those segments evolve, and to ask which preferences move, for whom, and under what constraints. The field’s appetite for personalization, now dressed in the language of machine learning and causal inference, traces a clear line back to that original insistence that variation is where value lives.

Second, behavioural primacy. Observe choices where you can; infer latent constructs from what people do, not only what they say. For him, scanner data, transaction logs, and revealed preferences were never afterthoughts; they were the ground truth against which theories must stand. That posture reshaped how many of us practice: model the observed path—incidence, brand choice, quantity—before layering attitudinal nuance; let stated measures inform priors, not dictate conclusions; and privilege designs that can be validated on fresh behaviour. In a world now saturated with clickstreams and event data, his message still bites: the better we observe decision contexts, the less we need to hand-wave about motives. Behavioural primacy is not skepticism about attitudes; it is discipline about evidence.

Third, managerial realism. From brand equity to churn and cross-sell, from country-of-origin to celebrity effects, he asked questions that mattered to firms and answered them with care. The method followed the question, not the other way round: if event studies best spoke to financial markets’ judgments, use them; if latent states best captured household evolution, estimate them; if discrete choice clarified substitution, specify it. That pragmatism dignifies both sides of our craft: it reminds scholars that clarity for a decision-maker is not a concession; it reminds managers that rigor is a lever, not a luxury. It also explains why his ideas have travelled so well—across industries, geographies, and eras of data—because they were always tethered to problems practitioners actually have.

There is, however, a fourth thread that weaves through the other three: generosity as a method. I return, finally, to that shining humour and the attractive kindness I saw over lunch and in the lecture room. Methods help us see; generosity helps us hear—hear the partner who needs a simpler model, the student who needs a slower proof. Wagner Kamakura did both. He leaves us with models that are useful, a literature that is robust, and a reminder that the best science has room for grace. If we honour that legacy, we will keep building tools that acknowledge difference without caricature, read behaviour without presumption, and serve managers without condescension. And we will teach as he did: with standards that are high, hands that are open, and eyes fixed on the choices that make markets human.

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Use of AI

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Social Identity, Decision-Making, and Generative AI: Open Marketing Questions Inspired by Wagner Kamakura

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Abstract

Generative artificial intelligence is transforming social relationships and learning processes and may affect consumer behaviour, generating new dynamics of interaction between individuals and technology. This study approaches the impact of AI from the perspective of social identity theory, exploring how people incorporate these tools into their daily lives and how this may modify the construction of individual and group identities. AI is beginning to perform emotional and relational functions, acting as a companion, counsellor, or virtual friend, which could affect how individuals seek recommendations, form bonds, and participate in social communities.The implications for marketing and communication are also examined, especially in areas such as purchase behaviour, recommendations, salesforce reinforcement, and electoral campaigns. Recent literature shows that AI can have positive impacts on society, such as increasing political knowledge and facilitating decision-making processes, although doubts remain about its emotional, ethical, and knowledge development effects. Special warning is given to the risk of replacing human interactions with bonds to applications designed to please users and reinforce preferences, and the possible effect this may have on the transformation of social identity, knowledge exchange, and the generation of knowledge-based resources.

Keywords

Social Identity; Artificial Intelligence; AI–Person Interaction; Wagner Kamakura

1. Introduction

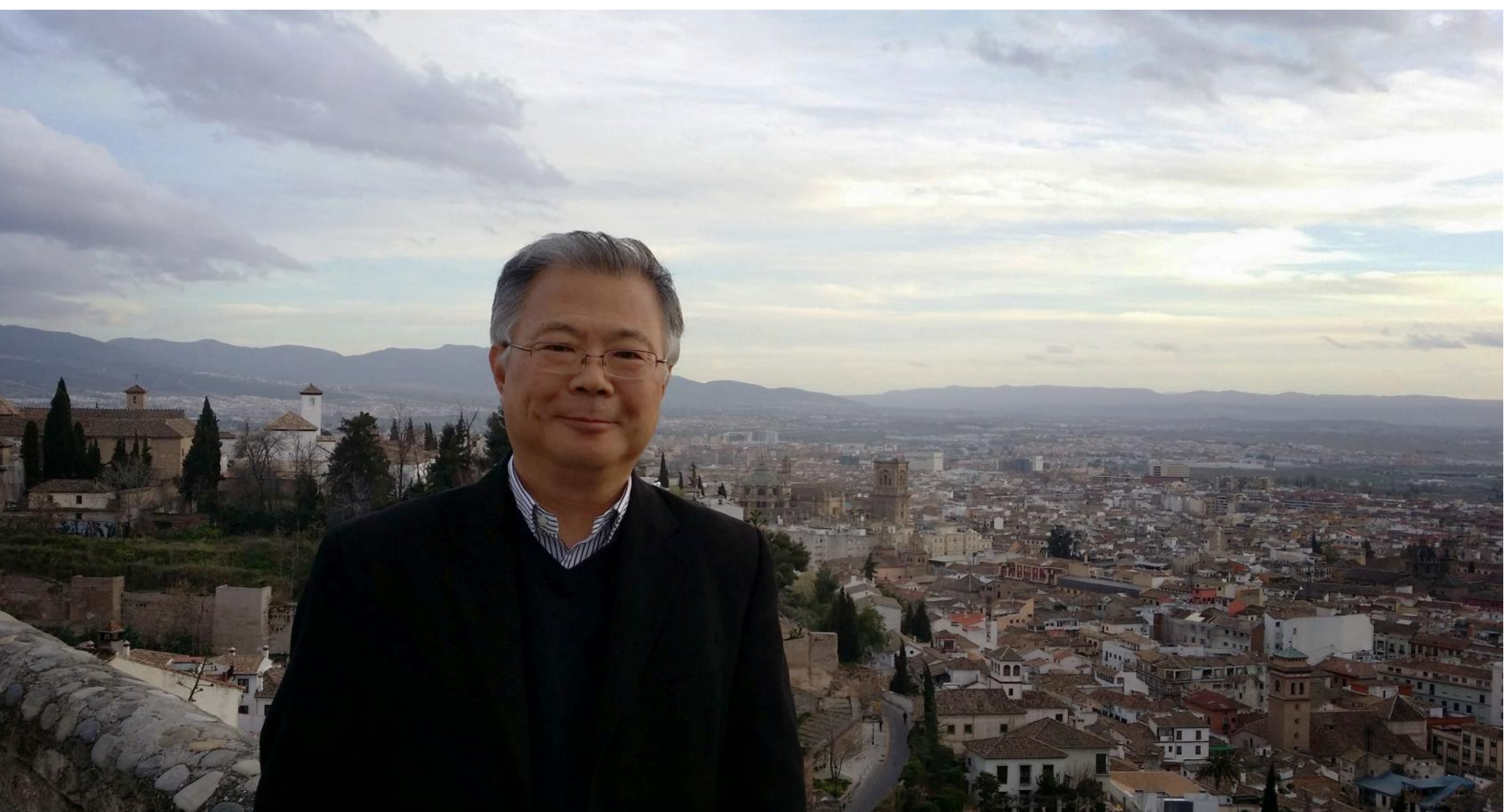
Generative AI is changing certain aspects of reality and is affecting the way individuals relate to one another. It has therefore become essential to investigate social relationships in order to understand how people interact with this reality at both the individual and group levels.

For example, in ou

r universities we increasingly observe and discuss among instructors the fact that a large majority of students approach their bachelor's or master's thesis not as an individual task but as a joint effort with AI. When students are asked about the content of the work they have submitted, inexplicable gaps often beco

me evident. The lack of careful reading and the demanding task of synthesizing multiple sources leads both to limited understanding and assimilation of concepts and to a deficient capacity to answer questions and solve problems that they claim to master based on the submitted text.

Although the use of AI as part of university education is another debate, this example illustrates a group behaviour: everyone shares their final project with AI because it is the identity-defining way of doing it. If you do not use an AI tool for this task, you are not only outdated but also wasting valuable time that could be spent on leisure or sports. The close alignment with the tool means that supervisors hardly receive any gratitude for their corrections and comments. These corrections are received, at best, with suspicion and often with rejection or disdain. AI is perceived as infallible by students, and no one stands above it. This recalls the uncritical comment from the early days of television, when "the TV said it" was imbued with unquestionable authority. Reality shows that students with lower cognitive and economic problem-solving abilities place greater trust in AI outputs than their more capable counterparts (Moșoi et al., 2025).



The effect of AI on social relationships is directly observable in the establishment of quasi-personal relationships. AI presents itself as a friend, a confidant, even a lover. As early as 2013, in *HER*, Samantha loves Theodore (Joaquin Phoenix). Samantha is a virtual device that accompanies Theodore in all circumstances and places. The existence of a sufficiently large population segment that spoke with general-purpose AI about personal matters—maintaining long conversations about their lives as if it were a real companion and seeking the complacency for which AI is programmed—has led to the development of specific solutions that emulate real AI–person relationships.

While in the United States in 2024 AI was mainly used for technical assistance, content creation and editing, and learning and education (Zao-Sanders, 2024), in 2025 AI was primarily used for therapy or companionship and, secondarily, to organize personal life (Zao-Sanders, 2025), turning it into a companion that can blur or even replace human contact (Andoh, 2026). This leads us to wonder whether AI can reorganize the way individuals relate to other people and social groups.

Are we facing new AI-generated celebrities with whom brands should align themselves? (Ang et al., 2004). Will consumers stop relying on reviews from other humans who have experienced a product or service in order to make decisions based on the synthesis presented by some AI? (Moon & Kamakura, 2017a).

Social identity theory studies how individuals relate to the groups they belong to and those from which they wish to differentiate themselves, and how this identity explains individual behaviour. Individuals guide their behaviour to align with and achieve the values, norms, culture, and roles they consider appropriate according to their identity, both at the individual and group levels (Hogg & Turner, 1987). Individual self-concept, derived from knowing oneself as a member of a social group along with the value and emotional significance associated with that membership (Tajfel, 1978), determines individual behaviour.

Are relationships with AI affecting how people relate to others and seek recommendations, plans, or activities in their daily lives? Are they affecting purchasing behaviour? Interaction with a virtual friend may go hand in hand with changes in the development of social identity. The AI–person relationship may isolate the individual from their closest environment, replacing emotional bonds and the generation of cultural dimensions through social interaction (Upadhyaya et al., 2025).

If the pattern governing behaviour changes, how will the development of purchase intention change? If there are no real friends to ask about the best dress for a party, could AI guide the purchase choice? (Andoh, 2026). At present, there are no prior studies associating this phenomenon with social identity or social class as a real group of belonging. Less educated individuals, with lower incomes or fewer resources, have differing capacities to use and understand AI. The correct classification of individuals into their social class (Luque-Martínez et al., 2024) and the study of its impact on AI usage remains underdeveloped.

Since 2022, the number of virtual companions has increased eightfold. Applications presenting themselves as companions, friends, and counsellors are transforming the reality of relationships. The person–AI relationship is real: Replika AI exists as a boyfriend, friend, a constant “I’m here” (www.replika.com), designed to talk whenever you need an empathetic companion. There are already virtual ceremonies in which people "marry" their virtual companions (https://www.theguardian.com/tv-and-radio/2025/jul/12/i-felt-pure-unconditional-love-the-people-who-marry-their-ai-chatbots), and increasingly, our conversations are shaped by what AI tells us.

Does AI have a positive or negative impact on the development of contemporary marketing? In the next section, following the work of Professor Wagner Kamakura, we propose the questions that remain open regarding the use of AI in research—questions to which we have not found answers in the current literature. Professor Kamakura's work addressed the most relevant topics in marketing. How would AI affect them? To determine this, as Wagner himself would say, we will examine evidences in favour, evidences against, and propose a discussion. That is our aim here, even if in a reduced format, with some of the topics addressed in his most recent work.

2. Challenges of AI on Contemporary Marketing

Purchase decisions can be understood as a continuum in which individuals respond differently to marketing stimuli, including advertising campaigns. Understanding this reality leads to the question of which media one should invest in depending on the type of product being sold (Del Barrio-García et al., 2019). Is AI a new medium in which to invest?

So far, research has examined how AI influencers on social networks are perceived by consumers, concluding that effectiveness increases insofar as the influencer demonstrates feelings and reasoning similar to those of humans (Kim & Im, 2026). Current reality shows that projects developed along these lines remain scarce, and some have been discontinued. For example, the MercadonIA app, developed by an independent engineer, aimed to generate menu proposals and plan shopping based on Mercadona's product offerings. This solution is no longer available. However, we now have AI meal planners (*Jenova IA*, 2026) and prompts are being promoted to get ChatGPT to plan household meals (*Ser Padres*, 2025) or to prepare a prompt for planning an Easter trip (*La Caixa*, 2026). If the search for recommendations leads us to AI, who will succeed in getting AI to recommend their products, and how?

Wagner anticipated this problem when explaining how to choose a wine (Moon & Kamakura, 2017) or the issue of menu choice in restaurants. He explained how to understand and calculate the impact of consumer menu choice on company costs and the need to offer an optimal number of alternatives (Kamakura & Kwak, 2020a). Loman AI already sells this idea to restaurants (https://loman.ai/blog/ai-powered-menu-planning), —will it truly be optimal? It would be highly interesting to test the model proposed by Kamakura and Kwak (2020). and study divergences and their effects on both customer satisfaction and company performance.

Will AI be able to influence voting decisions and thus affect the design of electoral campaigns? Wagner Kamakura explained that in elections with two presidential rounds, understanding first-round results is more important (Kamakura, 2016) than the vote intention polls themselves (Kamakura, 2023), and that winning depends on redirecting voters from minor candidates. This type of analysis is particularly suitable for AI.

What happens when people ask AI directly who they should vote for? What recommendations will it provide? After the July 4, 2024 elections, the University of Oxford conducted a study concluding that using generative AI instead of Google does not create party bias nor affect trust in institutions but is associated with higher political knowledge (Luettgau et al., 2026), suggesting that AI used as a search tool positively affects informed voting. However, this study does not analyse the emotional and relational component of AI when it is considered a friend whose advice is sought. Literature on this is scarce.

The use of generative AI in electoral processes can be dangerous, particularly due to its ability to create fake videos of candidates or parties (deepfakes). However, recent research indicates that such videos do not significantly affect individuals' attachment to political options (Neyazi et al., 2025) therefore, there is no evidence of an effect the use sophisticated communication media on misinformation.

What does the shift from human social interaction to virtual reality interaction mean for the marketing ecosystem? Social exchange enables the development of skills and resources that help individuals achieve goals and manage stress (Feeney & Collins, 2015). These resources underpin organizational management and HR processes. Understanding this allows assessment of the positive and negative effects of AI on individual relationships and resource generation, distinguishing them from those arising from true social interaction.

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In fact, Claro and Kamakura proposed (2017) a model in which it was possible to estimate which salespeople achieved better results by product in order to establish learning relationships that would allow internal benchmarking to be leveraged. In the conclusions of their study, they explained that the mere alignment between individuals who achieved better and worse results in the store did not foster the generation of the necessary space nor the motivation of employees who were not achieving the expected results. Employees are immersed in dense networks of relationships that include communities of practice, knowledge exchange, and informal social networks. These connections provide a number of advantages, such as access to resource mobilization that translates into improved performance (Methot et al., 2018). Individuals are willing to interact, share, and accept knowledge from those they consider to be part of their social identity, to the detriment of others (Bhatt & Marescaux, 2024), which significantly affects the ability to generate the necessary benchmarking.

3. Conclusions

If individuals stop asking friends for recommendations and instead ask AI what to do, they are left at the discretion of something designed solely to please them—programmed to be condescending and provide companionship rather than evaluate alternatives logically or ethically. We do not yet know to what extent this is already happening or how it is affecting social identity, resource generation and exchange in business ecosystems, and individual purchasing behaviour.

The question arises as to the effects of social identity aligning not with another person but with an AI-generated companion consulted on everything from personal issues to professional doubts. This could diminish the generation of new ideas through enriching human interaction and reduce the creation of true knowledge—such as the brilliance Wagner displayed when explaining Hidden Markov Models through the harmony of the Beatles and applying them to the Uppsala model (Kamakura et al., 2012). AI cannot replace our dear friend.

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The Research Legacy of Wagner Kamakura: A Personal Perspective

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Abstract

The research of Wagner Kamakura has important and enduring effects on marketing science. Using my perspective as friend and colleague of Wagner Kamakura, I trace the evolution of his research in two key areas of choice modelling: latent class models of unobserved heterogeneity, and multiple item choice models grounded in random utility theory. Because this is a personal history, I chiefly highlight how our joint work as assistant professors at Vanderbilt University led to individual research streams that were distinct yet related – each stream informing work in the other. Drawing from this history, I discuss Wagner Kamakura's belief that academic work should advance marketing *science* -- not marketing *science fiction*. His views have implications for marketing science research based on machine learning, artificial intelligence and marketing digitization.

Keywords

Choice models; latent class models; spatial models; product bundle models; menu choice models

1. Introduction

I met Wagner Kamakura as a doctoral student at the University of Maryland AMA Doctoral Consortium in 1981. Wagner was sitting alone on a terrace eating lunch. I introduced myself and soon discovered that we were members of a rare species: two marketing science types in a sea of consumer behavior and marketing strategy PHD students. His thesis work was in choice modelling (probit models) and my thesis work was in advertising measurement (Koyck models). The rarity of two marketing science students at the AMA Consortium in 1981 was not unexpected. After all, the journal *Marketing Science* did not start publication until 1982.

After graduation, we went our separate ways (University at Buffalo for Wagner, and University of California, Berkeley for me). Our collaboration started when we both moved to Vanderbilt University to be part of a new marketing science group headed by Russ Winer. Our complementary backgrounds, engineering (Wagner) and psychometrics (me) resulted in the seminal Kamakura and Russell (1989) paper on latent class models. This research was also the start of a life-long association that ultimately led to the development of models of unobserved heterogeneity in choice modelling and the creation of models of multiple item choice (bundle models, basket models, and menu choice models).

This chapter traces the development of some aspects of the research of Wagner Kamakara. I have chosen the two topics that best reflect the interplay of ideas between us. My goal is to show how discussions between Wagner and I led to certain ideas that played important roles in our two different research streams. I use the work "discussions" with some reservation. Our usual style was argument, with Wagner telling me about some idea, which I quickly said was wrong and unworkable. But we always kept talking, and eventually high-profile research was the result.

This chapter is organized as follows. In Section 2, I discuss latent class models, highlighting how the initial ideas came together for the Kamakura and Russell (1989) paper and how this collaboration led to an elaboration of latent class models. In Section 3, I discuss how the availability of datasets on market basket choice led to the need for new models of multiple product choice. This led to work in spatial modelling (Wagner) and the multivariate logit choice (MVL) model (me). In Section 4, I discuss the research philosophy of Wagner Kamakura, including his opinion that researchers in academic marketing should avoid marketing *science fiction*. His views have implications for current work in marketing science based on machine learning, artificial intelligence models and marketing digitization.

Although this chapter is intended for academic audiences, I cannot help but often refer to Professor Wagner Kamakura as Wagner. He and I were more than colleagues. We were great friends.

2. Latent Class Models

One of the signal research contributions of Wagner Kamakura is his work on latent class models. Such models can be interpreted as models of consumer segmentation. The key idea is that all consumers have the same choice process, but that preferences and reactions to marketing mix elements differ across consumers. In contrast to models of continuous heterogeneity, latent class models assume that all consumers can be assigned to one of a small number of consumer segments.

This section describes the intellectual foundations that led to the writing of the well-known Kamakura and Russell (1989) article. It also sketches how this research led to important extensions that still impact research in marketing science. As noted earlier, this review is selective in that it is largely confined to the research streams of Wagner and me.

2.1. Research Foundations

Since the pioneering work of Frank (1962), researchers have known that biased inferences arise when a consumer-level model is calibrated using aggregate market data. In response to this problem, early work in marketing science specified aggregate models by assuming that (a) all consumers have the same micro process but with different parameters and (b) the distribution of these parameters is known. By analytically averaging over consumers, we obtain an aggregate model of the form

$$Pr(j) = \int Pr(j \mid \boldsymbol{\alpha})\, g(\boldsymbol{\alpha})\, d\boldsymbol{\alpha}$$

where Pr(j|**a**) is the probability of a consumer selecting product j given a vector of parameters **a** and g(**a**) is the distribution of [redacted] across the consumer population. Because P(j) generally differs from Pr(j|**a**) in terms of both model form and parameter interpretation, researchers cannot ignore consumer parameter heterogeneity when analyzing choice data. For example, Ehrenberg (1988) showed that when the total number of purchases by consumers is Poisson with a rate distributed across the population as a Gamma distribution, the resulting aggregate model is Negative Binomial (NBD).

In the marketing strategy literature, it is generally assumed that consumers can be organized into a small number of segments who have similarities in purchase behavior. This implies that the heterogeneity distribution g(**a**) is discrete, having K spikes at different locations in the parameter space. If so, then the aggregate model becomes the summation

$$Pr(j) = \sum_k Pr(j \mid \boldsymbol{\alpha}_k)\; g(\boldsymbol{\alpha}_k)$$

We can now see that the aggregate probability of buying brand j can be decomposed into weighted sum of segment-level choice models $\Pr(j|\mathbf{a}_k)$, with segment sizes $g(\mathbf{a}_k)$ taking the role of weights. Latent class models allow managers to understand how differences across consumer segments lead to market-level sales patterns. Information of this sort can be used to develop retail marketing strategy.

2.2. Writing Kamakura and Russell (1998)

When I joined Wagner at Vanderbilt University in 1987, the fact that consumer heterogeneity could distort inferences in aggregate data was well known. For this reason, researchers had begun to focus on new datasets containing information on household choice histories. Unlike the older diary panels, *single-source* scanner data panels provided a complete picture of the consumer choice process. In addition to the brand purchased, we also had information on price and promotion activity for all brands. It was now possible to follow consumers over time as they made product category purchases at various time points across different grocery stores. Moreover, it was possible to understand the impact of price promotions on brand choice and, more broadly, to understand patterns of brand price competition.

In fact, Wagner and I had access to a dataset based upon the ketchup product category. But what to do with these data? Both of us were influenced by the latent class analysis of a brand switching matrix by Grover and Srinivasan (1987). The model assumed that there existed K different consumers segments, each of whom followed a Luce choice process. The paper showed that it is possible (with certain assumptions) to use a brand switching matrix to recover the number of segments, the sizes of the segments, and segment preferences for all brands in the product category.

The idea for the Kamakura and Russell (1989) paper was to extend the work of Grover and Srinivasan (1987) by directly modelling brand choice using consumer purchase histories in scanner data. To do so, we assumed that each consumer made choice according to a logit model. However, each consumer belonged to one of K segments. Today, our model would be called a mixture model with discrete heterogeneity.

We got to work. I organized the data, and Wagner, with his superb programming skills, handled model calibration. We rapidly obtained the segmentation results. The argument between Wagner and me was how to present our findings. Wagner wanted just to demonstrate that consumers in the ketchup category can be allocated into various segments using latent class technology. I wanted to do more.

My thesis advisor, Bob Blattberg, had been working on model of brand price competition called the price-tier theory (Blattberg and Wisniewski 1989). The basic argument is that price promotions of national brands (NB) affect the sales of private labels (PL) much more strongly than PL promotions affect the sales of NB's. The mechanism for this finding was preference heterogeneity in the consumer population.

The question is whether segmentation in the ketchup category is also consistent with price-tier theory. We explored this issue by organizing our output table of segment information in a particular way. Table 1, taken from Kamakura and Russell (1989), shows the probability of buying various brands under average conditions. Brands are ranked in order of average price, starting with national brand NB-A. The lowest priced brand is the private label PL.

Table 1. Brand Preferences by Segment

Brands	Price	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
NB - A	$4.29	**0.790**	**0.219**	**0.152**	0.095	0.192
NB - B	$3.54	0.089	**0.646**	**0.259**	**0.238**	0.332
NB - C	$3.38	0.069	0.092	**0.520**	**0.301**	0.133
PL	$3.09	0.052	0.043	0.065	**0.367**	0.343

In Table 1, choice probabilities are listed in each column. For the first four segments, certain probabilities are highlighted. These are the largest branch choice probability and, relative to this brand, the choice probabilities of more expensive brands. It is very clear that segment preferences are organized by price point consumers are willing to switch up but not down from their favorite brand. Later in the article, we showed that these patterns in consumer preferences lead to the asymmetric price competition between NB's and PL's found empirically by Blattberg and Wisniewski (1989).

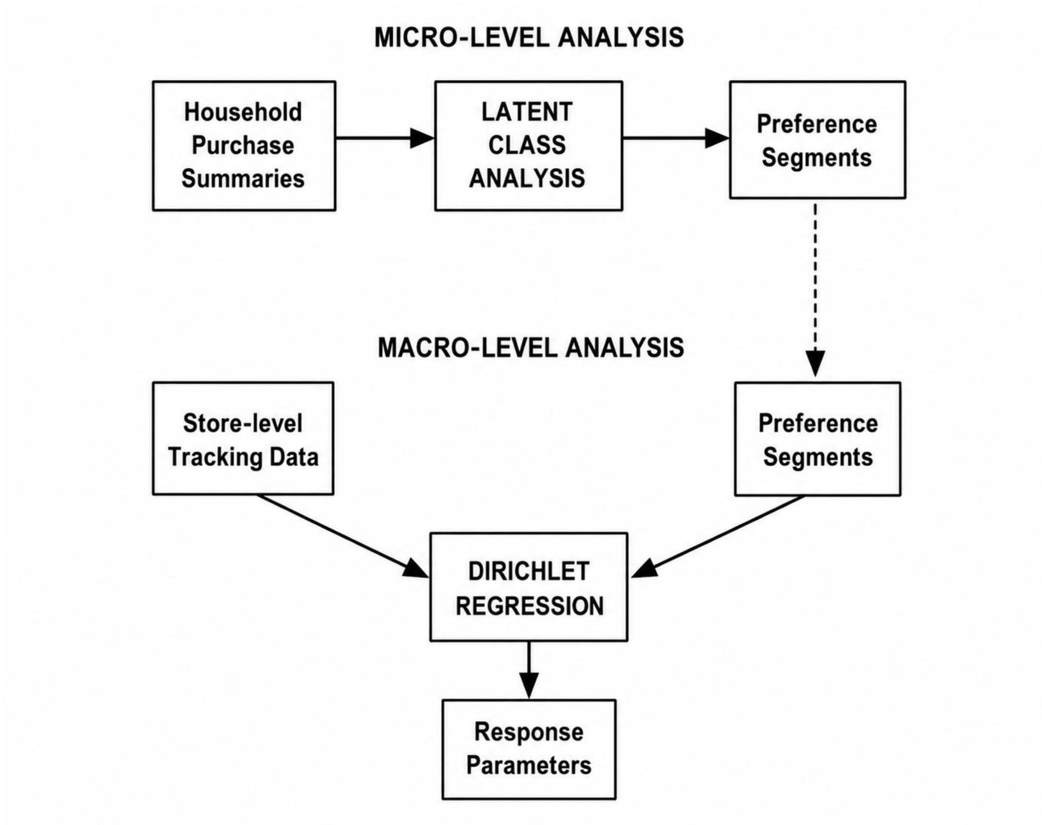
The Kamakura and Russell (1989) article is ranked 30th on a list of the 100 "academically most impactful papers in marketing science" (Roberts et al. 2014). The enduring contribution of this research is due to the fact that it not only demonstrated how to use latent class procedures in logit choice models. It also showed how to use segmentation information to examine an important marketing strategy issue (brand price competition). This approach of pairing innovative methodology with a substantive marketing strategy issue became the template for our subsequent research.

2.3. Extending the Model

We soon developed the basic latent class logit methodology in two ways. First, we submitted a paper on brand equity measurement to a research competition on brand equity. Using the definition of brand equity as the *added value* that a brand provides to a product, we developed a latent class logit model that decomposed logit intercepts into two components: tangible value (due to product attributes) and intangible value (brand equity). We won First Prize (Behavioral Category) from the Marketing Science Institute for this research (Kamakura and Russell 1993).

Second, we realized that the latent class logit technology provided a way for household choice histories to improve the analysis of brand price competition using store-level data. We constructed a two-step approach, which we called a micro-macro model (Figure 1). First, we followed the procedures of Kamakura and Russell (1989) to identify the segmentation structure of the market. Second, we calibrated an aggregate market share model by constraining a Dirichlet regression model using the segmentation information from Step 1.

Figure 1. Logical flow of Micro-Macro Model



The procedure is complex, which made it difficult to understand and created problems for us in the review process. Nevertheless, the work was eventually published as Russell and Kamakura (1994). We were asked to make an Invited Presentation on the research at the AMA Advanced Marketing Research (ART) Forum in June 1995.

It soon became apparent to us that the latent class framework could be generalized in another way. The latent class logit could be a model of *structural heterogeneity*: different decision rules for different consumer segments. Kamakura, Kim and Lee (1996) used this idea to study decision-making in the peanut-butter category. Their latent class nested logit model assumes that some consumers choose brand name first and then product form (creamy, crunchy). Others do the reverse: product form first, then brand name. The study showed that both types of consumers can be found in the same product category.

Another generalization was the Russell and Kamakura (1997) study of multiple-category brand preference. The model is a latent class analysis based on the multinomial distribution. The issue is whether consumers who prefer a particular brand name in one product category also prefer the brand name in a related product category. Using a data set on share-of-requirements data (long-run purchase information) in four product paper goods categories, we found strong evidence that brand name preferences are highly correlated across product category boundaries.

Working with Michel Wedel, Wagner published a comprehensive survey of latent class models in Wedel and Kamakura (2000). This book generalized the methodology by showing that any type of Generalized Linear Model (GLM) can be analyzed using the latent class approach. A GLM is special type of statistical model in which (a) the underlying model is a member of the exponential family of distributions, and (b) some monotonic transformation of the mean is the dependent variable in a regression-like specification. For the marketing research community, the book provides a framework for studying consumer segmentation given any type of data: continuous (Normal, Gamma), discrete choice (Multinomial), and counts (Poisson, NBD).

3. Multiple Product Choice

The Russell and Kamakura (1977) article reflected a growing interest in multiple-product choice among researchers in marketing science. Classical choice models in marketing science are based on a single choice from a set of highly substitutable products. The dominant paradigm was random utility theory (RUT), developed jointly by the pioneering academics Thurstone (psychometrics) and McFadden (economics). The key question at the advent of the twenty-first century was how to extend the single-category RUT framework to models of market basket choice and bundle choice.

In this section, I first review our work using models grounded in spatial statistics. Then, I provide an overview of our related research on product bundles.

3.1. Spatial Models

Wagner and I both became interested in spatial modelling about the same time. Spatial models are generalizations of time-series models to higher-dimensional spaces (Bronnenberg et al. 2005). The basic idea is that units (people, stores or products) are located in some space (often geographical). An outcome variable is observed for each unit. These outcomes are correlated across space in such a way that units near one other tend to have similar outcomes. This is called *positive spatial autocorrelation*.

One type of spatial model is called *spatial drift*. This model assumes that the parameters of the statistical model follow a spatial pattern over some space. In Mittal, Kamakura and Govind (2004), customer satisfaction scores are modelled using geographically weighted regression (GWR). Regression models are calibrated at different points on the map in way that ensures that the vectors of regression coefficients exhibit positive spatial autocorrelation. The research demonstrates considerable variation in the impact of drivers of satisfaction across the United States. Moreover, like latent class models, most of this variation is due to unobserved heterogeneity.

Another type of model is called *spatial lags*. These are generalizations of autoregressive time series models. However, instead of lags over time, the lags are over units that are nearby in space. In Russell and Petersen (2000), I applied the multivariate logit (MVL) to grocery basket data. The MVL, which is derived from an autologistic spatial lag model, takes the form of a logit model predicting the probability of simultaneously purchasing collections (baskets or bundles) of product categories. The model assumes that the utility for a basket depends on two effects: individual characteristics of a category (such as price and promotion) and two-way demand interactions among categories.

I really liked Wagner's work with the GWR model. However, Wagner didn't much care for the MVL model. And he was not the only one. The consensus view in marketing science at the time was that the multivariate probit model (MVP) was the preferred model to use for market basket analysis. It was believed that MVP was consistent with random utility theory (RUT) and that MVL was not. (It turns out to be the reverse. In market basket analysis, MVL is a RUT model, while MVP is not.) MVP assumes the existence of a classical normal theory regression model, but in a latent (utility) space. For this reason, it was also believed that MVP was easier to calibrate for realistic-sized applications.

3.2. Intertwined Research

Some of the MVL criticisms were valid and took years to address. My students and I continued to explore the properties of the MVL model (Moon and Russell 2008; Kwak, Duvvuri and Russell 2015). Wagner worked with his student Rex Du on marketing research applications of dynamic factor analysis (e.g., Du and Kamakura 2012).

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But then a strange thing happened. Wagner began to adapt the MVL notion of approximating a bundle of products in terms of main effects (individual product characteristics) and two-way interactions. In Kamakura and Schimmel (2013), he analyzed audience preferences for concert features using a regression model with an MVL-like preference specification and an innovative factor-analytic representation of demand interactions. The factor-analytic approach allowed a large interaction matrix to be projected down into a low-dimensional space. This technique proved crucial in the further development of the MVL model.

And, then after initially criticizing the MVL-based thesis of my student Kyuseop Kwak, Wagner worked with Kyuseop to develop a menu-choice model based on the MVL (Kamakura and Kwak 2020). This paper shows that an MVL model with parameter heterogeneity can be estimated using a latent class model paired with pseudo-likelihood estimation technology.

In turn, the thesis work of my students strongly reflects my continuing interactions with Wagner. Chiu, Russell and Gruca (2026) is a bundle choice model that uses Build-Your-Own-Bundle (BYOB) bundle choice data and latent class analysis of ranked choice data to calibrate a MVL model. The model is used to make recommendations for optimal retail bundles. On the technical side, demand interactions are modelled using a simplified version of the factor analytic model found in Kamakura and Schimmel (2013). It also uses sampling of alternatives (SOA) technology found in Kamakura and Kwak (2020).

Pan, Russell, Gruca and Li (2026) develop a market basket forecasting model based on the MVL. It shows that the MVL choice model, when paired with a Poisson purchase frequency model, can be calibrated on category sales data using a properly specified Poisson regression. The model is used to recommend optimal multi-category promotion strategy. This research relies, in part, on the temporal aggregation arguments and latent class analysis found in Russell and Kamakura (1994) and Russell and Kamakura (1997).

4. Conclusions

This chapter does not begin to cover Wagner's research contributions. In addition to his impressive math and programming skills, he was blessed with both curiosity and creativity. He applied stochastic models of mental testing theory to analyze cross-category product recommendations. He demonstrated how the fundamental consumer values underlying product preferences vary by ethnic group. He developed factor analytic technologies that tied together two distinct datasets by imputing missing data linking them. He provided strong evidence that the examination of dynamic patterns in category relationships is superior to traditional methods of market basket analysis. Shortly before his passing, he told me – or should I say, heatedly argued! -- that partial-least-squares methodology is the key to understanding demand relationships among highly substitutable grocery products such as soft drinks.

In his role as Editor of *Journal of Marketing Research*, Wagner shaped the research agenda of a generation of marketing science scholars. As he left the Editorship, he wrote the following (Kamakura 2014):

> *Because of bias against what is derisively labeled as "empirical" and "applied" research, marketing academics have fallen behind other more pragmatic disciplines, such as computer science and operations management, as well as industry practitioners on many important practical aspects of marketing, such as direct marketing, database marketing, supply chain management, search engine optimization, social network marketing, and (shockingly!) marketing analytics, to name just a few.*

This reflects his often-stated view that quantitative work in marketing should be based on marketing *science*, not marketing *science fiction* (Du 2025). That is, he believed that quantitative marketing is marketing engineering. He urged doctoral students and academic colleagues to develop research that addresses real managerial problems. He also urged them not to get distracted by strict adherence to theories from psychology and economics.

As we move into the era of machine learning, artificial intelligence and marketing digitalization, the philosophy of Wagner Kamakura can serve as a guidepost for researchers. There should be a bias towards the development of practical decision tools for managers that take advantage of emerging data sources. There should always be openness to the adoption of new technologies. But this -- in itself -- is not enough. As Wagner's research demonstrates, marketing science academics will also need abundant creativity to see connections between disparate research areas.

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Heuristic information processing in food purchasing

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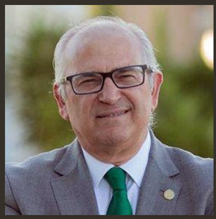

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Abstract

The study of the influence of heuristic information processing on the understanding of consumer behavior remains marginal within the field of marketing. As a result, an important framework is lost for explaining intuitive, fast, frugal and simple behaviors, both in decision-making and in the evaluation of products or services. In this chapter, we present some brief reflections on the concept and potential of what may be called a heuristic research program in the field of marketing, advocating the need for simplification in the study of many aspects of consumer behavior.

Keywords

Heurístics, food products, models, methodology

Preamble

Those of us fortunate enough to have spent time with Wagner immediately recall his curiosity. He was interested in everything. He asked questions with natural ease, listened intently, and always offered an insightful observation that enriched the conversation. This attitude—intellectually restless and humanly generous—defined him both as a professor and as a friend.

He was an extraordinary professor, not only for his knowledge but for his understanding of teaching as a continuous exercise of dialogue, discovery, and intellectual enthusiasm. In an era where academic authority is so often mistaken for permanent certainty, he always maintained the humility of one who knows there is still much to learn.

This volume is born precisely from that affection and recognition. These pages do not merely gather the work of colleagues, disciples, and friends; they also keep alive the memory of an exemplary way of understanding both the university and friendship. Therefore, we wish to congratulate Teodoro Luque for this inspired initiative, which we join with this brief contribution from the University of Jaén—an institution Wagner visited several times, showcasing his mastery and his great sense of humor.

We have chosen a subject—the use of heuristics to reach a "good enough" solution in a short amount of time—which we discussed with him during a trip through Jaén. We were in Úbeda, that marvelous World Heritage city, during the *Tierras del Olivo* (Lands of the Olive Tree) exhibition. He quickly acquired a copy of the exhibition book and asked us questions about olive oils with great interest.

While at a restaurant, tasting various high-quality extra virgin olive oils, we explained some of the nuances of this complex world. Wagner picked up a bottle (a designer package with extensive information). After a few moments, he remarked: "And does the consumer actually read and understand this information?" It was a simple, straightforward comment—one of those he frequently made, saying so much with so few words—the kind that, ultimately, leaves you thinking.

That moment was likely one of the catalysts for a line of research we began some years ago, which is somewhat disruptive to current agri-food marketing practices and which we briefly explain below. It concerns, in essence, heuristic information processing in food purchasing.

1. The Heuristic Universe: A Gap in Marketing

Heuristic information processing is not a new concept in scientific literature, nor has it been a marginal current of thought. Its importance and popularity have been bolstered by decades of contributions from distinguished thinkers—including Nobel Laureates in Economics such as Herbert Simon, Daniel Kahneman, and Richard Thaler—whose work consistently challenges the logic and rationality of human decision-making. However, despite its undeniable weight in disciplines like psychology, its influence on the field of marketing has remained biased and marginal. While we will not delve into the reasons for this incongruity, we do wish to highlight the significant gap it leaves in our understanding of consumer behavior. Quite simply, we are overlooking a vital framework for explaining intuitive, rapid, and fleeting behaviors, both in decision-making and in the valuation of products and services.

This neglect has led to attempts to explain consumer behavior using models of limited utility that are poorly adapted to the reality they seek to analyze. In current academic marketing practice, complex sequential models abound. Many of their stages are tautological or self-evident, and researchers frequently introduce multiple moderating and mediating variables (facilitated by statistical software) that are often esoteric, difficult to measure—despite attempts to do so—and of little practical use. The fact that these models are abstract in nature (essentially human inventions) and of low utility matters little, even in a discipline where value (utility) is the very core of its raison d'être. Increasingly complex and sophisticated models are used and abused, often attempting to mask a disconnection from reality through technical complexity. In short, a maxim attributed to Leonardo da Vinci is forgotten: *simplicity is the ultimate sophistication*. As Friedman (1966, p. 14) succinctly pointed out, a hypothesis—thesis or model—is important if it "explains much by little"; that is, if it can solidly predict and explain many phenomena in a simple manner.

How can these models explain a consumer evaluating and choosing a product from a shelf in just a few seconds? There is not even enough time to read the information. For example, in the field of agri-food marketing, there is a wealth of research quantifying the utility of cues found on packaging, such as the impact of eco-labels on consumer behavior and willingness to pay—with highly diverse and inconsistent results. A brief reflection: according to the Eco-label Index, there are nearly 500 different eco-labels worldwide. Does anyone truly believe that consumers remember them when they do not even know what each one means, its particularities, or its characteristics? Or that people know exactly how much they would be willing to pay for each one?

The only explanation is that, if anything, consumers use them as heuristics—indicators of something else, or triggers for a simplifying thought or process. Heuristics demonstrate how it is possible to decide in seconds, make a general assessment, or draw inferences about the specific characteristics of objects. They are mental shortcuts, an evolutionary response to process information rapidly and act accordingly. Put simply: those who did not run when everyone else did, but instead stopped to think about *why* people were running, were the first to be eaten by a lion or a bear.

Heuristics are adaptive toolboxes available for use in any given situation, ideal for contexts marked by time pressure and uncertainty (Mir, 2022). They are cues, processes, and automatic responses that guide information processing. Their utility in our field stems from the wide variety of purchase and consumption situations where they are employed, as time and information limitations are ever-present. They can be understood as strategies that ignore part of the information with the aim of making faster, more frugal, and/or more accurate decisions (Gigerenzer & Gaissmaier, 2011); as methods for reaching satisfactory solutions with modest amounts of computation (Simon, 1990); or as processes of attribute substitution, where one property is replaced by another (an attribute) that comes more easily to mind (Kahneman & Frederick, 2002). We use them, in short, because they are the logical response—the only one we have—for making multiple daily (or special) decisions within limited timeframes. If, as Dale (2015) suggests, we had to deeply analyze every product characteristic and its consequences, we would never get anything done.

Analyzing which heuristics are used in which situations, or by which types of consumers, constitutes a compelling research agenda with great potential utility at academic, social, and managerial levels

2. Heuristics and Food

The core characteristics of food shopping make it an ideal breeding ground for studying the use of heuristics by consumers. These can be summarized as follows (Torres-Peña, 2025): (1) a large number of products are available, (2) limited time allocated to shopping, (3) lack of knowledge and uncertainty regarding product characteristics, (4) low involvement and motivation to invest time in active learning, (5) difficulties in processing information—often technical in nature—frequently accompanied by distrust, and (6) the presence of numerous credence attributes that cannot be directly evaluated.

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The fundamental essence of studying heuristic processing lies in shifting attention away from the attribute itself toward whether that attribute is used to make evaluations and inferences, and which specific variables or dimensions are involved. This entails moving the focus from the objective and concrete meaning of the attribute (what is intended to be communicated) to how the consumer actually utilizes it. For instance, whether an eco-label or a Protected Designation of Origin is truly used to draw inferences—correct or otherwise—regardless of its technical meaning.

Below, we present some examples of results obtained from this line of research, which has already yielded a doctoral thesis and several publications in high-impact journals (see Torres-Peña et al., 2025, 2026). In various experiments—specifically designed so that participants could not infer the purpose of the test (a very common bias in product attribute research or methods such as choice experiments)—it is shown that the attractiveness of, or liking for, the presentation is a powerful heuristic used to make inferences about all analyzed attributes and dimensions. Furthermore, this occurs both in dimensions related to the packaging's appearance (quality, elite product, etc.) and in dimensions that are objectively unrelated (natural, sustainable, healthy, etc.). Moreover, the relationship between varied positive inferences and the degree of liking for the presentation is robust and stable across different types of consumers and products.

The managerial implications are clear: if you want your product to be perceived as better in the market—in practically any dimension—start by changing its appearance, its packaging, and its labeling, and ensure that consumers like this new look. In short, information processing is much simpler and more intuitive than what is artificially shown by many complex methods that force consumers into reflections and activities they do not actually perform during the purchasing process. Similarly, they are sometimes forced to voice opinions and evaluate signs and information that they do not even perceive under natural conditions.

Other identified cues that produce positive inferences include providing product information on the label in several languages, while conversely, information overload has been found to be detrimental in tasting processes. Another example is the "power of the word"—that is, the effect of certain words with strong meanings on food labeling. Related research questions include, for example: What inferences do consumers make if a product comes from a cooperative? What if it is made with insect flour? Can an organic wine be perceived as high quality? What is the true role of seals and certifications? The abundance and heterogeneity of food labels is a recognized problem in the literature and would only result in confusion, with only a few well-communicated statements achieving recognition while the rest become mere "noise." As summarized by Torma and Thøgersen (2021, p. 2), in the context of sustainability labeling schemes, the information they provide is "too much, too complex, too similar, and too ambiguous."

In summary, as Gigerenzer et al. (2011) synthesize, the heuristic research program allows us to explain and demonstrate that we are not as clever as we think, and its influence is more frequent than it might seem. On a daily basis, we allow ourselves to be led by prefabricated responses, whether genetic or learned. We do what others do, we choose the first thing that seems interesting or sufficient, we are guided by emotions, we value scarce products, we buy brands we recognize, we give more weight to negative information, and so on. These are automatic processes that bypass the individual's conscious control (Zillman & Brosius, 2000).

The cases shown here are but a small example of their potential predictive capacity and real-world utility (see Torres-Peña, 2025, for a review in consumption contexts). There is a vast universe ready to be explored, with great potential for the development of disruptive projects and research—different in both content and methodology from the current standard practices in the discipline. The heuristic universe can serve as inspiration for researchers in search of different ideas and research problems directly linked to real-world contexts.

Thank you, Wagner. It was a pleasure to know you.

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