

The Impact of Artificial Intelligence on Brand Name Change: Psychological Mechanisms and Purchase Intention

Myriam EL ALEM

Doctor in Marketing – University of Tunis El Manar – Faculty of Economic Sciences and Management of Tunis – Labo ERMA

DOI: <https://dx.doi.org/10.47772/IJRISS.2025.91100395>

Received: 23 November 2025; Accepted: 01 December 2025; Published: 12 December 2025

ABSTRACT

This study investigates how the use of artificial intelligence (AI) in brand name change decisions shapes consumer responses. Drawing on perceived functional improvement, signaling theory, and resistance-to-change frameworks, the research proposes and tests a structural model linking AI presence, perceived functional improvement, brand trust, resistance to change, and purchase intention. Using PLS-SEM, findings show that AI presence significantly enhances perceived functional improvement, which strengthens brand trust and subsequently reduces consumer resistance. Lower resistance then increases purchase intention. The study highlights the strategic value of AI as both a decision-support tool and a credibility signal in rebranding processes, offering theoretical insights and practical implications for AI-enhanced brand management.

Keywords: Artificial Intelligence; Brand Renaming; Perceived Functional Improvement; Brand Trust; Resistance to Change; Purchase Intention;; PLS-SEM.

INTRODUCTION

Artificial Intelligence (AI) has experienced explosive growth over the past decade, significantly contributing to the integration of various aspects of life and enabling the resolution of many complex challenges. In marketing and brand management, AI encompasses numerous associated functions and concepts, often being broadly defined to include various types of computer systems capable of directly executing or assisting tasks that previously required human emotions or cognition, using software and algorithms (Ameen, Tarhini & Reppel (2020).

The integration of artificial intelligence (AI) into marketing practices is transforming not only operations (automation, personalization) but also consumers' perceptions of brands. AI is used particularly in creative processes such as generating, modifying, or replacing brand names. These strategic decisions, historically made by human experts, are now increasingly being co-created or fully automated by AI systems capable of analyzing linguistic structures, optimizing semantic consistency, and anticipating consumer preferences. Recent work has shown that AI can improve the speed, creativity, and functional relevance of brand development, while reducing associated costs (Rege, 2025; Balabanova, 2025).

However, replacing or changing a brand name is perceived as a risky change by consumers, likely to cause confusion, disorientation, and resistance (Kapferer, 2007). It is a sensitive moment that can provoke rejection or resistance from consumers (Kapferer, 2007; Muzellec & Lambkin, 2006). Integrating AI into this process could transform this perception: when consumers perceive that AI improves the quality, relevance, or consistency of the new name or identity (Hwang & Wu, 2024; Hartmann, 2025), it can strengthen their trust in the brand (Gbadamassi & Diakité, 2025) and reduce their resistance to change. AI-assisted rebranding is therefore a promising but complex development and practice, requiring further study of its influence on functional perception, brand trust, and resistance to change.

The objective of this study is to examine the effect of integrating artificial intelligence into the brand name substitution process on improving functional perception, strengthening brand trust, and consequently reducing consumer resistance to change.

This study raises major questions: To what extent does the presence of AI in the brand name substitution process improve the perception of a functional improvement, strengthen brand trust, and help reduce consumer resistance to change?

To answer these questions, a mixed-methods approach will be used, combining a literature review on the use of AI in the brand name substitution process with an empirical study using a quantitative questionnaire. Theoretically, this research contributes to the emerging literature on AI-assisted branding by demonstrating the role of perceived functional improvement and trust in the acceptance of brand identity transformations. From a managerial perspective, the results offer decision-makers concrete guidance on the optimal integration of AI into rebranding strategies, showing that transparency, hybrid human-machine use, and highlighting perceived functional benefits can mitigate consumer resistance, improve buy-in to change, and ensure a smoother and more credible identity transition.

LITERATURE REVIEW

Advances in artificial intelligence are profoundly transforming brand management processes, particularly in name change decisions. Traditionally, renaming relied on managerial intuition and qualitative studies aimed at anticipating consumer resistance (Kapferer, 2007). Several studies show that AI can rapidly generate name proposals based on broad linguistic and semantic databases, while improving the relevance, consistency, and creativity of the proposed options (Rege, 2025; Balabanova, 2025). Applied studies demonstrate that AI can actively participate in the conceptual phases of rebranding; Hwang and Wu (2024) show that generative AI can add value in rebranding workshops by proposing ideas that human designers can then use to ensure cultural consistency. Applied studies demonstrate that AI can actively participate in the conceptual phases of rebranding. Hwang and Wu (2024) show that generative AI can add value to rebranding workshops by suggesting ideas that human designers can then use to ensure cultural consistency. At the strategic level, Gupta (2025) emphasizes that AI can strengthen the clarity, consistency, and international adaptability of brand identities, particularly in the choice of names aligned with the expectations of global markets. However, several authors point out that the contribution of AI must be regulated by human supervision to avoid the risks of cultural misalignment or a loss of perceived authenticity (Gbadamassi & Diakité, 2025).

From a theoretical point of view, the role of AI falls within the theory of perceived improvement, according to which AI tools, capable of optimizing the relevance, semantic coherence and quality of the new name, reinforce the perception of a functional gain (Huang & Rust, 2021). Signaling theory also suggests that the use of AI signals a rigorous, neutral, and data-driven process, increasing the legitimacy of change (Spence, 1973). Furthermore, uncertainty reduction theory indicates that AI helps mitigate perceived risks by simulating name acceptability and predicting negative reactions (Berger & Calabrese, 1975).

Finally, research on AI adoption in marketing shows that consumers attribute to AI the power of optimization and neutrality, which reduces resistance when the algorithm is perceived as improving the quality of the decision (Davenport, Guha, Grewal & Bressgott, 2020). Thus, AI is not merely a technical tool, but a cognitive and symbolic actor that restructures how name changes are conceived, evaluated, and accepted.

Research hypotheses and conceptual model

AI can be seen as a tool for improving the relevance of a new name, which represents a functional improvement for the consumer. According to Hartmann (2025), studies show that AI-generated visuals are sometimes judged to be more creative and attractive than those produced by human designers. Hwang & Wu (2024) demonstrate that AI can produce more varied and relevant proposals, although cultural adaptation requires human oversight. Recent studies (Cheng & Jiang, 2023; Longoni & Cian, 2022) show that AI-assisted marketing creatives are perceived as more relevant, accurate, and better suited to consumer expectations. The presence of AI acts as a signal of technological competence, suggesting that the resulting products will be more relevant, consistent, and effective. This is the basis of the Technology Acceptance Model (TAM) (Davis, 1989), which posits that perceived usefulness is a major determinant of a technology's positive evaluation. Thus, the presence of AI in the creation or substitution of a name logically reinforces the perceived functional improvement of the result.

H1 : The presence of artificial intelligence in the brand name substitution process increases the perceived functional improvement.

Consumer trust rests on two pillars: the perception of competence and reliability (Mayer, Davis & Schoorman, 1995). AI, when it improves functional performance, acts precisely on the dimension of technical competence (Schaefer, K.2016) and thus reinforces the perception of professional competence attributed to the brand.

Several studies show that the quality produced by AI increases trust in the technology (Hoff & Bashir, 2015; van Pinxteren et al., 2019) but also in the company that integrates it. Thus, the perception of a functional improvement constitutes an important antecedent to trust in the brand that adopts AI in its creative process.

H2 : The perceived functional improvement of the new brand name strengthens trust in the brand.

The literature on technology acceptance shows that trust can mitigate psychological barriers: when a user trusts the technology, they perceive less complexity or risk, which reduces inertia and promotes adoption. This mechanism can explain a decrease in resistance to change. According to Kapferer (2007) and Muzellec & Lambkin (2006), consumer resistance to rebranding stems from a disruption of familiar reference points, an increased perceived risk, and a possible feeling of loss of brand identity. In the specific case of AI, when it improves the perceived performance of the new name, trust in the brand and its decision-making process is strengthened, thereby reducing cognitive and emotional resistance. According to Kim, Ferrin, and Rao (2008), trust facilitates the acceptance of decisions perceived as risky or disruptive and reduces the fears and uncertainty associated with change (Morgan & Hunt, 1994). In rebranding, high trust mitigates negative reactions (Muzellec & Lambkin, 2006; Walsh et al., 2010). According to Longoni & Cian (2022), the use of AI perceived as beneficial decreases reactance and behavioral resistance.

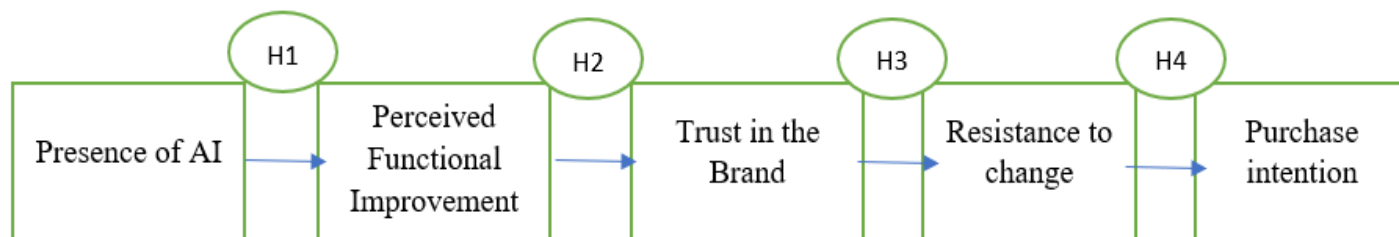
H3 : Trust in the brand reduces consumer resistance to brand name substitution.

The theory of resistance to change (Oreg, 2003; Claudy et al., 2015) shows that resistance constitutes a cognitive, emotional, and behavioral barrier that prevents the acceptance and adoption of new offerings. When this resistance decreases, the consumer becomes more receptive and more willing to engage in behaviors favorable to the product or brand. According to Kleijnen et al. (2009), a decrease in resistance increases openness to change and predisposes consumers to adopt the new offering. In the context of technological innovation, a decrease in reactance or skepticism increases the intention to adopt and purchase (Kim, Ferrin & Rao, 2008).

H4 : Reducing consumer resistance to change increases their intention to purchase the product.

The various links between the variables are represented by the explanatory conceptual model presented below:

The conceptual model of research



Source : Developed by the authors

Methods and Data

To gather the information necessary to test the hypotheses mentioned above, a quantitative survey was conducted online with 255 consumers aged 20 to over 50. A questionnaire was designed to collect data on consumer perceptions of the variables selected based on the literature review. The questionnaire was pre-tested with 10%

of the sample to verify its clarity and precision and to eliminate any potential biases related to misunderstanding the questions. This pre-test showed that all the questions were perfectly understandable to the respondents, allowing us to continue data collection. Data collection took place from September 2nd to 30th, 2025. The details of our sample will be presented in Table 1 below:

Table 1: Sample Details

Characteristics	Details	Percentages
Gender	Men	48.3%
	Women	51.7%
Age	21 - 30	56.8%
	31 - 40	18.7%
	41 -50	14.8%
	+ 50 ans	9.7%
Intellectual Level	Primary	4%
	Secondary	35%
	University	61%

Source : Developed by the authors

To measure the variables in our study namely, AI presence, perceived functional improvement, trust, resistance, and purchase intention. We used measurement scales previously published in the literature. These scales proved reliable and valid. For scales available only in English, we followed a double back-translation procedure. To ensure content validity, the vocabulary was adapted to the context of AI applications. The following table summarizes the different measurement tools.

Table 2 : Summary Table of Variables and Selected Measurement Scales

Variables	Adopted by	Number of items
IA Presence	Longoni, C., & Cian, L. (2022).	3
Perceived functional improvement	Cheng & Jiang (2022)	4
Trust in the brand	Hoff & Bashir (2015)	4
Resistance to change	Walsh, G. et al. (2010)	4
Purchase intention	Chen and Chang (2012)	3

Source : Developed by the authors

RESULTS

Validation of Measurement Scales

To examine the causal relationships between the latent variables of the conceptual model : AI presence, perceived functional improvement, trust, resistance, and purchase intention, the Partial Least Squares Structural Equation Modeling (PLS-SEM) method was applied using SmartPLS 3 software. The PLS analysis followed two main stages (Hair et al., 2021). First, the measurement model was evaluated to assess item reliability, the internal consistency of the scales, and convergent validity. Second, the structural model was examined to test the causal hypotheses. Coefficient estimation was performed using the bootstrapping procedure (5000 resamples), which provided the t-values, β coefficients, and p-values required to determine the statistical significance of the hypothetical relationships (Hair et al., 2021).

Table 3: Results of the Measurement Model Analyses

Variables	Items	Loadings	Cronbach's Alpha	Composite reliability	AVE
AI presence	IA_1	0.877	0.764	0.818	0.705
	IA_2	0.816			
	IA_3	0.806			
perceived functional improvement	PERF_1	0.867	0.841	0.903	0.757
	PERF_2	0.871			
	PERF_3	0.878			
	PERF_4	0.857	0.892	0.925	0.754
Trust in the brand	TRUST_1	0.811	0.877	0.915	0.730
	TRUST_2	0.894			
	TRUST_3	0.868			
	TRUST_4	0.843			
Resistance to change	RESIST_1	0.899	0.833	0.889	0.671
	RESIST_2	0.865			
	RESIST_3	0.867			
	RESIST_4	0.896			
Purchase intention	PI_1	0.909	0.869	0.920	0.793
	PI_2	0.886			
	PI_3	0.876			

Source: Developed by the authors

The results of the measurement model evaluation show that the indicators have loadings ranging from 0.811 to 0.909, thus exceeding the recommended threshold of 0.7 (Hair et al., 2009). This indicates that all items are correlated with their respective constructs. The values for Cronbach's Alpha and Composite Reliability (CR) are also satisfactory. The convergent validity of the constructs is confirmed, as all Average Variance Extracted (AVE) values are greater than 0.5 (Chin, 1998).

Results of the Structural Analysis

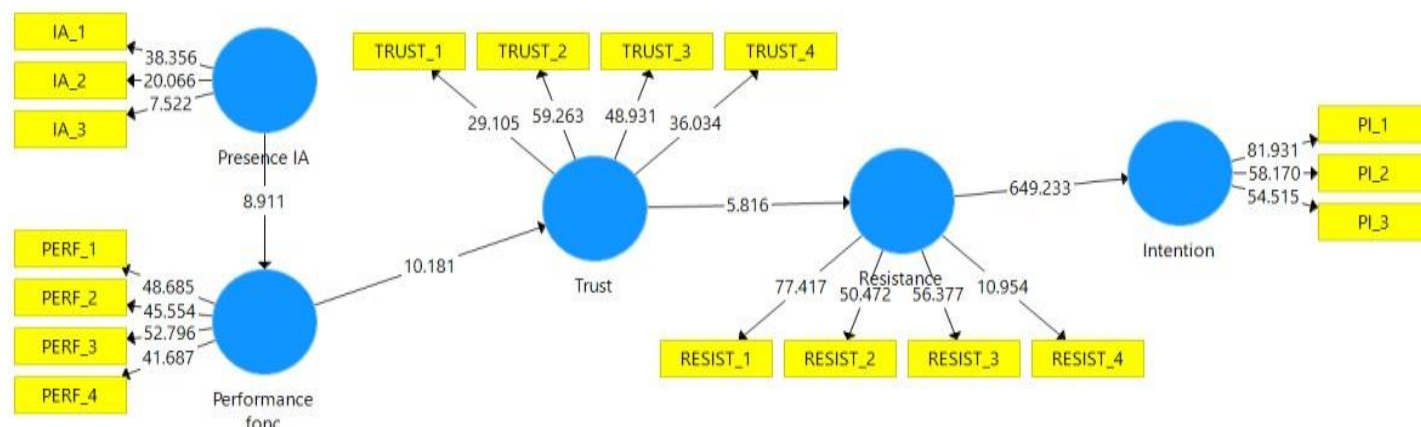
The results presented in the table below indicate that all hypotheses derived from our research model are confirmed. The β coefficients demonstrate strong magnitude, and the p-values confirm the statistical significance of all hypotheses. The structural model reveals significant causal relationships among all the variables studied.

Table 3: Significance of Causal Links

Liens	β (Path Coefficients)	P-values	Hypothesis Status
AI presence ---> Perceived functional improvement	8.911	0,000	Accepted
Perceived functional improvement ---> Trust in the brand	10.181	0,000	Accepted
Trust in the brand ---> Resistance to change	5.816	0,000	Accepted
Resistance to change ---> Purchase intention	649.233	0,000	Accepted

Source: Developed by the authors

The structural model will be presented in Figure 1 below:



DISCUSSION

The results of the structural model analyses show that all relationships between variables are significant, with each link exhibiting a positive β coefficient and p-values equal to 0.000, indicating strong statistical robustness. For the first hypothesis, the relationship between the presence of AI and perceived functional improvement is very strong and significant ($\beta = 8.911$, $p = 0.000$). In other words, when consumers know that artificial intelligence is being used in the brand name change process, they perceive greater accuracy, relevance, and quality in the proposed name. This confirms the idea that AI acts as a performance signal (Cheng & Jiang, 2022; Longoni & Cian, 2022), reinforcing expectations of efficiency and functional superiority.

Perceived functional improvement positively and significantly influences brand trust ($\beta = 10.181$, $p = 0.000$), thus validating hypothesis 2. This result aligns with competence-based trust models (Mayer et al., 1995), where the evaluation of perceived performance serves as the basis for trust formation. Brand trust significantly reduces resistance to change. A high level of trust reduces uncertainty and defensive reactions, strengthening acceptance of the rebranding-related changes. This result is consistent with the brand equity-trust theory (Hoff & Bashir, 2015 ; van Pinxteren et al., 2019), which explains that trust stabilizes the consumer-brand relationship and mitigates negative reactions to identity changes.

Finally, resistance to change strongly and significantly influences purchase intention. This relationship shows that the lower the resistance, the more substantially the purchase intention increases. This result aligns with the literature on resistance to innovation (Walsh, G. et al. (2010); Claudy et al., 2015), which posits that removing psychological barriers is a major determinant of the adoption and purchase of products associated with a brand change.

CONCLUSION THEORETICAL AND MANAGERIAL IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

This study highlights the central role of artificial intelligence in the brand name substitution process, showing that its presence significantly improves the functional perception of the new brand name, strengthens consumer confidence, reduces their resistance to change and, ultimately, increases their purchase intention.

This study makes a theoretical contribution by showing that the presence of AI in rebranding acts as a credible signal of functional improvement, strengthening trust and reducing resistance to change, thus enriching existing marketing models on trust, resistance, and innovation. It also demonstrates that AI should not be considered solely as a technical tool, but as a perceived actor influencing consumers' cognitive and behavioral judgments. From a managerial perspective, the results indicate that companies should transparently highlight the role of AI in creating or modifying their brand name to strengthen the credibility of the change, while combining human expertise and AI to reassure consumers and reduce resistance. Furthermore, accompanying the rebranding with clear communication about the functional benefits of the new name can foster buy-in and increase purchase intent, confirming the importance of a change strategy focused on both perceived performance and trust. However, several limitations must be highlighted: the sample used remains confined to a specific context, which limits generalization; the measurement of AI presence relies on self-reported perceptions that may be influenced by cognitive biases; and finally, the study focuses on a linear model that does not account for potential moderating effects such as technological expertise, involvement in the product category, or sensitivity to innovation. Future research could therefore explore diverse sectoral contexts, incorporate real-world behavioral purchasing measures, analyze the longitudinal effects of AI-assisted rebranding, or examine the role of moderating variables to better understand why some consumers more readily adopt an AI-generated name change than others. This extension would offer a more nuanced view of the impact of AI on rebranding acceptance dynamics.

BIBLIOGRAPHIE

1. Ameen, N., Tarhini, A., & Reppel, A. (2020). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, 114, 106548
2. Berger, C. R., & Calabrese, R. J. (1975). Some explorations in initial interaction and beyond: Toward a developmental theory of interpersonal communication. *Human Communication Research*.
3. Balabanova, K. (2025) — The Generative Artificial Intelligence in Branding and Visual Marketing. *EU-Scientists*
4. Chen, Y.-S., & Chang, C.-H. (2012). Enhance green purchase intentions: The roles of green perceived value, green perceived risk, and green trust. *Management Decision*, 50(3), 502-520
5. Cheng, Y., & Jiang, H. (2022). Customer-Brand Relationship in the Era of Artificial Intelligence: Understanding the Role of Chatbot Marketing Efforts. *Journal of Product & Brand Management*, 31, 252-264.
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, 295(2), 295-336.
6. Claudy, M. C., R. Garcia, and A. O'Driscoll. 2015. Consumer resistance to innovation—A behavioral reasoning perspective. *Journal of the Academy of Marketing Science* 43 (4): 528–44.
7. Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*.
8. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of IT. *MIS Quarterly*.
9. Gupta, S. (2025) — AI strategy for global brand identity, *ScienceDirect* Gbadamassi & Diakité (2025) When Generative AI Reinvents Brand Content
10. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications.

11. Hartmann, J. (2025). Can generative AI create superhuman visual marketing?. . Journal of the Academy of Marketing Science
12. Hartmann, J., & Luss, R. (2024). AI vs Human Creativity in Marketing. Journal of Advertising Research.
13. Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science.
14. Hoff, K., & Bashir, M. (2015). Trust in Automation. Human Factors.
15. Hwang, Y., & Wu, Y. (2024). A Study on Brand Design Methodology Using Generative AI. International Journal of Advanced Smart Convergence.
16. Kapferer, J.-N. (2007). The New Strategic Brand Management. Kogan Page.
17. Kleijnen, M., N. J. Lee, and M. Wetzels. 2009. An exploration of consumer resistance to innovation and its antecedents. Journal of Economic Psychology 30 (3): 344–57
18. Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). Trust and risk in decision making. Decision Support Systems.
19. Longoni, C., & Cian, L. (2022). Artificial Intelligence in Marketing. Journal of Marketing.
20. Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of Management Review.
21. Muzellec, L., & Lambkin, M. (2006). Corporate Rebranding. European Journal of Marketing.
22. Morgan, R. M., & Hunt, S. D. (1994). Commitment-Trust Theory. Journal of Marketing.
23. Oreg, S. (2003). Resistance to Change: Developing an Individual Differences Measure Journal of Applied Psychology, 88, 680-693.
24. Rege, S. (2025). Applications of Artificial Intelligence in Brand Design and Development. Journal of the Academy of Marketing Science.
25. Schaefer, K. (2016). The perception of trust in automation. Human–Computer Interaction.
26. Satyamangal Rege (2025) — Applications of Artificial Intelligence (AI) in Brand Design and Development: An Analytical Research .International Journal of Multidisciplinary Research and Analysis
27. Spence, M. (1973). Job market signaling. Quarterly Journal of Economics.
28. Van Pinxteren, M. et al. (2019). Trust in AI service agents. Journal of Service Management.
29. Walsh, G. et al. (2010). Consumer reactions to brand renaming. Journal of Product & Brand Management.