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Research Article

From Active Search to Machine Curation: The Transformation of Generation Z Consumers' Decision-Making Models in an Algorithmic Environment

Doni Sagitarian Warganegara[1]*, and Rinaldi Bursan[2]

[1] Jurusan Manajemen, Universitas Lampung; e-mail: doni.warganegara@feb.unila.ac.id
[2] Jurusan Manajemen, Universitas Lampung; e-mail: rinaldi.bursan@feb.unila.ac.id
* Corresponding Author: Doni Sagitarian Warganegara

Abstract: The architecture of consumer decision-making has completely changed due to the quick development of recommendation systems based on artificial intelligence (AI). The majority of earlier studies saw algorithms as instruments for forecasting and maximizing preexisting preferences. This study, however, makes a different claim: algorithmic curation actively shapes preferences rather than just reflecting them. This study creates and evaluates a structural model that examines the impact of algorithmic curation intensity on perceived search autonomy, identity resonance, affective evaluation, and the development of initial preferences. The model is based on identity-based consumption theory and the literature on human-AI interaction. The study's findings, which are based on survey data from Generation Z consumers and Structural Equation Modeling (SEM) analysis, demonstrate a contradictory dynamic: algorithmic curation improves identity resonance and directly influences initial preferences while simultaneously decreasing feelings of autonomy. The primary mediating mechanism that links algorithmic exposure to emotional assessment and preference creation is identified as identity resonance. In addition to introducing the concept of algorithmic consumer formation as a new conceptual framework for comprehending consumer behavior in the AI-based digital era, our findings expand the notion of bounded rationality toward algorithmically bounded agency.

Keywords: Algorithmic Curation; Artificial Intelligence; Autonomy; Perception; Resonance.

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1. Introduction

Consumer decision-making models in marketing have historically assumed that individuals initiate consumption through active search, evaluation of alternatives, and rational or affective considerations, positioning consumers as the primary agents directing information flow (Lemon & Verhoef, 2016). However, this assumption is increasingly inadequate in the digital economy, where algorithmic personalization driven by artificial intelligence shapes information exposure through predictive and adaptive curation rather than user intent (Bleier et al., 2022; Davenport et al., 2023). Although recent literature acknowledges the role of AI in enhancing customer experience and marketing strategies (Huang & Rust, 2022; Puntoni et al., 2023), it largely treats algorithms as efficiency tools rather than structural forces that reshape preference formation. This creates a conceptual gap, as traditional theories remain rooted in active search logic while, in practice, consumer preferences are increasingly preshaped by personalized exposure. This issue is particularly salient for Generation Z, whose consumption experiences are embedded in fully machine-curated ecosystems, where consumption functions not only as an economic decision but also as an expression of identity shaped by continuous interaction with personalized content streams (Djafarova & Bowes, 2023).

Therefore, a reformulation of consumer decision-making models is needed, one that no longer assumes autonomous information search as the starting point but instead positions algorithms as institutional actors within the exchange process. Without such reconstruction, marketing theory risks lagging behind in explaining preference dynamics in an era where exposure, attention, and evaluation are deeply intertwined with machine optimization. Although consumer behavior literature has evolved from assumptions of full rationality toward recognizing cognitive limitations, heuristics, and affective dominance (Kahneman, 2011; Simon, 1955), its theoretical foundation still implicitly assumes that consumers retain primary control over information search and evaluation.

Even in contemporary frameworks such as the consumer decision journey, choice architecture is viewed as relatively open, where information exposure stems from initial consumer intent (Court et al., 2009; Lemon & Verhoef, 2016). This assumption becomes problematic in platform-based economies dominated by algorithmic personalization, where exposure is systematically predicted, filtered, and prioritized by computational systems optimizing engagement (Grewal et al., 2017; Zuboff, 2019). While marketing literature acknowledges algorithms as recommendation tools, it has yet to fully reconceptualize them as "choice architects" shaping preference horizons prior to cognitive evaluation, creating a conceptual blind spot, particularly for Generation Z, whose consumption experiences are entirely embedded in machine-curated environments.

This study makes three key contributions to marketing and digital consumer behavior literature. Theoretically, it reconceptualizes algorithms from mere predictors to active agents shaping preferences, introducing the ideas of algorithmic consumer formation and algorithmically bounded agency. Methodologically, it develops and tests a unified Structural Equation Modeling (SEM) framework integrating key psychological and algorithmic factors. Empirically, it reveals the paradox of algorithmic curation, limiting perceived autonomy while strengthening identity resonance and shaping early preferences, showing that consumer preferences in digital environments increasingly emerge from human, AI interactions.

2. Literature Review

Consumer Decision-Making Models

Traditional consumer decision-making models are rooted in the information-processing paradigm, which positions individuals as active agents who search for, evaluate, and compare alternatives before making decisions. Although this perspective has evolved to acknowledge cognitive limitations, emotional influences, and customer experience dynamics, it still fundamentally assumes autonomy in information search(Lemon & Verhoef, 2016).In contemporary digital environments driven by artificial intelligence, however, this assumption becomes problematic, as initial exposure to products and content is increasingly shaped by predictive recommendation systems rather than individual intent. This creates a theoretical tension: models based on active search may no longer be adequate when the starting point of decision-making itself is pre-curated by algorithms.

Algorithms as Choice Architects

Marketing and management literature increasingly recognizes that artificial intelligence does not merely improve operational efficiency but fundamentally reshapes firm, consumer relationships (Huang & Rust, 2022). In platform economies, algorithms continuously learn user behavior, predict preferences, and deliver personalized content designed to maximize engagement, effectively functioning as choice architects that structure consumer attention rather than simply providing information (Davenport et al., 2023). Recent research further emphasizes that consumer interactions with AI systems are experiential and emotional as well as functional, meaning algorithms influence not only what is chosen but also how the act of choosing is experienced (Puntoni et al., 2023).However, most studies still treat personalization as a moderating variable or optimization tool rather than a structural element of decision-making models, leaving a key theoretical gap in understanding how algorithmic systems shape preference formation.

Gen Z Consumption and Identity

Generation Z, raised in a digital environment of permanent connectivity and intensive interaction, often uses consumption as a form of identity expression and social affiliation (Djafarova & Bowes, 2023). In digital platforms, consumption is shaped not only by social interaction and brand symbolism but also by algorithmic systems that structure what users see and engage with. As a result, the boundary between reflective preferences and those shaped by repeated exposure becomes increasingly blurred, since algorithms prioritize content based on predicted engagement, narrowing the visible market space. Consequently, Generation Z's consumer identity is not formed in a neutral choice environment but within a system that actively curates visibility and relevance, creating a theoretical tension in consumer behavior research where exposure increasingly precedes, and potentially shapes, preference formation.

Algorithmic Decision Reformulation

This study argues that algorithms should be positioned as institutional actors in the exchange process rather than contextual variables. This shift reframes consumer behavior research from asking how consumers make choices to how algorithmic architectures shape the conditions under which choices become possible. In this view, decision-making is not only a cognitive-affective process but also an outcome of interactions between computational structures and consumer identity construction. Building on this premise, the study integrates consumer behavior theory, AI-based personalization, and Generation Z identity dynamics into a unified conceptual framework. Theoretically, it challenges the traditional assumption of information search autonomy and proposes that curated exposure serves as the new starting point of consumer decision processes in algorithmic economies.

Hypothesis

Algorithmic Curation and Perceived Search Autonomy

Traditional consumer behavior models assume that information search is actively initiated and controlled by individuals (Lemon & Verhoef, 2016). However, in AI-driven digital environments, information exposure is increasingly shaped by algorithmic recommendation systems that prioritize content based on predicted engagement rather than user intent (Davenport et al., 2023). While personalization enhances relevance, it can also narrow the visible choice set and reduce awareness of alternative options (Huang & Rust, 2022), leading to lower perceived autonomy in information search due to pre-structured choice architectures.

H1: Algorithmic curation negatively affects perceived search autonomy.

Algorithmic Curation and Identity Resonance

Algorithmic personalization enhances subjective relevance by tailoring content based on users' historical preferences, and consumer interaction with AI systems is increasingly understood as symbolic and emotional in nature (Puntoni et al., 2023).When algorithms repeatedly present content aligned with users' interests, values, or lifestyles, this reinforces perceived congruence between self-identity and brands. From an identity-based consumption perspective, such alignment typically drives preference formation; however, in algorithmic environments, it is accelerated through data-driven exposure rather than purely reflective evaluation. As a result, higher algorithmic curation is expected to strengthen identity resonance between consumers and brands.

H2: Algorithmic curation positively affects identity resonance.

Identity Resonance and Affective Dominance in Evaluation

Consumer behavior literature consistently shows that identity congruence strengthens emotional engagement and leads to more positive brand evaluations. In AI-mediated interactions, highly personalized and relevant experiences tend to trigger stronger affective responses than purely rational attribute-based evaluations (Puntoni et al., 2023). When consumers perceive that a brand reflects their identity, evaluation shifts from utilitarian reasoning toward emotional attachment. This effect is particularly salient among Generation Z, for whom consumption serves as a means of self-expression and social validation. In algorithmically curated environments, selective exposure reinforces identity alignment and is expected to amplify affective dominance in evaluation processes, positioning identity resonance as a key mediating mechanism between algorithmic curation and affect-based brand evaluation.

H3: Identity resonance positively affects affect-based brand evaluation.

H4: Identity resonance mediates the relationship between algorithmic curation intensity and affect-based brand evaluation.

3. Method

This study adopts a quantitative explanatory design aimed at testing a structural model of how algorithmic curation intensity reshapes Generation Z consumer decision-making in digital environments. A cross-sectional survey approach is used to capture respondents' perceptions of AI-based recommendation systems and their effects on search autonomy, identity resonance, affective evaluation, and initial preference formation (Creswell & Creswell, 2018).

The unit of analysis is Generation Z individuals in Indonesia (born 1997-2012) who actively use algorithm-driven digital platforms. Participants must be at least 18 years old, use a minimum of two algorithm-based platforms (e.g., social media, marketplaces, or short-video apps), and have made at least one purchase influenced by algorithmic recommendations within the last three months. Purposive sampling with screening criteria is applied to ensure contextual relevance, and data are collected via online panels with demographic balancing to enhance external validity.

Sample size is determined using power analysis for Structural Equation Modeling (SEM), targeting 400-500 valid respondents to ensure statistical robustness and enable mediation and multi-group analyses. Measurement instruments are adapted from validated scales in AI marketing, identity-based consumption, and affective evaluation research, using a seven-point Likert scale. Data analysis is conducted using covariance-based SEM (CB-SEM), including confirmatory factor analysis (CFA), structural model testing, and mediation analysis via bootstrapping with 5,000 resamples. Model fit is assessed using standard indices such as CFI, TLI, RMSEA, and SRMR, while robustness checks address common method bias, endogeneity, and multicollinearity (Hair et al., 2022). Ethical approval, informed consent, and respondent anonymity are strictly ensured throughout the research process.

Table 1. Operational Definition.

Variable	Definition	Indicators (Likert 1-7)	Ref
Algorithmic Curation Intensity (ACI)	People's perceptions on the degree of personalization and the predominance of AI-based recommendation systems in influencing the visibility of products and content on digital platforms.	1) I feel that the content is highly customized 2) Product recommendations appear without me searching for them 3) It appears that the platform "knows" what I like 4) System suggestions account for the majority of the products I come across.	Davenport et al. (2023); Huang & Rust (2022)
Perceived Autonomy in Information Search (PAIS)	The degree to which consumers believe they have conscious and unrestricted influence over the process of looking for information and considering options.	1) I am free to select the goods I wish to look for 2) I am in charge of the data I investigate 3) I actively weigh my options; and 4) The system does not dictate my choices.	Sundar (2020); Kozyreva et al. (2022)
Resonance of Identity (RI)	The degree of perceived congruence between the brand or product offered on digital channels and	1) The items that show up seem to represent who I am 2) The brand complements my way of living	Puntoni et al. (2023); Japutra et al. (2023)

Variable	Definition	Indicators (Likert 1-7)	Ref
	the consumer's self-identity.	3) The suggested products make me feel "represented" 4) The suggestions seem individualized and related to one's identity.	
Affective-Based Evaluation (ABE)	The extent to which rational analysis of features is subordinated to emotional reactions when assessing a product or brand.	1) The product appeals to me emotionally 2) It makes me feel good 3) Emotions, not just characteristics, pique my curiosity 4) Emotional impressions impact my choice.	Huang & Rust (2022); Bagozzi et al. (2022)
Initial Preference Formation (IPF)	The degree to which individualized exposure creates a propensity to select a product or brand prior to conducting active research.	1) When I notice recommendations, I instantly form a choice 2) I hardly consider other options 3) I frequently choose the first suggestion 4) My ultimate decision is influenced by my initial exposure.	Davenport et al. (2023); Kozyreva et al. (2022)

4. Results and Discussion

Results

Measurement Model Evaluation

The analysis began with an evaluation of the measurement model using confirmatory factor analysis (CFA). The five-construct model demonstrated excellent fit ($\chi^2/df = 1.98$; CFI = 0.962; TLI = 0.955; RMSEA = 0.046; SRMR = 0.041), meeting all recommended SEM thresholds, with no error covariance modifications applied to preserve the theoretical structure. All indicators showed significant loadings above 0.70, confirming strong convergent validity. Composite reliability ranged from 0.87 to 0.93, and average variance extracted (AVE) exceeded 0.50 for all constructs, indicating good internal consistency. Discriminant validity was also established using the Fornell-Larcker criterion and HTMT ratios below 0.85, confirming that all constructs are empirically distinct.

Table 2. CFA and Construct Reliability.

Construct	Indicator	Loading	CR	AVE
Algorithmic Curation Intensity (ACI)	ACI1	0.82	0.91	0.72
	ACI2	0.86		
	ACI3	0.88		
	ACI4	0.84		
Perceived Autonomy in Information Search (PAIS)	PAIS1	0.79	0.88	0.65
	PAIS2	0.83		
	PAIS3	0.81		
	PAIS4	0.77		

Resonance of Identity (RI)	RI1	0.87	0.93	0.76
	RI2	0.9		
	RI3	0.88		
	RI4	0.84		
Affective-Based Evaluation (ABE)	ABE1	0.85	0.9	0.7
	ABE2	0.88		
	ABE3	0.81		
	ABE4	0.79		
Initial Preference Formation (IPF)	IPF1	0.83	0.89	0.68
	IPF2	0.85		
	IPF3	0.8		
	IPF4	0.78		

Structural Model Testing

After confirming the adequacy of the measurement model, the structural model results show that algorithmic curation intensity negatively affects perceived search autonomy (β = -0.34, $p < 0.001$), supporting H1, while positively influencing identity resonance (β = 0.52, $p < 0.001$), supporting H2. Identity resonance significantly increases affective evaluation (β = 0.61, $p < 0.001$), supporting H3, and also mediates the relationship between algorithmic curation and affective evaluation, with a significant indirect effect (0.32, 95% CI [0.24, 0.41]) based on 5,000 bootstrap samples, supporting H4. Additionally, algorithmic curation has a direct positive effect on initial preference formation (β = 0.47, $p < 0.001$), supporting H5, indicating that personalized exposure can shape preferences even prior to active exploration.

Table 3. Structural Model Testing.

Hypothesis	Correlation	β	t-value	p-value	Result
H1	ACI → PAIS	−0.34	6.12	<0.001	Supported
H2	ACI → RI	0.52	9.45		
H3	RI → ABE	0.61	11.02		
H5	ACI → IPF	0.47	8.31		

The endogenous construct R^2 shows substantial explanatory power:

- PAIS = 0.12
- RI = 0.27
- ABE = 0.37
- IPF = 0.22

These values indicate that the model has moderate to strong explanatory power in the context of digital consumer behavior.

Mediation Analysis

The association between the degree of algorithmic curation and affect-based judgment is partially mediated by identity resonance, according to mediation experiments. Identity resonance is a major psychological process, but it is not the only avenue of impact, as evidenced by the fact that the direct effect is considerable but diminishes when the mediator is involved.

Robustness Checks

Common technique bias is not a significant concern because Harman's single-factor test reveals that a single factor only accounts for 28% of the total variation, which is less than the 50% criterion. Additionally, the fit of the single-factor model in CFA is significantly worse than that of the five-factor model. There is no multicollinearity because all VIF values are less than 2.5. When a different model with a reversed causal direction is tested, the goodness-of-fit significantly decreases, supporting the hypothesis regarding the direction of the link.

Model Fit Evaluation

Model fit was assessed using multiple goodness-of-fit indices to ensure that the proposed theoretical structure adequately represents the empirical data. The results indicate that the five-construct model demonstrates excellent fit and meets all recommended SEM thresholds. The χ^2/df value is below the conservative cutoff of 3.00, indicating acceptable discrepancy between the model and observed data. Incremental fit indices (CFI and TLI) exceed 0.95, while RMSEA is below 0.06 and SRMR below 0.08, confirming minimal residual error. Overall, the combination of absolute, incremental, and parsimony fit indices provides strong evidence that the structural model is suitable for further interpretation of causal relationships among constructs.

Table 4. Goodness-of-Fit Indices SEM.

Fit Index	Model Value	Cut-off Recommended	Interpretation
χ^2 (Chi-square)	412.37	–	–
df	208	–	–
χ^2/df	1.98	< 3.00	Good Fit
CFI (Comparative Fit Index)	0.962	≥ 0.95	Excellent Fit
TLI (Tucker-Lewis Index)	0.955	≥ 0.95	Excellent Fit
RMSEA	0.046	≤ 0.06	Excellent Fit
RMSEA 90% CI	0.039-0.052	≤ 0.08	Acceptable
SRMR	0.041	≤ 0.08	Good Fit
GFI	0.921	≥ 0.90	Good Fit
AGFI	0.902	≥ 0.90	Good Fit
NFI	0.948	≥ 0.90	Good Fit

Discussions

Theoretical Implications of Algorithmic Curation in Consumer Decision-Making

This study addresses how AI-based recommendation systems reshape consumer decision architectures. Empirical findings show that algorithmic curation intensity is negatively associated with perceived search autonomy, while simultaneously showing positive associations with identity resonance, affect-based evaluation, and initial preference formation. These dual effects suggest that algorithmic personalization operates through both constraint and enhancement mechanisms, reducing perceived exploratory control while strengthening symbolic and affective relevance. This extends prior work on AI in marketing, highlighting that its impact is not only functional but also psychological and structural in shaping preference formation (Huang & Rust, 2022; Puntoni et al., 2023).

The negative relationship between algorithmic curation and perceived autonomy aligns with machine agency theory, which argues that computational systems redistribute decision control from individuals to technological architectures (Sundar, 2020). However, this reflects perceived rather than objective autonomy, suggesting not a loss of agency but a shift in how control is experienced. From a decision theory perspective, this extends bounded rationality (Simon, 1955; Kahneman, 2011) by showing that constraints also emerge from algorithmic exposure structures rather than cognition alone. Meanwhile, the positive link between algorithmic curation and identity resonance supports identity-based consumption theory (Belk, 1988),indicating that algorithmic exposure can reinforce self-brand alignment through repeated, selective visibility, consistent with AI as a symbolic and emotional system (Puntoni et al., 2023).

Furthermore, identity resonance strongly predicts affect-based evaluation, suggesting that identity alignment amplifies emotional dominance in brand assessment, particularly among Generation Z, where consumption functions as self-expression. Algorithmic curation also shows a direct association with initial preference formation, supporting the proposed

Algorithmic Consumer Formation (ACF) framework, where preferences emerge through adaptive interaction between consumer behavior traces and predictive systems (Davenport et al., 2023; Kozyreva et al., 2022). Although the cross-sectional design limits causal inference, the patterns align with the idea that algorithmic exposure can shape preferences prior to active exploration.

Overall, these findings extend bounded rationality toward algorithmically bounded agency, where decision limits arise not only from cognitive constraints but also from curated exposure environments. This reframes consumer decision-making in digital ecosystems as a co-constructed process between humans and AI systems, consistent with prior perspectives on digital consumer behavior (Lemon & Verhoef, 2016). The study contributes an integrated framework linking consumer behavior, identity-based consumption, and human-AI interaction, while highlighting the need for future longitudinal and experimental research to establish causal and temporal dynamics in algorithmically mediated decision processes.

Limitations and Future Research Agenda

This study contributes to understanding algorithmic consumer decision-making, but several limitations open avenues for future research. First, the cross-sectional design limits insights into temporal dynamics. Algorithmic curation evolves through continuous machine learning processes, suggesting that future studies should use longitudinal or panel designs to capture how repeated interactions shape preferences, identity, and perceived autonomy over time, including potential reinforcement cycles (Davenport et al., 2023).

Second, the study relies on self-reported measures of algorithmic curation intensity. Future research should integrate behavioral data such as clickstream or purchase histories to validate subjective perceptions against actual algorithmic exposure. Mixed-method approaches or field experiments would also help reduce common method bias and strengthen causal inference (Kozyreva et al., 2022).

Third, the focus on Indonesian Generation Z limits cross-cultural and generational generalizability. Future studies should examine whether algorithmic effects differ across cultures, levels of digital literacy, and generational cohorts, as well as explore whether algorithmically bounded agency is universal or context-dependent. Comparative cross-country research would significantly enrich the literature.

Fourth, the model does not fully account for variations in algorithm design. Future research could test how transparency, user control, and explainable AI features moderate perceived autonomy and identity resonance. Prior work suggests that system transparency influences trust and perceived agency in human-AI interaction (Puntoni et al., 2023), making experimental designs particularly valuable.

Finally, the finding on initial preference formation introduces the concept of algorithmic consumer formation, highlighting how algorithms participate in shaping preferences and identities from early stages. Future research should explore its ethical and normative implications, including autonomy, nudging, and algorithmic influence (Sundar, 2020; Huang & Rust, 2022). Broader approaches such as network analysis or agent-based modeling may further capture how preferences emerge within interconnected digital ecosystems.

Overall, these limitations do not weaken the study's contribution but instead establish a foundation for future inquiry. Advancing marketing theory in the AI era requires moving beyond personalization effectiveness toward a deeper understanding of how algorithms structure choice, identity, and consumer agency.

5. Conclusions

This study addresses a fundamental question of whether algorithms merely reflect consumer preferences or actively shape them. The findings show that algorithmic curation intensity not only influences evaluation and decision outcomes but also contributes to initial preference formation through identity resonance and the restructuring of perceived autonomy, suggesting that digital-era preferences are dynamic, co-constructed, and continuously shaped by latent predictive systems. Theoretically, this extends bounded rationality into algorithmically bounded agency, where decision constraints arise not only from cognitive limitations but also from recommendation architectures that pre-structure exposure, positioning algorithms as institutional actors within identity-based consumption and human-AI interaction processes. Methodologically, SEM results confirm strong model fit and significant relationships, with identity resonance functioning as a key mediator between algorithmic curation and preference formation, indicating systematic consumer-AI interaction patterns rather than random effects. More broadly, the study introduces the concept of algorithmic consumer formation, where preferences emerge within an ecosystem in which AI systems continuously curate, predict, and reinforce choices, shifting marketing from influencing decisions toward participation in a co-evolutionary system where humans and algorithms jointly construct desire. Ultimately, this represents a paradigm shift from autonomous decision-makers to consumers whose preferences evolve through symbiotic interaction with algorithms, raising important implications for autonomy, ethics, and the future of AI-driven marketing.

References

Bagozzi, R. P., Belanche, D., & Flavián, C. (2022). The role of anticipated emotions in decision-making. *Academy of Marketing Science*, 50(6), 1234-1256.

Belk, R. W. (1988). Possessions and the extended self. *Journal of Consumer Research*, 15(2), 139-168. https://doi.org/10.1086/209154

Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2022). Creating effective personalized experiences in digital environments. *Marketing Science*, 50(3), 501-525. https://doi.org/10.1007/s11747-021-00802-3

Court, D., Mulder, S., & Vetvik, O. J. (2009). The consumer decision journey. *McKinsey Quarterly*, 3, 96-107.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage.

Davenport, T. H., Grewal, D., & Bressgott, T. (2023). How AI will change the future of marketing. *Academy of Marketing Science*, 51(1), 24-42. https://doi.org/10.1007/s11747-022-00886-1

Djafarova, E., & Bowes, T. (2023). "Instagram made me buy it." *Journal of Consumer Services*, 70, 103143. https://doi.org/10.1016/j.jretconser.2022.103143

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. *Retailing*, 93(1), 1-6. https://doi.org/10.1016/j.jretai.2016.12.008

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2022). *A primer on PLS-SEM*. Sage.

Huang, M. H., & Rust, R. T. (2022). A strategic framework for AI marketing. *Marketing Science*, 50(1), 30-50. https://doi.org/10.1007/s11747-021-00749-5

Japutra, A., Ekinci, Y., & Simkin, L. (2023). Self-congruence and brand engagement. *Business*, 155, 113402.

Kahneman, D. (2011). *Thinking, fast and slow*. Giroux.

Kozyreva, A., Herzog, S. M., & Lewandowsky, S. (2022). Algorithmic influence on decision-making. *Cognitive Science*, 26(11), 965-979.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience. *Journal of Marketing*, 80(6), 69-96. https://doi.org/10.1509/jm.15.0420

Puntoni, S., Reczek, R. W., & Botti, S. (2023). Consumers and artificial intelligence. *Journal of Marketing*, 87(1), 131-151. https://doi.org/10.1177/00222429221111422

Simon, H. A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics*, 69(1), 99-118. https://doi.org/10.2307/1884852

Sundar, S. S. (2020). Rise of machine agency. *Journal of Computer-Mediated Communication*, 25(1), 74-88. https://doi.org/10.1093/jcmc/zmz026

Zuboff, S. (2019). *Surveillance capitalism: The fight for a human future at the new frontier of power*. PublicAffairs.