



Artificial Intelligence for Digital Marketing Strategies (AI4DMS): An Explanatory PLS-SEM Study of Higher Education

Juan Mejía-Trejo 

Centro Universitario de Ciencias Económico-Administrativas (CUCEA) Universidad de Guadalajara, México, 1 Periférico Norte N.º 799, Núcleo Universitario Los Belenes, C.P. 45100, Zapopan, Jalisco, México
✉ jmejia@cucea.udg.mx



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AI capabilities

ABSTRACT

This study proposes and empirically tests the AI4DMS (Artificial Intelligence for Digital Marketing Strategies) framework to examine how AI Impact Perceptions (AIB), AI Knowledge (AKM), Analytical-Digital Skills (ADS), AI Influence on Decisions (AID), and AI Marketing Applications (AIM) interact across seven hypotheses. Grounded in absorptive capacity and dynamic capability perspectives, the model was tested using PLS-SEM (SmartPLS 4.1.1.2) with data from 258 digitally active higher education students (pre-organizational population with incipient exposure to AI-related activities in business contexts). The measurement model achieved satisfactory reliability and validity (α , CR > 0.70; AVE > 0.50; HTMT < 0.85), and all hypotheses were supported. The strongest paths were AIB $\rightarrow$ AKM ($\beta = 0.771$) and ADS $\rightarrow$ AIM ($\beta = 0.610$). AI4DMS follows a recursive logic in which perceptions enhance knowledge, knowledge supports analytical-digital skills, and these shape perceived readiness for AI-supported marketing decision processes. While conceptually linked to digital marketing, the findings reflect pre-organizational perceptions of AI-related capabilities, rather than firm-level adoption or actual consumer behavior.

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1. Introduction

Artificial Intelligence (AI) is reshaping digital marketing by enhancing targeting precision, automating tasks, and enabling real-time consumer analysis. In today's competitive, data-driven environment, AI has shifted from being optional to a strategic necessity. Functions such as customer segmentation, automated content creation, campaign optimization, and hyper-personalization are now AI-driven, fostering business success in the digital era (Balakrishnan et al., 2020). This trend aligns with broader academic discussions on the transformative impact of AI on business and engineering paradigms (Vial, 2019; Duan et al., 2019). According to the World Economic Forum (2020, October 20), projections suggest that AI and automation could displace 85 million jobs and create 97 million new roles by 2025, many related to innovation and marketing. These figures represent forward-looking estimates and are not empirically assessed in the present study. As a result, professionals with AI competencies—such as digital literacy, analytical thinking, and innovation—are increasingly in demand. Firms adopting AI in marketing report 5–10 % revenue growth and operational gains through forecasting, pricing, and dynamic content delivery (Balakrishnan et al., 2020).

This study aims to explain how AI-related perceptions, knowledge, and analytical-digital skills interact to shape perceived readiness for AI-supported marketing processes and decision environments. In response, the AI4DMS model is proposed as an explanatory framework that integrates these dimensions within a recursive capability-building logic.

This model aligns with the Sustainable Development Goals (SDGs) 4, 8, and 9 and supports ethical, inclusive, and sustainable innovation. It also resonates with global frameworks such as the Oslo Manual (Organisation for Economic Co-operation and Development, & Eurostat, 2018) and the 2030 Agenda (United Nations, 2015), positioning AI not only as a tool for competitiveness but also for responsible development.

However, existing studies largely adopt linear or fragmented perspectives, focusing on isolated relationships between AI-related capabilities and marketing outcomes within pre-organizational contexts. This limits the understanding of how AI-related perceptions evolve into knowledge, how knowledge is transformed into analytical-digital capabilities, and how these capabilities are strategically deployed and refined through consumer decision-making feedback. The AI4DMS model addresses this gap by offering an integrated explanation of these relationships at a pre-organizational level.

Accordingly, this study focuses on pre-organizational perceptions of AI-related capabilities rather than on observed firm-level implementation. The research question is how do AI-related perceptions, knowledge, and analytical-digital skills interact to explain perceived readiness for AI-supported marketing processes and decision environments?

2. Related Work and Background

Recent studies highlight AI's expanding role in marketing. Recent academic evidence indicates that artificial intelligence enables personalized customer journeys, automated content generation, and scalable engagement strategies in digital marketing environments (Ziakos & Vlachopoulou, 2023). According to Organisation for Economic Co-operation and Development (2024), prior evidence indicates that AI adoption has been associated with higher firm productivity, particularly among top-performing organizations, although these outcomes depend on factors such as digital infrastructure, leadership, and skill development.

Recent academic research documents the widespread adoption of artificial intelligence in digital marketing, particularly for task automation, personalization, and data-driven decision-making. Comprehensive reviews suggest that AI tools are increasingly embedded in marketing activities and have been associated with improvements in customer engagement, targeting accuracy, and strategic performance (Haleem et al., 2022; Ziakis & Vlachopoulou, 2023). Moreover, prior analytical studies report that organizations adopting AI-driven marketing solutions have experienced enhanced operational efficiency and performance outcomes, reinforcing the strategic value of AI-enabled marketing capabilities. These findings provide a relevant background for understanding AI-related capabilities in pre-organizational contexts (Gurjar et al., 2024).

The AI4DMS model addresses these trends from a pre-organizational perspective by offering an integrated framework to assess individual competencies and organizational readiness for AI-enhanced digital marketing.

3. Theoretical Framework and Hypotheses Development

The AI4DMS ex-ante model offers a structured conceptual framework mapping dynamic inter-relationships among five core constructs essential for AI integration in digital marketing: AI Impact Perceptions on Business (AIB), AI Knowledge in Digital Marketing (AKM), AI Analytical and Digital Skills (ADS), AI Influence on Consumer Decisions (AID), and AI Applications in Marketing Strategies (AIM). Each construct is measured through nine reflective indicators. The model outlines seven directional hypotheses (H1–H7), forming a logical sequence from perception to application within a capability-building process.

To enhance conceptual clarity, the constructs included in the AI4DMS framework are briefly characterized as follows. AIB captures how individuals perceive the impact and strategic value of AI in business contexts; AKM reflects individuals' level of familiarity and understanding of AI in digital marketing; ADS represents the analytical and digital skills associated with the use of AI tools; AID refers to the perceived influence of AI on consumer decision processes; and AIM reflects the perceived role of AI in marketing strategy applications.

Although related, these constructs represent distinct but interrelated dimensions of AI-related capability formation. AIB reflects evaluative perception, AKM reflects conceptual understanding, ADS reflects applied capability, AID reflects perceived influence on decisions, and AIM reflects perceived strategic application. This distinction preserves the conceptual integrity of each construct while allowing their integration into a sequential explanatory model.

In conceptual terms, individuals in pre-organizational contexts who perceive the impact of AI on business (AIB) are more likely to develop AI knowledge in digital marketing (AKM) (H1) and analytical and digital skills (ADS) (H2). AI knowledge in digital marketing (AKM) enhances both the perceived influence of AI on consumer decisions (AID) (H3) and the development of analytical and digital skills (ADS) (H4), while analytical and digital skills (ADS) influence AID (H5) and AI applications in marketing strategies (AIM) (H6). AID, in turn, contributes to the refinement of AIM (H7), completing a recursive capability-building cycle.

Grounded in recent literature (2020–2025) and informed by absorptive capacity and dynamic capability perspectives, the model was empirically validated using Partial Least Squares Structural Equation Modeling (PLS-SEM), confirming the robustness of its constructs and structural relationships.

3.1. AI Impact Perceptions on Business and AI Knowledge in Digital Marketing

Ziakis and Vlachopoulou (2023) report that artificial intelligence is increasingly adopted in digital marketing contexts, providing a relevant background for examining how individuals in pre-organizational settings perceive and develop AI-related capabilities. Prior literature indicates that when AI is perceived as strategically valuable, it is associated with increased investment in AI-related knowledge. Aljehani et al. (2024) and Chatterjee et al. (2021) confirm that positive managerial perceptions foster organizational learning and motivate investment in AI knowledge and capability development. Accordingly, the following hypothesis is proposed: H1: «AI Impact Perceptions on Business (AIB) positively influence AI Knowledge in Digital Marketing (AKM)».

3.2. AI Impact Perceptions on Business and AI Analytical and Digital Skills

When individuals in pre-organizational contexts perceive AI as transformative (AIB), they are more likely to develop AI Analytical and Digital Skills (ADS), reflecting early-stage capability formation rather than organizational investment. These perceptions shape readiness for innovation and promote employee upskilling. Empirical studies support this: Oraif (2024) found that positive AI perceptions in education predicted digital skill acquisition. Similarly, Gurjar et al. (2024) noted that firms recognizing AI's strategic value prioritize building analytical capabilities (ADS). Hence: H2: «AI Impact Perceptions on Business (AIB) positively influence AI Analytical and Digital Skills (ADS)».

3.3. AI Knowledge in Digital Marketing and AI Influence on Consumer Decisions

AI knowledge in digital marketing (AKM) supports individuals in interpreting how tools such as predictive analytics and personalization influence consumer decisions (AID) at a perceived level. Rabby et al. (2021) assert that AI-driven marketing improves the buying experience and responsiveness. Similarly, Gurjar et al. (2024) emphasize that deeper AI understanding enhances strategic digital engagement, providing a theoretical basis for considering AKM as relevant for the perceived influence of AI on consumer decisions (AID). Therefore: H3: «AI Knowledge in Digital Marketing (AKM) positively influences AI Influence on Consumer Decisions (AID)».

3.4. AI Knowledge in Digital Marketing and AI Analytical and Digital Skills

Proficiency in AI for digital marketing (AKM) fosters the development of analytical and digital skills (ADS) required for effective strategy. Reed et al. (2025) stress that integrating AI demands strong analytical abilities to avoid bias in marketing. Vangalla (2024) adds that AI's data-processing power improves targeting and personalization (ADS), enhancing the relevance of marketing content. Hence: H4: «AI Knowledge in Digital Marketing (AKM) positively influences AI Analytical and Digital Skills (ADS)».

3.5. AI Analytical and Digital Skills and AI Influence on Consumer Decisions

Proficiency in AI analytical and digital skills (ADS) supports individuals in understanding how personalized, data-driven strategies may influence consumer decisions (AID) at a perceived level. Hal-eem et al. (2022) show that skilled professionals using AI enhance the customer experience. Similarly,

Guerra-Tamez et al. (2024) emphasize that analytical skills help identify effective content for re-engagement, providing a theoretical basis for considering ADS as relevant for the perceived influence of AI on consumer decisions (AID). Hence:

H5: «AI Analytical and Digital Skills (ADS) positively influence AI Influence on Consumer Decisions (AID)».

3.6. AI Analytical and Digital Skills positively influence AI Applications in Marketing Strategies

AI analytical and digital skills (ADS) enable individuals to understand and develop capabilities related to the implementation of AI applications in marketing strategies (AIM) through data-driven decision-making, personalization, and predictive analytics (Haleem et al., 2022). These skills help identify effective content to re-engage customers and enhance the online experience, ultimately influencing consumer behavior. Therefore:

H6: «AI Analytical and Digital Skills (ADS) positively influence AI Applications in Marketing Strategies (AIM)».

3.7. AI Influence on Consumer Decisions and AI Applications in Marketing Strategies

AI Influence on Consumer Decisions (AID) shapes engagement with content, pricing, and assistants—producing behavioral data to optimize strategies (AIM). Understanding AID allows individuals to recognize how AI-driven insights can inform predictive, automated, and personalized marketing applications. Ziakis and Vlachopoulou (2023) stress that AI–consumer interactions drive adaptive strategies, while Brewis et al. (2023) show that AI insights improve targeting and planning, providing a theoretical basis for considering AID as a relevant input for the perceived development of AI applications in marketing (AIM). Hence:

H7: «AI Influence on Consumer Decisions (AID) positively influences AI Applications in Marketing Strategies (AIM)».

Beyond supporting the seven hypotheses, the AI4DMS model aligns with international frameworks for responsible and inclusive innovation. Its emphasis on digital competencies, adaptability, and AI-driven strategy reflects principles from the Oslo Manual (Organisation for Economic Co-operation and Development, & Eurostat, 2018) and the UN’s 2030 Agenda (United Nations, 2015). Specifically, it advances SDG 4 (Quality Education), SDG 8 (Decent Work), and SDG 9 (Innovation), positioning the model as a tool for both digital marketing and sustainable development in educational and organizational contexts. See Figure 1. The theoretical novelty of the AI4DMS model lies in its recursive capability-building logic, integrating learning, capabilities, and strategic application within a dynamic framework.

4. Methodology

This study adopts a quantitative, explanatory research design aimed at validating the AI4DMS model and examining the relationships among perceptions, knowledge, analytical-digital skills, consumer decision influence, and AI-based marketing applications. Given the increasing role of artificial intelligence in digital marketing—particularly in automation, personalization, and data-driven

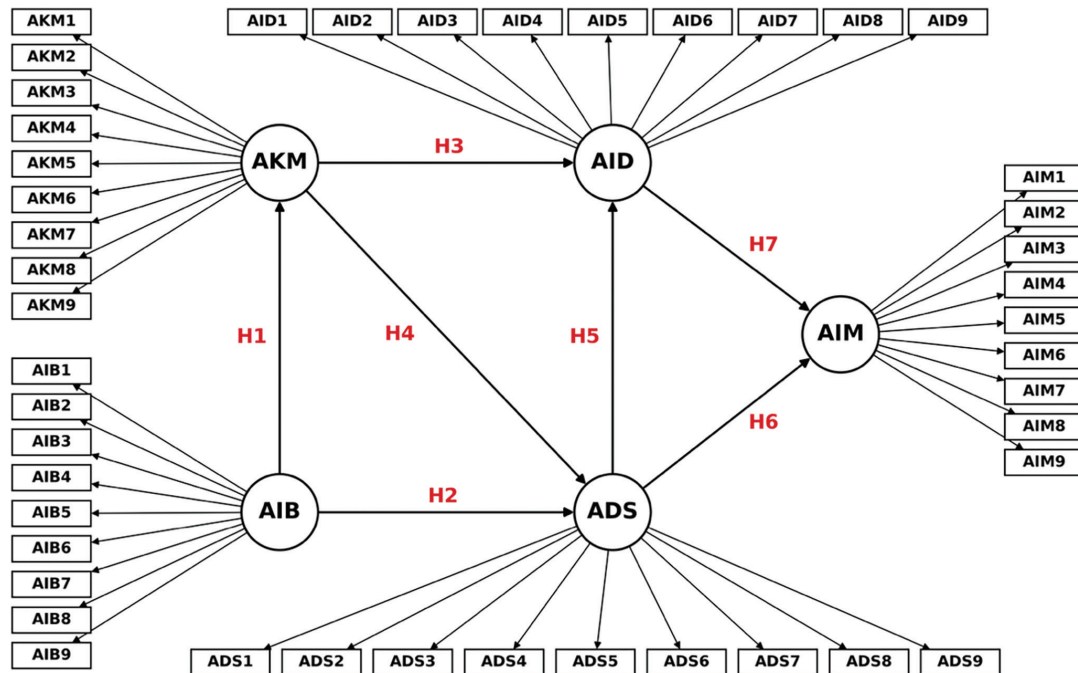


Figure 1. The AI4DMS ex-ante explanatory framework highlighting the recursive capability-building logic

Notes: AI Impact Perceptions on Business (AIB); AI Knowledge in Digital Marketing (AKM); AI Applications in Marketing Strategies (AIM); AI Analytical and Digital Skills (ADS); AI Influence on Consumer Decisions (AID). Source: Own elaboration using SmartPLS 4.1.1.2.

decision-making—the methodological approach focuses on capturing how individuals understand, interpret, and perceive the application of AI within digital marketing contexts. To ensure the theoretical robustness of the model, a structured review of recent academic literature (2020–2024) was conducted to identify the key constructs underlying AI-related capability formation in digital marketing within a pre-organizational context. This review informed the selection and operationalization of five latent variables: AI Impact Perceptions on Business (AIB), AI Knowledge in Digital Marketing (AKM), AI Analytical and Digital Skills (ADS), AI Influence on Consumer Decisions (AID), and AI Applications in Marketing Strategies (AIM). These constructs represent the cognitive, capability-based, behavioral, and strategic dimensions of AI integration and constitute the theoretical foundation of the AI4DMS framework.

4.1. Model Proposition

The five key constructs mentioned above, along with their corresponding indicators, were theoretically interrelated to form an ex-ante model and then operationalized through the design of a structured questionnaire using a 7-point Likert scale, enabling the measurement of perceptions and behaviors associated with each construct based on a collected sample.

4.2. Data Analysis Technique

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a multivariate statistical technique used to analyze complex relationships between observed and latent variables. It is especially suitable for exploratory research, theory development, and predictive modeling. Unlike covariance-based SEM, PLS-SEM is variance-based and does not require data normality or large sample sizes, making it ideal for models with multiple constructs and indicators (Hair et al., 2023). It estimates both the measurement model (relationships between constructs and indicators) and the structural model (relationships between constructs) simultaneously. After data collection, the responses were analyzed using this technique, which allowed for the validation and refinement of the model. The resulting ex-post model confirmed the reliability, validity, and significance of the hypothesized relationships among the constructs.

4.3. Demographic Data

Based on the results obtained from the frequency analysis of 258 subjects, the results of the frequency demographic data analysis are exhibited in Table 1.

Table 1. Demographic profile of the research sample in Higher Education

Measure	Items	Frequency	Percentage	
Age	18-29	200	77.5 %	100 %
	30-39	30	11.6 %	
	40-49	20	7.8 %	
	50-59	8	3.1 %	
Gender	Male	111	43.0 %	100 %
	Female	147	57.0 %	
Marital Status	Single	248	96.1 %	100 %
	Married	10	3.1 %	
Education Level	Undergraduate	100	38.7 %	100 %
	Master Degree	100	38.7 %	
	Doctor Degree	58	22.6 %	
Type Educational Institute or University	Public	253	98.1 %	100 %
	Private	5	1.9 %	

Source: Own elaboration.

4.4. Sampling Based on PLS-SEM Technique

The structural model depicted in Figure 1 follows a recursive capability-building logic to explain the use of artificial intelligence in marketing strategies (AIM). The model comprises two exogenous constructs—AI Knowledge in Digital Marketing (AKM) and AI Impact Perceptions on Business (AIB)—which serve as foundational antecedents in the development of AI-related capabilities at a pre-organizational level.

These antecedents influence two intermediate constructs: AI Influence on Consumer Decisions (AID) and AI Analytical and Digital Skills (ADS). While AKM and AIB exert indirect effects on AIM, ADS and AID function as the only direct predictors of AI use in marketing strategies, reflecting a mediated and sequential process through which knowledge and perceptions are transformed into actionable marketing applications.

Sample size adequacy was assessed using statistical power analysis following Cohen's (1988) criteria. In the proposed structural model, the construct with the highest number of direct predictors is ADS, which is explained by three antecedent variables. Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = .05$, and a desired statistical power of 0.80, Cohen's guidelines indicate a minimum required sample size of approximately 77–85 observations for detecting meaningful effects in multiple regression models.

The final sample of 258 valid responses collected through an online questionnaire substantially exceeds this minimum requirement, ensuring adequate statistical power, stable parameter estimation, and robust hypothesis testing within the PLS-SEM framework. Although this sample size is not sufficient to reliably detect small effects ($f^2 = 0.02$), this does not represent a methodological limitation, as the primary objective of the study is to examine substantively meaningful and practically relevant relationships rather than marginal effects.

Overall, the sample size employed is methodologically appropriate for PLS-SEM, a variance-based technique that prioritizes prediction accuracy and explanatory power over global model fit and is well suited for models with moderate sample sizes and complex mediation structures (Hair et al., 2023).

4.5. Data Collection

This study employed a virtual snowball sampling strategy, a non-probabilistic method commonly used to reach interconnected participants within digital environments. This technique was appropriate for identifying and recruiting higher education students enrolled at undergraduate, master's, and doctoral levels with digital experience and awareness of AI in educational and marketing contexts—key to the focus of the AI4DMS (Artificial Intelligence for Digital Marketing Strategies) framework.

The initial invitation was distributed through academic networks, institutional mailing lists, and online learning communities affiliated with the AI4DMS initiative. Participation was strictly voluntary, anonymous, and without compensation. Prior to answering the questionnaire, participants were provided with a concise explanation of the key concepts related to AI and digital marketing, ensuring a consistent baseline of understanding.

From an initial pool of approximately 1,000 invited participants, 500 individuals accessed the survey, and 258 complete and valid responses were retained for analysis. The instrument was administered via Google Forms between January 6 and May 6, 2025.

Thus, the resulting sample reflects the perceptions of digitally active higher education students, representing a pre-organizational population with incipient exposure to AI-related activities in business contexts, offering meaningful insights into pre-organizational perceptions of AI-related capabilities within digital marketing contexts, as conceptualized in the AI4DMS model.

4.6. Questionnaire Design

The questionnaire was based on five constructs central to the AI4DMS framework: AIB, AKM, ADS, AID, and AIM. Each was measured using nine items adapted from peer-reviewed literature

(2020–2024), crafted to reflect participants’ perceptions, knowledge, behaviors, and skills related to AI in digital marketing. The design also drew on foundational works in scale development and multivariate analysis in social sciences (Hair et al., 2023; Mejía-Trejo, 2023), guiding indicator construction.

Responses were collected using a 7-point Likert scale (1 = Strongly disagree, 7 = Strongly agree). The five constructs, though distinct, are interrelated in a structural model comprising seven hypotheses (H1–H7): where AIB, AKM, and ADS serve as predictors of AID and AIM. The model was validated through Partial Least Squares Structural Equation Modeling (PLS-SEM).

5. Results

This section presents the findings derived from the structural equation modeling using Partial Least Squares (PLS-SEM) with SmartPLS 4.1.1.2 software. The results are organized into three main components: the evaluation of the measurement model, the structural model assessment, and the confirmation of the ex-post model based on empirical data.

5.1. Measurement Model Evaluation

A comprehensive evaluation was conducted using established PLS-SEM guidelines to assess the quality of the reflective measurement model for the AI4DMS framework (Hair et al., 2023).

Internal consistency reliability was confirmed by examining Cronbach’s alpha (α) and composite reliability (CR) values for each construct. All constructs (AIB, AKM, AID, ADS, AIM) exceeded the recommended threshold of 0.70 (Hair et al., 2023), indicating high internal consistency.

Convergent validity was supported by Average Variance Extracted (AVE) values, all above the 0.50 threshold. This demonstrates that each construct explains more than 50 % of the variance of its observed indicators, fulfilling the minimum criterion for convergent validity (Fornell & Larcker, 1981).

Indicator reliability was evaluated through outer loadings. All retained indicators loaded above 0.70 and were statistically significant at $p < .001$ based on 5,000 bootstrap samples, confirming the reliability of each indicator (Hair et al., 2023).

Together, these results confirm that the measurement model demonstrates acceptable levels of reliability and validity, thus meeting the requirements for proceeding with structural model assessment.

Item purification followed established PLS-SEM guidelines (Hair et al., 2023). Indicators with outer loadings below 0.70 were considered for removal when their exclusion improved composite reliability (CR), average variance extracted (AVE), and discriminant validity (HTMT). Cross-loadings were also examined to ensure that each indicator loaded higher on its intended construct. In total, 10 out of 45 indicators were removed due to insufficient outer loadings or cross-loading concerns. Notably, several behaviorally anchored items (e. g., AIM4, ADS2) were excluded because respondents, as a pre-organizational population, reported limited direct experience with AI implementation. Consequently, these items showed lower reliability and consistency, reflecting the perception-based nature of the sample rather than measurement error. Their removal improved the overall robustness of the measurement model while preserving the conceptual integrity of the constructs. See Table 2.

Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. As shown in Table 3, the square roots of the AVEs (diagonal values) are greater than the inter-construct correlations, satisfying the Fornell-Larcker criterion. Additionally, all HTMT values are below the conservative threshold of 0.85 (Henseler et al., 2015), confirming discriminant validity.

Table 2. Assessment of internal consistency, outer loadings, and convergent validity for the AI4DMS measurement model

Factor 1	Indicators	Author	AIB. AI Impact Perceptions on Business. Perceived benefits and changes brought by AI in business environments. Cronbach's Alpha (≥ 0.70) = 0.894; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.898; rho_C (Composite Reliability ≥ 0.70) = 0.919; AVE (≥ 0.50) = 0.654.	Outer loading (t-Value)	p Value
AIB	AIB1	3	I believe AI improves operational efficiency in companies.	0.832 (34.043)	0.000
	AIB2	1	I consider AI a competitive advantage for digital businesses.	0.784 (22.450)	0.000
	AIB3	1,3	I trust that AI enhances business decision-making.	0.860 (49.046)	0.000
	AIB4	2	I believe companies can increase profits by using AI for strategic pricing.	0.847 (35.016)	0.000
	AIB5	4	I think companies are ready to adopt AI.	0.772 (26.6601)	0.000
	AIB6	1	I consider AI useful for creating marketing content.	0.752 (20.531)	0.000
	AIB7	5	I believe AI is reliable in predicting industry changes.	Removed to improve model fit and reliability	
	AIB8	6	I believe AI is replacing human interaction in customer service.		
	AIB9	7	I believe AI will significantly change job roles in the future.	0.726 (17.997)	0.000
Factor 2	Indicators	Author	AKM. AI Knowledge in Digital Marketing. Familiarity and understanding of AI technologies in digital marketing contexts Cronbach's Alpha (≥ 0.70) = 0.929; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.930; rho_C (Composite Reliability ≥ 0.70) = 0.941; AVE (≥ 0.50) = 0.668.	Outer loading (t-Value)	p Value
AKM	AKM1	9	I have used e-commerce platforms with integrated AI.	Removed to improve model fit and reliability	
	AKM2	8	I believe AI is useful for analyzing consumer purchasing trends.	0.743 (19.218)	0.000
	AKM3	9	I believe AI improves customer loyalty.	0.802 (26.738)	0.000
	AKM4	9	I believe AI enhances dynamic pricing strategies in digital marketing.	0.814 (31.561)	0.000
	AKM5	9	I believe AI transforms customer service strategies.	0.853 (41.008)	0.000

	AKM6	8	I believe AI increases the effectiveness of digital marketing strategies.	0.856 (35.205)	0.000
	AKM7	8	I believe AI improves marketing decision-making.	0.841 (41.516)	0.000
	AKM8	9	I believe AI is effective for automated ad buying.	0.791 (21.716)	0.000
	AKM9	9	I believe AI helps predict demand in competitive markets.	0.831 (37.754)	0.000
Factor 3	Indicators	Author	AIM. AI Applications in Marketing Strategies. Practical implementation and effectiveness of AI in core marketing functions. Cronbach's Alpha (≥ 0.70) = 0.899; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.900; rho_C (Composite Reliability ≥ 0.70) = 0.925; AVE (≥ 0.50) = 0.712.	Outer loading (t-Value)	p Value
AIM	AIM1	9	I believe AI improves customer segmentation in digital marketing.	Removed to improve model fit and reliability	
	AIM2	9	I believe AI optimizes personalized digital ads based on my interests and behavior.	0.810 (32.074)	0.000
	AIM3	3,12	I believe AI analysis of consumer behavior is accurate.	Removed to improve model fit and reliability	
	AIM4	3	I use AI to automate marketing campaigns.		
	AIM5	9	I believe AI has improved social media management.	0.846 (38.3504)	0.000
	AIM6	9,12	I believe chatbots are effective in customer interactions.	Removed to improve model fit and reliability	
	AIM7	3,12	I believe AI has optimized strategies like web design, content marketing, etc.	0.868 (41.065)	0.000
	AIM8	9	I believe AI is effective in competitor analysis.	0.831 (37.033)	0.000
	AIM9	3	I believe AI significantly increases ad effectiveness.	0.861 (33.098)	0.000
Factor 4	Indicators	Author	ADS. AI Analytical and Digital Skills. Skills and confidence in interpreting, applying, and learning AI-powered digital tools. Cronbach's Alpha (≥ 0.70) = 0.833; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.838; rho_C (Composite Reliability ≥ 0.70) = 0.889; AVE (≥ 0.50) = 0.666.	Outer loading (t-Value)	p Value
	ADS1	10	I feel comfortable interpreting AI-generated data.	Removed to improve model fit and reliability	
	ADS2	11	I have used digital tools that integrate AI.		
	ADS3	10	I trust AI algorithms to analyze market trends.		
	ADS4	11	I believe AI can replace human decision-making in data analysis.		

(continued)

Table 2. Assessment of internal consistency, outer loadings, and convergent validity for the AI4DMS measurement model (continued)

ADS	ADS5	11	I am willing to learn how to use AI tools for data analysis.	0.773 (20.001)	0.000
	ADS6	10	I believe AI is important for optimizing business strategies.	0.836 (33.783)	0.000
	ADS7	11	I consider my knowledge of AI algorithms in digital business to be strong.	Removed to improve model fit and reliability	
	ADS8	11	I believe AI facilitates predictive analysis for decision-making.	0.824 (32.889)	0.000
	ADS9	10	I believe AI is reliable for evaluating advertising performance.	0.831 (32.196)	0.000
Factor 5	Indicators	Author	AID. AI Influence on Consumer Decisions. Extent to which AI systems shape consumers' online shopping behavior. Cronbach's Alpha (≥ 0.70) = 0.869; rho_A (Dijkstra–Henseler's ≥ 0.70) = 0.903; rho_C (Composite Reliability ≥ 0.70) = 0.899; AVE (≥ 0.50) = 0.600.	Outer loading	p Value
AID	AID1	6	I often follow AI-based recommendations when shopping online, even if I don't fully trust them.	0.705 (16.204)	0.000
	AID2	6	I find AI recommendations more reliable than other people's opinions.	Removed to improve model fit and reliability	
	AID3	6	I prefer receiving personalized offers through AI instead of generic promotions.		
	AID4	2	AI has significantly changed how I search for information before making a purchase.	0.808 (29.257)	0.000
	AID5	6	I feel comfortable with AI managing my purchasing decisions.	0.738 (17.515)	0.000
	AID6	2,6	I believe AI enhances my online shopping experience.	0.870 (52.679)	0.000
	AID7	2	I feel more secure when AI adjusts prices in real time in a transparent way.	0.780 (27.306)	0.000
	AID8	2,6	I use virtual assistants or chatbots to make purchases online.	Removed to improve model fit and reliability	
	AID9	2,6	I have noticed that AI influences my buying decisions.	0.734 (18.051)	0.000

Notes. List of authors: 1. Ziakis & Vlachopoulou (2023); 2. Brewis et al. (2023), 3. Rabby et al. (2021). 4. Chatterjee et al. (2021); 5. Duan et al. (2019); 6. Guerra-Tamez et al. (2024); 7. Organisation for Economic Co-operation and Development (2024). 8. Oraif (2024); 9. Gurjar et al. (2024); 10. Reed et al. (2025); 11. Vangalla (2024); 12. Haleem et al. (2022).

AI Impact Perceptions on Business (AIB); AI Knowledge in Digital Marketing (AKM); AI Applications in Marketing Strategies (AIM); AI Analytical and Digital Skills (ADS); AI Influence on Consumer Decisions (AID).

- rho_A. Dijkstra–Henseler's rho_A is a reliability coefficient used to assess internal consistency in PLS-SEM. Values above 0.70 indicate acceptable reliability.

- rho_C. Composite Reliability assesses the internal consistency of construct indicators. Values between 0.70 and 0.90 are considered satisfactory. Values above 0.95 may suggest indicator redundancy or common method bias (Hair et al., 2023).
- AVE (Average Variance Extracted). An AVE > 0.50 indicates that a construct explains more than 50 % of the variance in its observed indicators, thereby supporting convergent validity (Fornell & Larcker, 1981).
- Indicators are according to Likert Scale 1-7 (1. Strongly Disagree; 2. Disagree; 3. Somewhat Disagree; 4. Neither Agree nor Disagree; 5. Somewhat Agree; 6. Agree; 7. Strongly Agree).

Source: Own elaboration using SmartPLS 4.1.1.2.

Table 3. AI4DMS measurement model discriminant validity

Fornell & Larcker Criteria (Diagonal= Root Square -AVE-) for discriminant validity HTMT Criteria Ratio<= 0.85<=0.90 for convergent validity					
	ADS	AIB	AID	AIM	AKM
ADS	0.816	0.884	0.455	0.787	0.767
AIB	0.765	0.809	0.462	0.895	0.843
AID	0.423	0.442	0.774	0.463	0.485
AIM	0.686	0.804	0.438	0.844	0.886
AKM	0.677	0.771	0.458	0.809	0.817

Notes: HTMT, The Heterotrait–Monotrait ratio of correlations (HTMT) assesses discriminant validity by ensuring that constructs are conceptually distinct. A threshold of 0.90 is acceptable when constructs are conceptually similar; a more conservative threshold of 0.85 is recommended in stricter evaluations (Henseler et al., 2015). Bootstrapping is used to test whether HTMT values are significantly lower than 1.0, providing statistical confidence. HTMT is considered a conservative test, minimizing the risk of Type II error —i. e., failing to detect a lack of discriminant validity when it exists (Franke & Sarstedt, 2019).

Source: Own elaboration using SmartPLS 4.1.1.2.

5.2. Structural Model Assessment

To evaluate the structural model of the AI4DMS framework, several statistical criteria were considered in accordance with recommended PLS-SEM procedures (Hair et al., 2023). First, multicollinearity was examined using the inner Variance Inflation Factor (VIF). All VIF values were found to be below the conservative threshold of 3.3, indicating no collinearity issues among the predictor constructs and supporting the robustness of the model estimates. The results generated using SmartPLS 4.1.1.2 are presented in Figure 2 illustrating the empirically validated relationships of the AI4DMS framework, showing how AI perceptions initiate learning and capability development, and how AI-influenced consumer decision-making reinforces strategic AI applications. These results should be interpreted as reflecting pre-organizational perceptions of AI-related capabilities rather than actual implementation or organizational behavior, while supporting the recursive process proposed in Figure 1.

All the structural model assessment of the AI4DMS framework confirmed all seven hypotheses (H1–H7), indicating statistically significant relationships among the constructs. The coefficient of determination (R^2) indicates the explanatory power of the model for each endogenous construct. The results show that AKM is explained at $R^2 = 0.594$, ADS at $R^2 = 0.604$, AID at $R^2 = 0.233$, and AIM at $R^2 = 0.497$, indicating moderate to substantial levels of explained variance according to PLS-SEM standards (Hair et al., 2023). These findings reinforce the explanatory capacity of the AI4DMS framework in modeling AI-related capability formation at a pre-organizational level. The hypothesis testing results and effect sizes for the AI4DMS structural model are presented in Table 4, and the validated structural paths are summarized in Figure 2.

Table 4. The structural model assessment of the AI4DMS framework: hypothesis testing and predictive power

Hypotheses	Paths	*Path [<i>t-value</i> ; <i>p-value</i>]	Result	*Interval		Effect Size	
				25 %-97.5 % Confidence	Crossing 0?	(0.02<=; 0.15 <=0.35)	Effect (Small; Medium; Large)
H1: «Higher AIB Higher AKM»	AIB -> AKM	0.771 [26.097; 0.000]	Accepted	[0.704; 0.821]	No	1.465	Large
H2: «Higher AIB Higher ADS»	AIB -> ADS	0.599 [6.650; 0.000]	Accepted	[0.396; 0.751]	No	0.368	Large
H3: «Higher AKM Higher AID»	AKM -> AID	0.316 [4.183; 0.000]	Accepted	[0.161; 0.455]	No	0.071	Small
H4: «Higher AKM Higher ADS»	AKM -> ADS	0.216 [2.864; 0.004]	Accepted	[0.073; 0.368]	No	0.048	Small
H5: «Higher ADS Higher AID»	ADS -> AID	0.209 [2.796; 0.005]	Accepted	[0.089; 0.332]	No	0.031	Small
H6: «Higher ADS Higher AIM»	ADS -> AIM	0.610 [11.863; 0.000]	Accepted	[0.523; 0.692]	No	0.606	Large
H7: «Higher AID Higher AIM»	AID -> AIM	0.180 [3.383; 0.001]	Accepted	[0.075; 0.285]	No	0.053	Small

Notes:

- AI Impact Perceptions on Business (AIB); AI Knowledge in Digital Marketing (AKM); AI Applications in Marketing Strategies (AIM); AI Analytical and Digital Skills (ADS); AI Influence on Consumer Decisions (AID).
- In mode Bootstrapping the * is the result of path with two-tailed *t-values* and *p-values* (in parentheses) in complete (slower) percentile with 2.5 %-97.5 % interval confidence (based on n= 5000 subsamples) and 0.05 significance level.
- Effect size. 0.02, 0.15, and 0.35 are interpreted as small, medium, and large (Cohen, 1988).

Source: Own elaboration using SmartPLS 4.1.1.2.

5.3. Predictive Relevance

Although predictive relevance (Q^2) is commonly reported in PLS-SEM studies, the present research focuses on explanatory model assessment given its exploratory, perception-based nature and its focus on a pre-organizational context characterized by incipient exposure to AI-related practices. As such, model evaluation prioritizes reliability, validity, and explanatory power (R^2 and f^2), which are appropriate for capturing early-stage AI-related capability formation. While Q^2 is acknowledged as a complementary indicator of predictive relevance, its absence does not affect the confirmatory nature of the

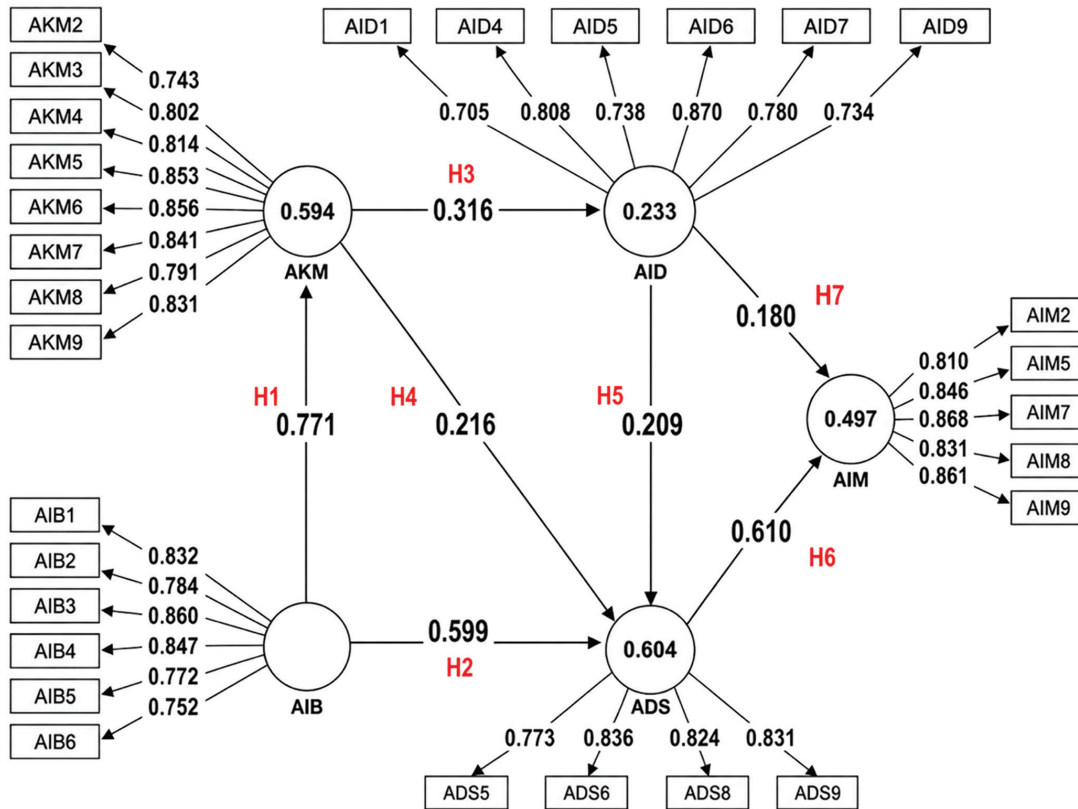


Figure 2. The AI4DMS ex-post PLS-SEM structural model results with validated paths and effect sizes

Notes:

- AI Impact Perceptions on Business (AIB); AI Knowledge in Digital Marketing (AKM); AI Applications in Marketing Strategies (AIM); AI Analytical and Digital Skills (ADS); AI Influence on Consumer Decisions (AID).
- Coefficients of determination represent the amount of explained variance of the endogenous constructs in the structural model. Therefore, values of 0.25, 0.50, 0.75 for target constructs are considered as weak, medium, and substantial, respectively (Hair et al., 2023).
- Source: Own elaboration using SmartPLS 4.1.1.2.

study, which is grounded in hypothesis testing and the evaluation of structural relationships; rather, it only limits the assessment of predictive capability (Hair et al., 2023; Henseler et al., 2009).

6. Discussion

The findings derived from the AI4DMS framework provide an integrated explanation of how AI Impact Perceptions on Business (AIB), AI Knowledge in Digital Marketing (AKM), and AI Analytical

J. Mejía-Trejo

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and Digital Skills (ADS) interact to shape perceived readiness for AI-supported marketing processes. Rather than reflecting isolated relationships, the results reveal a coherent developmental process in which perceptions of AI impact initiate learning and capability formation, supporting perceived capability development and perceived influence on decision processes.

From this perspective, AI Impact Perceptions on Business (AIB) operate as a foundational cognitive trigger that stimulates both the acquisition of AI Knowledge in Digital Marketing (AKM) and the development of AI Analytical and Digital Skills (ADS). These capabilities support the perceived readiness for the deployment of AI Applications in Marketing Strategies (AIM), while AI Influence on Consumer Decisions (AID) contributes incrementally to the perceived refinement of strategic actions. Collectively, this pattern supports the recursive capability-building logic proposed by the AI4DMS model, illustrating how cognitive, operational, and strategic dimensions co-evolve as part of a perceived capability formation process related to AI-supported marketing contexts.

6.1. Theoretical Contribution

This section interprets the findings from a theoretical perspective, emphasizing how the AI4DMS framework advances the understanding of perceived readiness and AI-related capability formation in digital marketing as a dynamic, learning-driven, and capability-based process rather than a linear sequence of implementation stages.

6.1.1. Technical Discussion of Structural Model Results

The structural assessment of the AI4DMS model demonstrates consistent relationships among AI Impact Perceptions on Business (AIB), AI Knowledge in Digital Marketing (AKM), AI Analytical and Digital Skills (ADS), AI Influence on Consumer Decisions (AID), and AI Applications in Marketing Strategies (AIM). Instead of reiterating statistical estimates, this discussion focuses on interpreting the structural patterns that explain how AI-related capability formation unfolds at the pre-organizational level as an interconnected process involving learning, capability development, and capability enactment.

The results indicate that AI Impact Perceptions on Business (AIB) play a central role in initiating both learning and skill formation, consistent with theoretical perspectives on absorptive capacity and dynamic capabilities, where sense-making precedes capability development. AI Knowledge in Digital Marketing (AKM) and AI Analytical and Digital Skills (ADS) emerge as complementary mechanisms: knowledge facilitates internal capability development and external consumer influence, while skills enable the translation of learning into effective strategic application through AI Applications in Marketing Strategies (AIM).

Importantly, AI Influence on Consumer Decisions (AID) is not positioned as a terminal outcome of AI-related capabilities at a pre-organizational level, but rather as an element that contributes to strategic refinement. Although its effect is more modest relative to internal capabilities, the relationship between AID and AIM supports the feedback logic embedded in the AI4DMS framework, whereby insights derived from AI-influenced consumer behavior inform ongoing adjustments in AI-enabled marketing strategies. Overall, the model explains AI-related capability formation and perceived readiness as a structured yet adaptive process in which learning and capability development are continuously informed by perceived market interaction within a pre-organizational population with incipient exposure to AI-related activities in business contexts.

Beyond the interpretation of structural patterns, the AI4DMS framework advances a theoretical perspective that conceptualizes perceived readiness and AI-related capability formation in digital

marketing as a cognitively driven and adaptively evolving process within a pre-organizational population with incipient exposure to AI-related activities in business contexts. The model explains how AI Impact Perceptions on Business (AIB) initiate a developmental sequence in which learning and capability development are progressively constructed, reinforcing the view that digital transformation extends beyond technological implementation to encompass perception, interpretation, and strategic sense-making (Vial, 2019; Duan et al., 2019).

From a theoretical standpoint, the central role of AIB highlights how beliefs regarding AI shape what organizations and individuals choose to learn and develop. This aligns with established theories of absorptive capacity and organizational learning, which emphasize that perception and prior understanding condition the acquisition and deployment of new knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002). Within the AI4DMS framework, AI Knowledge in Digital Marketing (AKM) functions as a mediating mechanism that supports both internal capability development and outward-facing strategic influence.

Furthermore, AI Analytical and Digital Skills (ADS) constitute the operational foundation that enables the effective translation of knowledge into strategic action through AI Applications in Marketing Strategies (AIM). By integrating AI Influence on Consumer Decisions (AID) as a feedback mechanism rather than a terminal outcome, the AI4DMS framework extends existing linear models of AI-related capabilities at a pre-organizational level illustrating how consumer interaction contributes to continuous capability adjustment and strategic learning.

Collectively, the AI4DMS model bridges cognitive, behavioral, and technological dimensions of AI-related capability formation within a single explanatory framework, offering a theoretically grounded account of how AI-related marketing capabilities are perceived to evolve through continuous learning, adaptive processes, and perceived market feedback within a pre-organizational context.

6.2. Practical Contribution

The AI4DMS framework also provides actionable insights for organizations and educational institutions, particularly in pre-organizational or training contexts, seeking to support AI-related capability development in digital marketing. The model offers practical guidance across learning processes, capability development, and human capital alignment at a pre-organizational level.

First, the prominence of AI Impact Perceptions on Business (AIB) underscores the importance of leadership framing and strategic narratives in shaping AI-related capability development trajectories at a pre-organizational level. Positioning AI as a strategic enabler rather than a purely technical tool supports learning and capability development processes, highlighting the role of communication and interpretative framing in digital transformation contexts.

Second, the interaction between AI Knowledge in Digital Marketing (AKM) and AI Analytical and Digital Skills (ADS) emphasizes that AI-related capability development at a pre-organizational level requires integrated learning approaches that combine conceptual understanding with applied, decision-oriented practice. Experiential learning environments support the transition from AI awareness to the development of analytical and digital skills (ADS) and the understanding of their potential application in marketing contexts.

Third, AI Analytical and Digital Skills (ADS) play a critical role in translating AI-generated insights into actionable strategies through AI Applications in Marketing Strategies (AIM), supporting interdisciplinary collaboration between marketing and analytics professionals. The inclusion of AI Influence on Consumer Decisions (AID) reinforces the importance of embedding consumer feedback into agile decision-making processes, enabling continuous strategic refinement.

From an educational and workforce development perspective, the progression from perception and knowledge to skills, behavior, and strategic application provides a structured foundation for competency-based curriculum design. In this way, the AI4DMS framework supports broader objectives related to innovation, quality education, and inclusive digital transformation, consistent with international policy frameworks advanced by the Organisation for Economic Co-operation and Development and the United Nations.

7. Conclusion

This study set out to explain how AI-related perceptions, knowledge, and analytical–digital skills interact to shape perceived readiness for the application of artificial intelligence in digital marketing contexts. By validating and interpreting the AI4DMS framework, the research contributes to both theoretical understanding (*Scientia*) and practical application (*Praxis*) of AI-driven digital transformation, in line with the journal’s emphasis on multidisciplinary and innovation for sustainable development. Rather than reiterating hypothesis testing, the conclusions synthesize the model’s explanatory insights. The findings demonstrate that AI-related capability formation at a pre-organizational level is best understood as a capability-building process, in which perceptions of AI impact initiate learning, learning enables skill development, and these capabilities support strategic AI applications. Importantly, AI-influenced consumer decision-making contributes to the perceived refinement of such strategies, reinforcing a recursive logic of learning and adaptation rather than a linear adoption pathway.

7.1. Theoretical and Practical Contributions

From a theoretical perspective (*Scientia*), the AI4DMS model advances existing research on digital transformation by integrating cognitive, behavioral, and technological dimensions within a single explanatory framework. The study provides empirical insights into how AI-related capability development and perceived readiness depend not only on technological availability but also on perception-driven learning processes within a pre-organizational context, extending prior models that treat digital transformation as predominantly technical or infrastructural. By conceptualizing consumer interaction as a feedback mechanism, the framework also contributes to theoretical discussions on dynamic capabilities and organizational learning in AI-related contexts at a pre-organizational level.

From a practical perspective (*Praxis*), the model offers conceptual and educational insights for organizations and educational institutions seeking to align AI-related capabilities at a pre-organizational level with human capital development and strategic objectives. The progression from perception and knowledge to skills, strategic application, and market feedback provides a structured reference for designing training programs, capability-building initiatives, and AI-supported marketing strategies (at a perceived and preparatory level). In this regard, the AI4DMS framework supports broader policy and development priorities related to quality education, innovation, and inclusive economic growth.

7.2. Research Scope and Limitations

This study presents some limitations that frame its scope. The sample is composed of higher education students across undergraduate, master’s, and doctoral levels, predominantly aged 18–29, resulting in a relatively homogeneous group in terms of demographic and professional experience. Consequently, the findings should be interpreted as reflecting pre-organizational stages of AI capability formation,

and caution is required when extending these results to organizational or managerial decision-making contexts.

A key limitation of this study is that the research question addresses firm-level AI-related capabilities at a pre-organizational level in marketing strategy and decision-making contexts, while the empirical evidence is based on a pre-organizational population. Therefore, the findings should not be interpreted as reflecting actual firm-level adoption or managerial behavior, but rather as early-stage capability formation and perception-based readiness.

Despite these methodological constraints, the study remains a valuable and timely contribution. The AI4DMS model offers a replicable, statistically robust structure that addresses a growing need to understand how perceptions, skills, and strategic action intersect in the adoption of artificial intelligence in digital marketing strategies. Its relevance extends beyond the academic context, offering a framework applicable to workforce development, marketing innovation, and digital transformation policy—particularly in alignment with OECD (2024) priorities. As such, this work lays a foundation not only for future empirical research, but also for practical interventions in AI capability-building and education strategy.

This limitation also suggests that future research should validate the AI4DMS framework in organizational and managerial settings, using samples composed of professionals and decision-makers to enhance external validity and practical generalizability.

7.3. Future Research

Despite these constraints, the AI4DMS model establishes a solid foundation for future research. It is recommended that upcoming studies explore its application in corporate or multi-country settings, using longitudinal or experimental designs to enhance external validity. Further research could also investigate the model's relevance in industries undergoing rapid digital transformation, in line with the strategic guidance provided by recent OECD policy frameworks (OECD, 2024).

Finally, the findings should be interpreted as reflecting early-stage AI-related capability formation within a pre-organizational population, providing insight into how future professionals may develop AI-related competencies relevant for digital marketing contexts.

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