KMANPUB | AI and Tech in Behavioral and Social Sciences Vol. 4 No. 3 (2026): 1-7

Article history:
Received 17 February 2026
Revised 10 June 2026
Accepted 17 June 2026
Initial Publication 26 June 2026
Final Publication 01 July 2026

The Future of Marketing: Using Agentic AI to Transform Segmentation and Positioning

Alireza Faed[1*]

[1] School of Marketing, Seneca Business, Seneca Polytechnic, Toronto, Ontario, Canada

*** Corresponding author email address:** alireza.faed@senecapolytechnic.ca

A r t i c l e I n f o

Article type:
Original Research

How to cite this article:
Faed, A. (2026). The Future of Marketing: Using Agentic AI to Transform Segmentation and Positioning. *AI and Tech in Behavioral and Social Sciences*, *4*(3), 1-7.
https://doi.org/10.61838/kman.aitech.5643

A B S T R A C T

This study developed and empirically tested an operational framework for using agentic artificial intelligence (AI) in market segmentation and positioning. A descriptive survey design was used. The target population consisted of marketing managers, data analysts, and AI specialists working in 250 active companies in Tehran that had implemented AI-related marketing projects during the previous two years. A stratified random sample of 152 participants completed a 42-item researcher-developed questionnaire scored on a five-point Likert scale. Content validity was assessed by eight experts, and internal consistency was acceptable (Cronbach's alpha = .92). The data were analyzed using descriptive statistics and partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. The descriptive results indicated that the lowest mean scores were observed for human skills (M = 2.78) and agent-based market simulation (M = 2.85), whereas the highest mean was observed for ethical and privacy factors (M = 3.45). The structural results showed that all hypothesized paths were statistically significant. The strongest path was from agent design to agent learning (β = .567), followed by agent learning to market simulation (β = .523) and operational implementation to success (β = .512). The model explained 58.3% of the variance in implementation success. The findings suggest that agentic AI can substantially improve segmentation and positioning when organizations develop integrated data infrastructure, robust agent design, human analytical skills, continuous monitoring routines, and clear ethical and privacy safeguards.

Keywords: *agentic AI; artificial intelligence in marketing; market segmentation; positioning; agent-based simulation; PLS-SEM*

1. Introduction

Marketing is being reshaped by the combined use of big data, machine learning, automation, and AI-enabled decision support. In segmentation and positioning, this shift matters because organizations increasingly need to detect behavioral microsegments, personalize value propositions, and adapt positioning strategies in near real time. Conventional segmentation based mainly on demographic, geographic, psychographic, or periodic behavioral profiles remains useful, but it is often too static for environments characterized by rapid preference changes, digital traces, and dense customer interactions (Kotler & Keller, 2016).

Agentic AI extends conventional marketing analytics by using autonomous or semi-autonomous software agents that perceive an environment, process information, learn from feedback, and act toward a defined goal. This idea builds on the classic theory of intelligent agents, in which agents are described as autonomous, reactive, proactive, and socially capable entities (Wooldridge & Jennings, 1995). In marketing, such agents can be used to model consumer behavior, simulate market reactions, support dynamic segmentation, test positioning alternatives, and personalize marketing actions.

Recent marketing literature emphasizes that AI can influence marketing research, strategy, and action, including segmentation, targeting, and positioning (Davenport et al., 2020; Huang & Rust, 2021). However, the practical adoption of agentic AI requires more than technical algorithms. Organizations also need integrated customer data, interpretable agent design, staff capabilities, governance routines, and ethical controls. The present study addresses this operational gap by testing a staged framework for agentic AI adoption in segmentation and positioning.

2. Literature Review and Hypotheses

Agentic AI in marketing draws on three theoretical foundations: intelligent-agent theory, rational choice theory, and consumer behavior theory. Intelligent-agent theory clarifies how autonomous computational entities can perceive, reason, and act. Rational choice theory explains decision rules under constraints, which is useful when modeling consumer agents. Consumer behavior theory provides the behavioral variables that can be translated into agent attributes, preference functions, and purchase rules (Becker, 1976; Blackwell et al., 2001; Wooldridge & Jennings, 1995).

Agent-based modeling is particularly relevant to marketing because it can represent heterogeneous consumers and simulate emergent market-level outcomes from individual-level decision rules. Rand and Rust (2011) note that agent-based models are useful when marketing phenomena are too complex for conventional analytical or empirical approaches (Rand & Rust, 2011). In the context of segmentation and positioning, agent-based simulation can allow teams to test segmentation rules, observe spillover effects, and evaluate positioning scenarios before real-market deployment.

A practical agentic AI framework should include data infrastructure, agent design, agent learning, agent-based market simulation, operational implementation, monitoring and updating, human skills, and ethical/privacy factors. The structural model tested in this study is presented in Figure 1. Based on this model, five hypotheses were tested: H1, organizational data infrastructure positively affects agent design; H2, agent design positively affects agent learning; H3, agent learning positively affects agent-based market simulation; H4, market simulation and operational implementation positively affect implementation success; and H5, monitoring, human skills, and ethical/privacy factors positively affect implementation success.

3. Methods and Materials

3.1. Design and Participants

This applied study used a descriptive survey design. The population included marketing managers, data analysts, and AI specialists employed in 250 active companies in Tehran that had implemented AI-related marketing projects during the previous two years. Using the Krejcie and Morgan (1970) sample-size approach, the final sample was set at 152 respondents and selected through stratified random sampling (Krejcie & Morgan, 1970).

3.2. Instrument and Measures

Data were collected using a researcher-developed 42-item questionnaire. Items were scored on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument covered eight implementation variables: data infrastructure, agent design, agent learning, agent-based market simulation, operational implementation, monitoring and updating, human skills,

AITBSS
AI and Tech in Behavioral and Social Sciences
E-ISSN: 3041-9433

and ethical/privacy factors. The variables and their operational focus are summarized in Table 1.

Table 1

Study constructs and measurement structure

Construct	Items	Operational focus
Data infrastructure	5	Integration, cleaning, and availability of behavioral, CRM, online, and social-media data.
Agent design	6	Definition of agent goals, decision rules, interaction architecture, and segmentation logic.
Agent learning	5	Use of historical data, reinforcement learning, unsupervised learning, and feedback-based improvement.
Agent-based market simulation	6	Simulation of consumer agents, market scenarios, positioning alternatives, and competitive reactions.
Operational implementation	5	Deployment of agents for real-time segmentation, personalization, and positioning support.
Monitoring and updating	5	Performance tracking, model updating, error detection, and feedback-loop management.
Human skills	5	Marketing analytics, data literacy, AI understanding, and cross-functional collaboration.
Ethics and privacy	5	Privacy protection, algorithmic transparency, consent, and customer-data governance.

Note. The table consolidates the 42 questionnaire items into the eight variables tested in the structural model.

Content validity was evaluated by eight experts. Internal consistency was acceptable for the overall instrument (Cronbach's alpha = .92).

3.3. Data Analysis

Data were analyzed at descriptive and inferential levels. Descriptive analysis included means, standard deviations, and agreement frequencies. PLS-SEM was used to test the structural relationships among variables, following common recommendations for prediction-oriented models with latent constructs (Hair et al., 2022). The significance level was set at .05. Model adequacy was evaluated using SRMR, NFI, RMSEA, and the explained variance of the dependent construct.

4. Findings and Results

4.1. Descriptive Findings

As shown in Table 2, the descriptive results indicate moderate readiness for agentic AI adoption rather than strong maturity. Ethical and privacy factors had the highest mean score (M = 3.45), suggesting that respondents perceived privacy and ethical safeguards as relatively more developed than other areas. The lowest mean scores were observed for human skills (M = 2.78) and agent-based market simulation (M = 2.85), indicating a practical capability gap in the skills and simulation layers needed for advanced agentic AI adoption.

Table 2

Descriptive statistics of the main research variables

Variable	Items	Mean	SD	Agreement n	Agreement %
Data infrastructure	5	3.28	0.96	67	44.08%
Agent design	6	3.05	1.02	54	35.53%
Agent learning	5	2.92	1.08	43	28.29%
Agent-based market simulation	6	2.85	1.11	38	25.00%
Operational implementation	5	3.15	0.95	62	40.79%
Monitoring and updating	5	3.08	0.98	58	38.16%
Human skills	5	2.78	1.15	35	23.03%
Ethics and privacy	5	3.45	0.89	89	58.55%

Note. Agreement refers to responses of 4 or 5 on the five-point Likert scale.

4.2. Measurement and Model Adequacy

Table 3 summarizes the principal measurement and model-adequacy evidence. The overall questionnaire reliability was strong (Cronbach's alpha = .92). The structural model explained 58.3% of the variance in implementation success, which is adequate for an applied organizational model. SRMR (.062) and RMSEA (.048) indicated acceptable fit. NFI (.89) was slightly below the common .90 benchmark; therefore, the fit should be described as marginal-to-acceptable rather than unequivocally strong.

AITBSS
AI and Tech in Behavioral and Social Sciences
E-ISSN: 3041-9433

Table 3

Measurement quality and structural model adequacy

Evidence	Reported value	Interpretation
Content validity	8 experts	Expert review supported item relevance and clarity.
Internal consistency	Cronbach's alpha = .92	Overall reliability was acceptable.
Explained variance	R^2 for success = .583	The model explained 58.3% of implementation success.
SRMR	.062	Acceptable residual fit.
NFI	.89	Marginal-to-acceptable; slightly below .90.
RMSEA	.048	Acceptable approximation error.

4.3. Structural Model and Hypothesis Testing

All structural paths were statistically significant (Table 4). The strongest path was from agent design to agent learning (β = .567), followed by agent learning to market simulation (β = .523) and operational implementation to success (β = .512). These results support the staged logic of the framework: high-quality data infrastructure enables agent design, well-designed agents learn more effectively, and learning quality improves simulation and implementation outcomes. The coefficients are visualized in Figure 2.

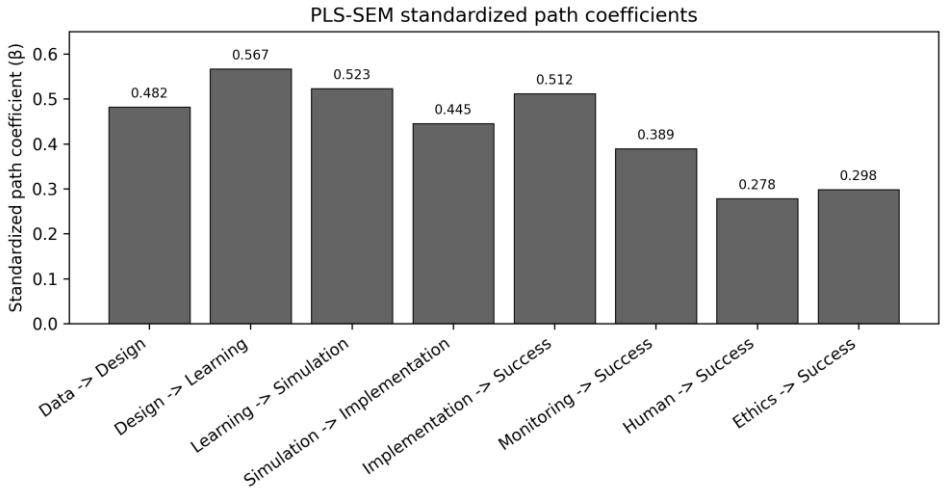
Table 4

PLS-SEM structural path coefficients and hypothesis decisions

Hypothesis	Path	β	t	p	Decision
H1	Data infrastructure -> Agent design	.482	6.342	< .001	Supported
H2	Agent design -> Agent learning	.567	7.891	< .001	Supported
H3	Agent learning -> Market simulation	.523	6.905	< .001	Supported
H4a	Market simulation -> Operational implementation	.445	5.876	< .001	Supported
H4b	Operational implementation -> Success	.512	7.102	< .001	Supported
H5a	Monitoring and updating -> Success	.389	4.956	< .001	Supported
H5b	Human skills -> Success	.278	3.451	.001	Supported
H5c	Ethics and privacy -> Success	.298	3.789	< .001	Supported

Figure 1

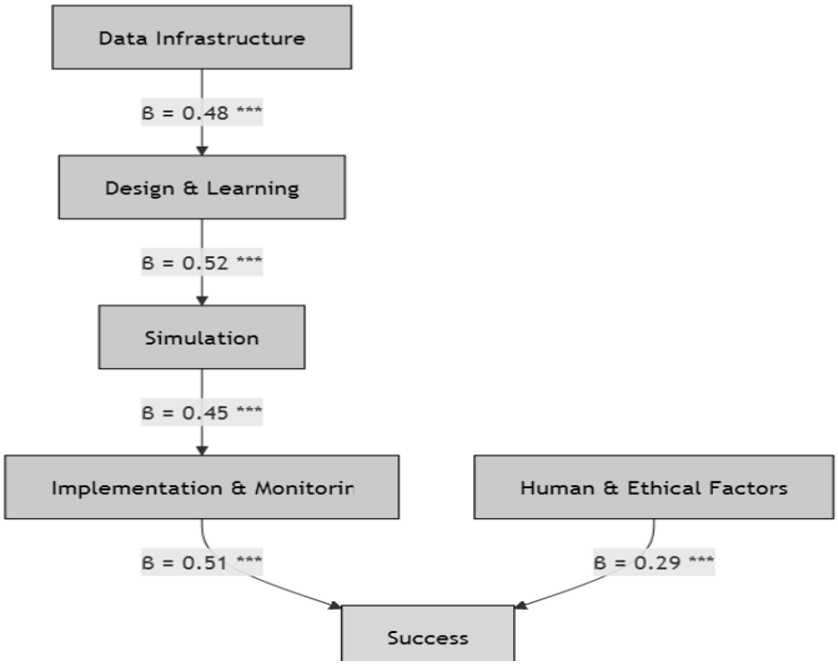
Standardized structural path coefficients



AITBSS
AI and Tech in Behavioral and Social Sciences
E-ISSN: 3041-9433

Figure 2

Final Model



4.4. Integrated Interpretation

The results suggest that agentic AI adoption in segmentation and positioning is constrained less by ethical awareness than by practical capability. Ethical and privacy safeguards received the highest descriptive score, whereas human skills and market simulation received the lowest scores. The structural findings indicate that design and learning stages are central to the success chain. In other words, organizations are unlikely to benefit from agentic AI simply by acquiring tools; they must build data pipelines, define agent architectures, train agents on usable data, test strategies in simulated markets, and continuously update the system after deployment.

5. Discussion

The findings confirm that agentic AI can transform segmentation and positioning when it is treated as an integrated socio-technical system. The descriptive results show that companies have made some progress in ethical and privacy awareness, but human capability and agent-based simulation remain weak points. This is consistent with the broader AI marketing literature, which emphasizes that AI value depends on the interaction between technology, strategy, customer understanding, and organizational capability (Davenport et al., 2020; Huang & Rust, 2021).

The structural model also shows that implementation success depends on an ordered chain rather than isolated variables. Data infrastructure affects agent design; design affects learning; learning supports market simulation; simulation supports implementation; and implementation, monitoring, human skills, and ethical safeguards jointly affect success. This pattern is theoretically consistent with agent-based modeling logic, where the value of the model depends on the credibility of agent rules, the quality of the input data, and the ability to learn from simulated and observed outcomes (Rand & Rust, 2011; Wooldridge et al., 2000).

The relatively low score for human skills is substantively important. Agentic AI systems require staff who understand both marketing logic and data-driven experimentation. Without such skills, segmentation outputs may be treated as black-box recommendations, positioning simulations may be poorly interpreted, and feedback loops may fail. Similarly, the low score for agent-based market simulation indicates that many organizations may still be using AI mainly for analytics or automation rather than for pre-market strategic experimentation.

AITBSS
AI and Tech in Behavioral and Social Sciences
E-ISSN: 3041-9433

6. Practical Implementation Framework

The practical implication of the findings is a staged implementation framework. Table 5 translates the empirical model into managerial actions that marketing teams can use when deploying agentic AI for segmentation and positioning.

Table 5

Practical framework for implementing agentic AI in segmentation and positioning

Stage	Managerial action	Expected output
1. Data infrastructure	Integrate CRM, online behavior, transaction, and social-media data.	Clean, labeled, and accessible customer-data environment.
2. Agent design	Define consumer, seller, and mediator agents, goals, rules, and interaction logic.	Documented agent architecture aligned with segmentation and positioning goals.
3. Agent learning	Train agents on historical data and update them through feedback mechanisms.	Adaptive agents capable of identifying behavioral patterns.
4. Market simulation	Test alternative segmentation and positioning scenarios before market launch.	Evidence-based selection of strategies with lower implementation risk.
5. Implementation and monitoring	Deploy agents in real marketing processes and monitor performance indicators.	Real-time segmentation, personalization, and continuous correction.
6. Human and ethical governance	Train marketing teams and define privacy, transparency, and appeal mechanisms.	Trustworthy and interpretable AI-supported marketing practice.

7. Limitations and Future Research

This study has several limitations. First, it used a self-report survey; therefore, the findings may be affected by common-method bias and differences in respondents' technical knowledge. Second, the study was conducted among companies in Tehran, and generalization to other regions, industries, or international markets should be made cautiously. Future studies should report a complete measurement model and test the framework in multiple sectors using longitudinal data, behavioral logs, and actual marketing-performance indicators such as conversion rate, retention, customer lifetime value, and campaign return on investment.

8. Conclusion

The study shows that agentic AI has substantial potential to transform segmentation and positioning, but implementation success requires coordinated investment in data infrastructure, agent architecture, learning mechanisms, simulation capacity, operational deployment, monitoring, human skills, and ethical safeguards. The strongest structural link was between agent design and agent learning, emphasizing that the quality of the agent architecture is central to the value of the system. The lowest descriptive scores for human skills and agent-based simulation indicate that organizational readiness remains incomplete. Accordingly, marketing teams should treat agentic AI not as a stand-alone tool but as a governed, continuously updated decision-support system for strategic marketing.

Authors' Contributions

Alireza Faed was responsible for conceptualization, methodology, data collection, analysis, interpretation, and manuscript preparation.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

The data that support the findings of this study may be made available by the author upon reasonable request, subject to institutional permission and confidentiality restrictions.

Acknowledgments

I would like to express our gratitude to all individuals helped do the project.

Declaration of Interest

The author declares no known competing financial or non-financial interests related to this study.

AITBSS
AI and Tech in Behavioral and Social Sciences
E-ISSN: 3041-9433

Funding

No funding information was provided in the source manuscript. The author should insert the funding source or state that the research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Ethics Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

References

Becker, G. S. (1976). *The economic approach to human behavior*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226217062.001.0001

Blackwell, R. D., Miniard, P. W., & Engel, J. F. (2001). *Consumer behavior* (9th ed.). Harcourt College Publishers. https://www.scirp.org/reference/referencespapers?referenceid=1298292

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*, 24-42. https://doi.org/10.1007/s11747-019-00696-0

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE. https://doi.org/10.1007/978-3-030-80519-7

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*, 30-50. https://doi.org/10.1007/s11747-020-00749-9

Kotler, P., & Keller, K. L. (2016). *Marketing management* (15th ed.). Pearson. https://fil.welib.org/md5/8e430253989370bab3f58b80330cfed7.pdf

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*(3), 607-610. https://doi.org/10.1177/001316447003000308

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, *28*(3), 181-193. https://doi.org/10.1016/j.ijresmar.2011.04.002

Wooldridge, M., & Jennings, N. R. (1995). Intelligent agents: Theory and practice. *The Knowledge Engineering Review*, *10*(2), 115-152. https://doi.org/10.1017/S0269888900008122

Wooldridge, M., Jennings, N. R., & Kinny, D. (2000). The Gaia methodology for agent-oriented analysis and design. *Autonomous Agents and Multi-Agent Systems*, *3*(3), 285-312. https://doi.org/10.1023/A:1010071910869

AITBSS
AI and Tech in Behavioral and Social Sciences
E-ISSN: 3041-9433