International Journal of Basic and Applied Sciences, 14 (8) (2025) 643-651

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/vamvmv23
Research paper

Perceived Usefulness of AI Across Digital Marketing Stages: An Empirical Study of Adoption Intention in Saudi Retail SMEs

Maha Ali Ateeq AlGhamdi *, Asad Ur Rehman Muhammad Sadiq, Wail Alhakimi

Graduate School of Management, Post Graduate Centre, Management and Science University (MSU), University Drive, Off Persiaran Olahraga, Section 13, 40100, Selangor, Malaysia
**Corresponding author E-mail: ALsaadmha@gmail.com*

Received: November 19, 2025, Accepted: December 30, 2025, Published: January 2, 2026

Abstract

The landscape of digital marketing is transformed by Artificial Intelligence (AI) technologies that improved personalization, efficiency, and customer engagement. However, research on AI adoption is limited, especially in Saudi retail small and medium-sized enterprises (SMEs). This study addresses this gap by examining how the perceived usefulness of AI in different digital marketing stages influences adoption intention. Drawing on the Technology Acceptance Model (TAM) and the RACE framework (Plan, Reach, Act, Convert, Engage), five hypotheses were developed to test the effects of perceived usefulness on adoption intention across these stages. Data were collected through surveys from 450 decision-makers in Saudi retail SMEs. Structural Equation Modeling (SmartPLS) was used for analysis. The results support four hypotheses. Perceived usefulness in the Plan, Reach, Convert, and Engage stages positively influenced adoption intention (H1, H2, H4, H5). The Act stage showed no significant effect (H3). These findings highlight that AI's perceived value differs across marketing stages. The study contributes to theory by extending TAM in a multi-stage marketing context. It shows that adoption intention is shaped by how useful AI is perceived across customer journey stages. Practically, the results guide managers to focus AI investments in stages where perceived usefulness drives stronger adoption, especially Reach, Convert, and Engage. For policymakers, the findings emphasize the need for targeted support and training to enhance AI readiness in Saudi SMEs.

Keywords: *Perceived Usefulness; AI Adoption Intention; Digital Marketing; RACE Model; TAM; Retail Sector, SMEs, Saudi Arabia.*

1. Introduction

Saudi Arabia's retail sector is rapidly transforming through technology adoption (Monsha'at, 2024). Retailers increasingly integrate physical stores with online and mobile platforms to serve a young, tech-savvy population (Reuters, 2023). However, most Saudi retail SMEs face structural and financial limitations that restrict innovation and technological adoption (Al-Tayyar et al., 2021; Saudi-US, 2024). Compared to global peers, Saudi SMEs contribute less to GDP and employment, highlighting the need to enhance their competitiveness (Saudi-US, 2024).

Marketing is one of the most critical challenges for these firms. SMEs often lack well-developed digital marketing strategies, leading to limited visibility and growth (Basri, 2020). Artificial Intelligence (AI) technologies can help overcome these marketing barriers; eventually supporting the overall performance of SMEs. AI technologies automate marketing activities, which enhances targeting and improves decision-making (Dam et al., 2019; Kar, 2023). Yet, the extent to which Saudi retail SMEs intend to adopt AI depends largely on how useful managers perceive these technologies to be.

According to the Technology Acceptance Model (TAM), perceived usefulness (PU) is a core precursor of technology adoption intention (Davis, 1989). A wide range of research investigated the relationship between PU and adoption intention of various new technologies (e.g., Palos-Sanchez et al., 2021; Park & Kim, 2023). However, most studies treat PU in marketing activities in general without considering the usefulness within distinct stages of the customer life cycle

The RACE framework divides the customer lifecycle into five stages: Plan, Reach, Act, Convert, and Engage (Chaffey, 2024). Each stage involves different marketing activities and potential benefits from AI applications. Understanding how PU varies across these stages can explain why SMEs adopt AI in some areas but not others.

However, there is no practical evidence of how the PU of AI in each stage of RACE influences the AI adoption intention specifically in the Saudi Arabian context. This calls for more research in this regard. The related Saudi studies just scratch the surface to understand the role of AI in organizations. Ahmed (2023) gained insights about the usage of AI technologies in the promotion of Saudi sports tourist services. Ben Khalifa et al. (2023) attempted to identify the reality of using AI technologies in Saudi e-marketing using simple descriptive statistics, means, and standard deviation. Aloufi et al. (2021) identified how AI technologies support various marketing processes theoretically by conducting a critical evaluation of the related research, studies, and literature. Basri (2020) studied empirically and quantitatively AI adoption in social media in Saudi Arabia's SMEs and the subsequent impact on performance.

Accordingly, existing studies on AI adoption intention in Saudi Arabia are limited. Most have focused on descriptive assessments of AI use (Basri, 2020; Ben Khalifa et al., 2023; Aloufi et al., 2021). No studies have been found that examine the psychological or behavioral factors influencing adoption intention. In particular, no study, to the researcher's knowledge, has explored how PU of AI across RACE stages influences adoption intention among Saudi retail SMEs. In response to the identified gap, the current study aims to fill this gap by investigating how the PU of adopting various AI technologies in throughout the customer life cycle journey (from the Plan, Reach, Act, Convert, to the Engage stage) affect the adoption intention of AI technologies. This focus will deepen understanding of AI adoption behavior in SMEs.

2. RACE Model

The PRACE or RACE (to simplify) model is one of the most widely recognized digital marketing frameworks, comprising five stages (starting from Plan, Reach, Act, Convert, and Engage). Such a stage classification helps in planning and managing the complete customer lifecycle (Chaffey, 2024). It provides a clear structure that connects marketing planning, customer reach, engagement, and conversion into one continuous process. Each stage represents a step in the digital marketing funnel, from initial campaign planning to long-term customer engagement (Chaffey & Smith, 2022). RACE's stages, Figure 2, simplify how marketers organize, execute, and monitor campaigns across multiple channels. The RACE model is adopted in the current study because of its simplicity and effectiveness. The model is widely applied to evaluate business strategies or marketing performance (e.g., Dilami et al., 2021; Nevalainen, 2020; Rautela, 2021).

Nevalainen (2020) finds it helpful in managing social media strategies. Other studies, such as Rojalin (2020), applied RACE to measure key performance indicators of digital marketing activities. Similarly, Dilami et al. (2021) used RACE to assess organizational digital marketing strategies. Rautela (2021) highlights that RACE enables marketers to structure digital marketing activities systematically.

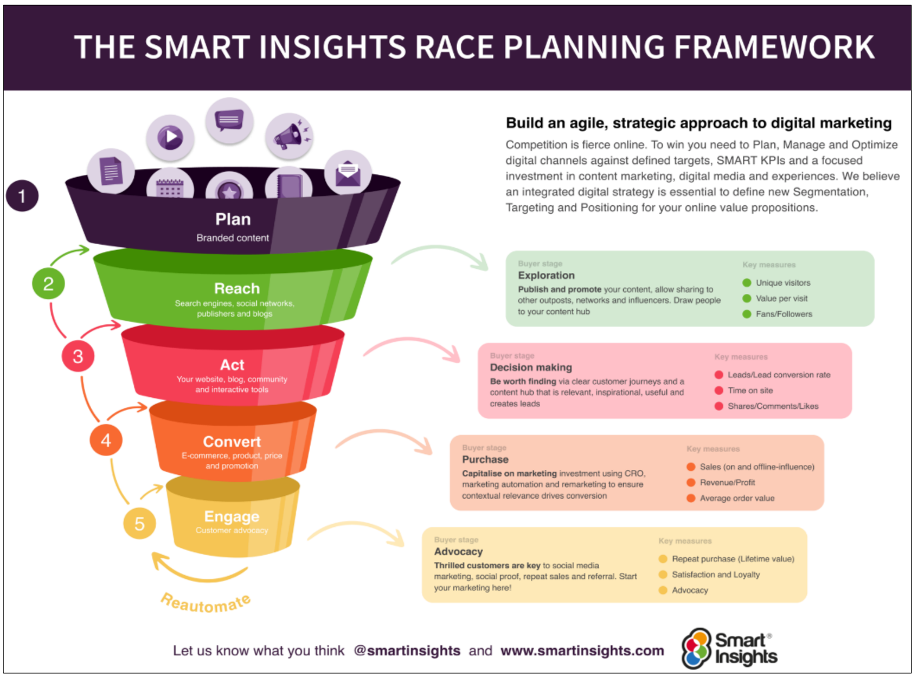

Fig. 1: RACE Marketing Planning Framework (Chaffey, 2024).

In short, RACE summarizes and rearranges the main online marketing activities that involve a form of management within digital marketing. The model excels at providing a structured, data-driven, and customer-focused approach that goes beyond making a sale, emphasizing long-term customer relationships, multi-channel integration, and measurable results. This makes it particularly well-suited to modern digital marketing environments.

3. TAM: The Technology Acceptance Model

Originally, TAM was developed by Davis (1986, 1989). The model is one of the most influential theoretical frameworks for predicting and explaining why users may accept and adopt new technologies, such as AI. TAM is basically built upon the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975). TRA posits that behavioral intentions are determined by an individual's attitudes and subjective norms. Davis adapted this framework to the technological context, focusing on two key cognitive beliefs: PEOU and PU. The former, PEOU, refers to the degree of individual beliefs about how using technology will be effort-free. While the latter, PU, refers to the extent to which an individual believes that using a particular technology will enhance their job-related performance. The two constructs, in turn, influence users' attitudes toward using the technology, their behavioral intentions to use it, and their actual usage behavior at the ultimate stage.

AI technologies in digital marketing—such as predictive analytics, chatbots, recommendation systems, and automated content generation—represent advanced and often complex innovations. Their successful implementation depends largely on marketers' cognitive perceptions of usefulness. In the current research, TAM, which focuses on users' acceptance of technological innovation, provides a strong theoretical foundation for examining the relationship between PU and adoption intention. In the context of Saudi SMEs, where digital transformation and AI adoption are still evolving, understanding how marketers perceive AI's usefulness provides essential insight into adoption intentions.

4. Perceived Usefulness

Numerous scholars ensured the significant role of PU as a determinant of technology adoption/adoption intention. (e.g., Chen & Aklikokou, 2020; Palos-Sanchez et al., 2021; Park & Kim, 2023).
To understand the concept, both "perceived" and "usefulness" should be clarified. Perception refers to a belief or opinion based on how things appear (Cambridge.org, 2024). It represents an individual's subjective experience. If perceived quality is a subjective judgment about product superiority (Zeithaml, 1988), then similarly, PU represents a subjective judgment about a system's overall usefulness, separate from its actual utility (Stylidis et al., 2015).
Usefulness is what drives people to accept/reject a system. 'Useful' is a term that refers to "the capability of being used advantageously." People tend to use technology if they believe it improves performance in a job (Davis, 1989). According to PU, it is defined to be "the degree to which a person believes that using a particular system would enhance his or her job performance" Davis, 1989, p. 320).

5. Adoption Intention

TAM implies that Behavioral Intention (BI) is influenced by PU (Davis, 1989). BI causes a substantial portion of behavior variance (Ajzen & Fishbein, 1970). BI refers to the extent to which a person has formulated conscious plans to perform or not perform behavior in the future. Therefore, it plays a critical role in determining whether individuals will adopt technology. (Ajzen, 1991).
In the current study, AI adoption intention serves as a mediating variable between PU of AI in DM within RACE and digital marketing performance. Intention as an instant antecedent of behavior is defined as the strength of the mind to think in a specific manner as a means to pursue behavior. (Ajzen, 1991). It shows the readiness to complete a specific behavior. (Ajzen, 1991) and reflects the commitment, plan, or decision to perform an action or achieve a particular goal (Wang et al., 2019).
The intent to adopt technology positively influences adoption behaviors, and marketers who intend to adopt a specific technology develop more significant levels of actual adoption compared to marketers who lack the intention to adopt Brown et al. (2003). This claim was emphasized in numerous studies. In India, for example, e-pharmacy adoption indicated that users' behavioral intentions were linked to actual adoption outcomes. (Srivastava & Raina, 2021). Such claims reflect the role of intentions in pushing marketers to engage in actual behavior. Consequently, making marketing decisions for new technology can be done based on willingness to adopt (adoption intentions). In the current study, BI is defined as the intention to adopt AI technologies for digital marketing activities.

6. Hypotheses Development

Many studies identified PU as a significant determinant of technology adoption. (Chen & Aklikokou, 2020; Palos-Sanchez et al., 2021; Park & Kim, 2023).
Theoretically, TAM posits that individuals accept and use technology when they perceive it as helpful; accordingly, PU is a motivational factor. In the current research, TAM can represent the degree of belief that AI can be helpful for the effectiveness of marketing strategies throughout RACE (e.g., better customer targeting, optimized spending, and more personalized content). Therefore, the relationships between PU of AI in each stage of RACE and AI adoption intention in digital marketing can be viewed through the lens of TAM.
Empirically, researchers emphasized the role of PU in impacting adoption intention. For example, Salah and Ayyash (2024) Showed that the integration of AI positively and significantly influences the adoption of e-commerce. Alnajim and Fakieh (2023) Evaluated the impact of PU of using an ML-based classification model in social media marketing on the intention to use social media when planning travel to Saudi Arabia. The findings revealed that PU is one of the factors that significantly impacts tourists' intentions to use social media for their travel planning. Suleiman et al. (2021) Confirmed that PU (represented in enhanced digital marketing performance) of AI (web interactivity) impacts the intention to use.
Based on the above articulation, PU of AI adoption in the Plan, Reach, ACT, Convert, and Engage Phases may have a positive impact on the adoption intention of AI. To ensure such impacts, further evidence is required, particularly from Saudi Arabian entities. The proposed model, Figure 2, is composed of five hypotheses as follows:
H1: The perceived usefulness of AI adoption in the Plan Phase has a positive impact on AI adoption intention in DM.
H2: The perceived usefulness of AI adoption in the Reach Phase has a positive impact on the AI adoption intention of AI in DM.
H3: The perceived usefulness of AI adoption in the Act Phase has a positive impact on the AI adoption intention of AI in DM.
H4: Perceived usefulness of AI adoption in the Convert Phase has a positive impact on AI adoption intention in Digital marketing.
H5: The perceived usefulness of AI adoption in the Engage Phase has a positive impact on the AI adoption intention of AI in DM.

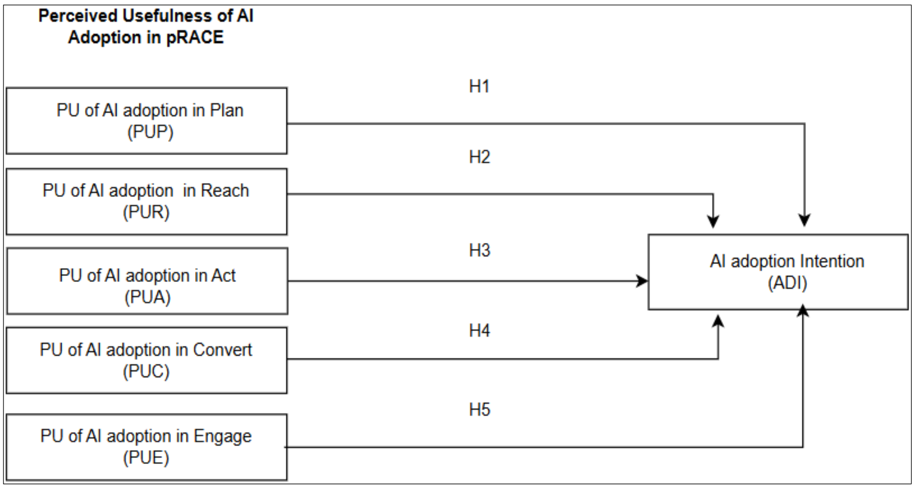

Fig. 2: The Proposed Model.

7. Methodology

A quantitative research design is chosen to examine how PU of AI throughout the customer life cycle (RACE stages) influences adoption intention among retail SMEs in Saudi Arabia. The focus is on understanding marketers' and managers' perceptions of AI usefulness and its role in enhancing adoption behavior in digital marketing activities.

A well-developed questionnaire was used to collect primary data. The instrument was built basically on TAM (Davis, 1989) and the RACE framework (Chaffey, 2024), two well-established frameworks. The first section is dedicated to demographic data, while the second section is for PU of AI across the five RACE stages, and the third section is for AI adoption intention. The questionnaire items were adopted or adapted from validated instruments in previous studies on PU and technology adoption intention. Perceived usefulness (PU) was measured using adapted items from Davis (1989) and Wilson et al. (2021), which capture usefulness in terms of work quality, effectiveness, productivity, and task ease. These items were reworded to reflect AI applications in digital marketing within each stage of the RACE framework. For instance, in the Plan stage (PUP), items described how AI supports market data analysis or automates customer segmentation. Similar adaptation procedures were applied for the Reach (PUR), Act (PUA), Convert (PUC), and Engage (PUE) stages. The wording was refined to suit marketers and SME business owners in the Saudi retail context.

All the questions are based on a five-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree". The instrument was customized to reflect the Saudi retail context, ensuring relevance to local digital marketing practices and AI applications.

The target population consisted of Saudi retail SMEs engaged in digital marketing. A convenience sampling approach was used to recruit respondents directly involved in marketing, IT, or AI functions, including marketing managers, digital specialists, and IT professionals. Data was collected through online and direct survey distribution channels to maximize participation.

A pretest and Pilot Study were conducted to ensure clarity and validity; The questionnaire underwent expert review by industry professionals and academics. Their feedback was used to refine the language and content of the items. Subsequently, the pilot study participants were a small sample drawn from the target population. Results from the pilot confirmed the instrument's reliability and validity. Cronbach's alpha values for all constructs exceeded the 0.70 threshold, indicating strong internal consistency. Exploratory factor analysis further confirmed acceptable factor loadings, demonstrating convergent validity.

8. Results

The study involved 450 respondents from Saudi retail SMEs, offering balanced gender representation (52.7% male, 46.7% female), as shown in Table 1. The education levels indicate a highly qualified sample, with nearly three-quarters holding master's or PhD degrees. This suggests that participants possess strong analytical and strategic capabilities relevant to AI and marketing innovation. The age distribution shows a mix of young innovators and experienced professionals, with most participants aged 40 or older, indicating maturity and leadership in AI-related decision-making. Regarding experience, over half of the respondents have more than ten years in their roles, providing informed and realistic insights into AI adoption practices. The position distribution reflects a balance between strategic and operational roles. Business owners and senior managers represent the leadership perspective, while digital marketing managers provide practical implementation insights. This diverse composition strengthens the reliability and generalizability of the findings, ensuring that the study captures both the strategic and operational dimensions of AI adoption in Saudi retail SMEs.

Table 1: Demographic Data Analysis

Variable	Category	Frequency	Percent (%)
Gender	Male	237	52.7
	Female	210	46.7
	Missing	3	0.7
Education	Master's/PhD or Higher	327	72.7
	Bachelor's/College	105	23.3
	Diploma/High School	15	3.3
	Missing	3	0.7
Age	Under 30	78	17.3
	30–39	135	30.0
	40–49	141	31.3
	50+	96	21.3
Position	Business Owners	135	30.0
	Digital Marketing Managers	110	24.4
	Marketing Directors	90	20.0
	Heads of Strategy/Digital Transformation	70	15.6
	Other Senior Managers	45	10.0
Experience	< 1 Year	45	10.0
	1–5 Years	78	17.3
	6–10 Years	99	22.0
	> 10 Years	228	50.7

9. Measurement Model

According to the two-step approach of Gerbing and Anderson (1988) for testing the Structural Equation Modeling (SEM) framework, the measurement model was tested first. The focus is on the measurement model, using Confirmatory Factor Analysis (CFA) to evaluate the psychometric properties of the constructs (Figure 3).

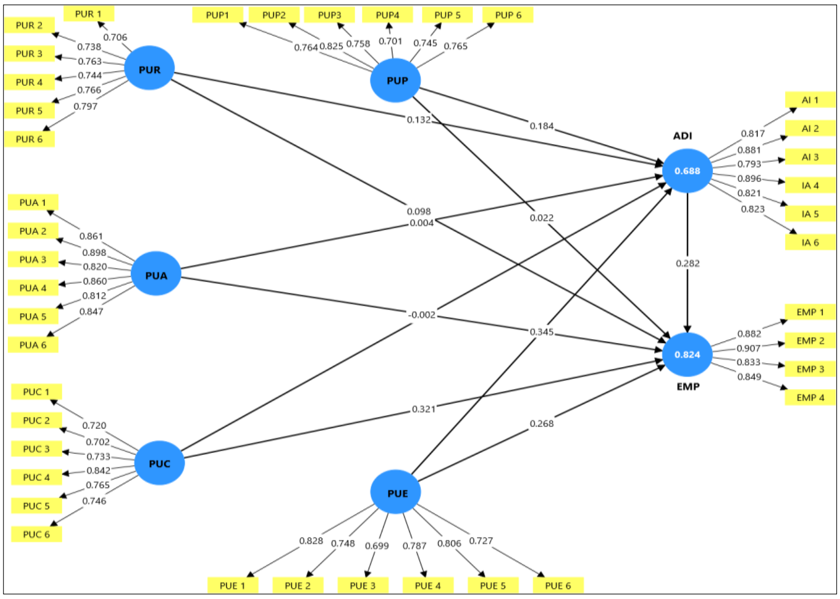

Fig. 3: Measurement Model.

Reliability was examined at both the construct and indicator levels using Cronbach's Alpha (CA) and Composite Reliability (CR). Cronbach's Alpha values ranged from 0.847 to 0.923, exceeding the recommended threshold of 0.70 (Hair et al., 2019). This indicates strong internal consistency among the measurement items. Composite Reliability values also met the required standard, ranging from 0.850 to 0.940, confirming stable and consistent measurement across constructs. In most cases, CR values were higher than CA values, as expected, since CR accounts for item loading strength. Overall, these results demonstrate that all constructs achieved satisfactory levels of reliability.

Convergent validity was evaluated through outer loadings (Figure 3) and Average Variance Extracted (AVE), Table 2. Most outer loadings ranged from 0.699 to 0.907, indicating strong correlations between indicators and their respective constructs. Although PUE 3 is (0.699), slightly below 0.70, it was retained due to its proximity to the threshold. The AVE values ranged from 0.567 to 0.754, exceeding the minimum acceptable level of 0.50 (Fornell & Larcker, 1981). This indicates that each construct explains more than half of the variance in its indicators. Therefore, convergent validity was confirmed for all constructs in the model.

Table 2: Reliability Tests

	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
ADI	0.92	0.92	0.71
PUA	0.92	0.93	0.72
PUC	0.85	0.85	0.57
PUE	0.86	0.86	0.59
PUP	0.85	0.86	0.58
PUR	0.85	0.85	0.57

Discriminant validity was tested using the Heterotrait–Monotrait ratio (HTMT), Table 3. The method is based on comparing correlations across constructs with those within a construct. Henseler et al. (2015) suggest that values below 0.85 show strong discriminant validity. Other studies allow thresholds of 0.90 or 0.95 in exploratory research (Roemer et al., 2021). Values above 0.90 may suggest redundancy. This means that constructs may not be fully distinct. HTMT values ranged from 0.620 to 0.927. Some values were above 0.85, but none exceeded 0.95. Since this study is exploratory, the 0.90 threshold is acceptable. The results suggest that the constructs remain distinct. A few values that passed 0.90 are noted as a limitation. This may reflect the closeness of constructs related to AI adoption in digital marketing. It does not mean the measures are flawed. Overall, discriminant validity is supported in this research.

Table 3: Discriminant Validity HTMT Test

	ADI	PUA	PUC	PUE	PUP
ADI					
PUA	0.620				
PUC	0.865	0.726			
PUE	0.884	0.736	0.917		
PUP	0.836	0.670	0.911	0.927	
PUR	0.796	0.676	0.905	0.855	0.872

Overall, the findings indicate that the measurement model possesses strong reliability and validity. All constructs exhibit adequate internal consistency and convergent validity, supporting the model's overall robustness.

Table 4: Multicollinearity VIF Test

	ADI
ADI	
PUA	1.942
PUC	4.849
PUE	4.856
PUP	3.442
PUR	3.180

10. Structural Equation Modelling

For estimate and evaluate the structural paths, a structural model was conducted (Figure 4).

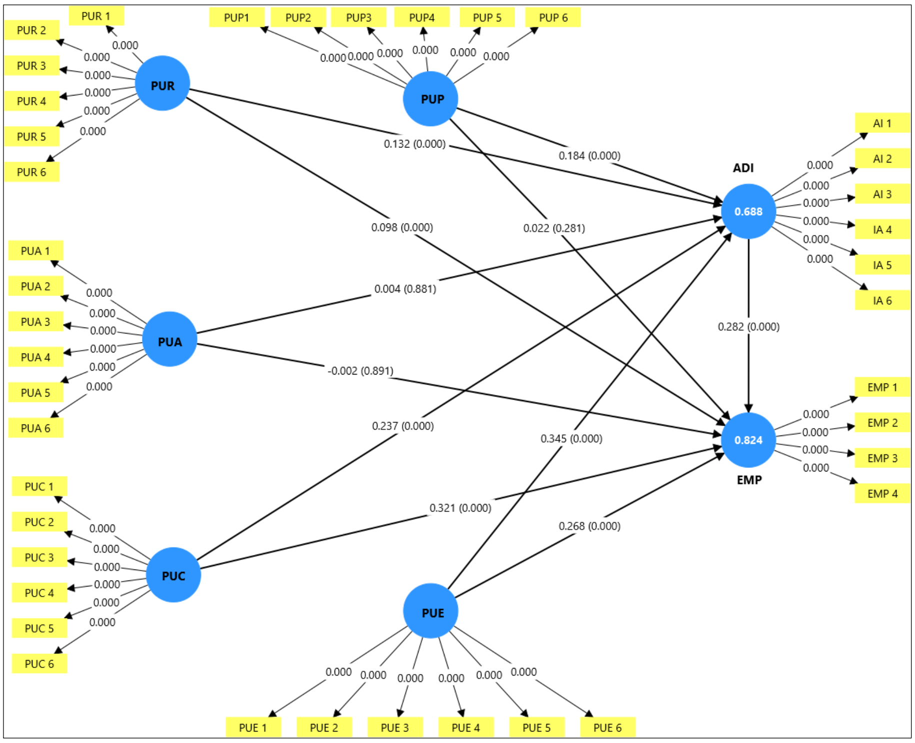

Fig. 4: The Structural Model.

The path coefficient results indicate that four of five stages exhibit significant PU on AI adoption intention (ADI). The usefulness of AI in the Engage stage (PUE → ADI, $\beta = 0.345$, $p < 0.001$) has the strongest positive impact, followed by the Convert stage (PUC → ADI, $\beta = 0.237$, $p < 0.001$), the Plan stage (PUP → ADI, $\beta = 0.184$, $p < 0.001$), and the Reach stage (PUR → ADI, $\beta = 0.132$, $p < 0.001$). Accordingly, these statistical results indicate that when marketers perceive AI as useful in engaging customers, converting leads, planning marketing activities, and reaching audiences, their intention to adopt AI increases. However, the Act stage (PUA → ADI, $\beta = 0.004$, $p = 0.881$) shows no significant relationship, suggesting that the perceived usefulness of AI in facilitating customer actions does not meaningfully affect adoption intention. Overall, the results highlight that PU in the later RACE stages—particularly Engage and Convert—plays a stronger role in driving AI adoption intentions among Saudi retail SMEs.

Table 5 presents the f^2 (effect size) of each predictor on AI-adoption intention (ADI. The results show that PUP and PUR have negligible effects ($f^2 = 0.032, 0.018$, respectively). PU in Plan and Reach stages has minimal impact on adoption intention. PUC (Convert) has a small effect ($f^2 = 0.044$), suggesting that AI in the conversion stage modestly enhances ADI. Whereas PUE (Engage) shows a medium effect ($f^2 = 0.091$), highlighting the important role of AI in engagement activities in driving adoption intention. In contrast, PUA (Act) has no effect ($f^2 = 0.000$), indicating that AI in the Act stage does not contribute to adoption intention.

The effect size complements the path coefficient results. PU in the Plan and Reach stages is statistically significant. Though, their small effect sizes indicate that these relationships have limited practical relevance for AI adoption intention. The situation is different for the Engage stage. The highest path coefficient and a medium effect size have been observed, indicating that AI tools designed to enhance customer engagement are not only statistically significant but also fundamentally impactful. Looking at the Convert stage, a comparable but less pronounced trend exists, with a significant relationship and a small effect size. Dissimilarly, the Act stage exhibits no meaningful influence in each analysis. Therefore, AI usefulness at this stage does not encourage adoption. Overall, the consistency between the coefficient and effect size results underscores the importance of the far along RACE stages (engagement and conversion) in driving AI adoption among Saudi retail SMEs. At the same time, early-stage AI applications appear to play a far more limited role in practice.

Table 5: Effect size, Path Coefficients, Explanatory and Predictive Power

	Effect Size(f^2)	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
PUA -> ADI	0.000	0.004	0.024	0.150	0.881
PUC -> ADI	0.044	0.237	0.033	7.261	0.000
PUE -> ADI	0.091	0.345	0.039	8.938	0.000
PUP -> ADI	0.032	0.184	0.032	5.774	0.000
PUR -> ADI	0.018	0.132	0.028	4.630	0.000
R-square	0.688				
R-square adjusted	0.687				
Q^2predict	0.685				

Additionally, as Table 5 illustrates, the model shows strong explanatory power. The R^2 value of 0.688 means that the perceived usefulness variables explain 68.8% of the variation in AI adoption intention. The adjusted R^2 of 0.687 confirms the model's stability. The slight difference between the two values shows that the model is not overfit. The Q^2predict value of 0.685 is well above zero. This indicates high predictive relevance. Overall, the model effectively explains and predicts AI adoption intention among Saudi retail SMEs.

11. Hypothesis Testing

As illustrated in Table 6, the hypothesis results show that most relationships are significant. Perceived usefulness in the plan (PUP) stage has a strong positive effect on AI adoption intention ($\beta = 0.184$, $p < 0.001$). The PU in the reach stage (PUR) also shows a significant influence ($\beta = 0.132$, $p < 0.001$). in the convert stage, PUC has a higher positive effect ($\beta = 0.237$, $p < 0.001$). In the engage stage, (PUE) has the greatest impact ($\beta = 0.345$, $p < 0.001$).

However, in the act stage, (PUA) is not significant ($\beta = 0.004$, $p = 0.881$). This means that usefulness in the interaction stage does not drive adoption intention. The Act stage focuses on immediate interactions. These include clicks, views, and short-term responses. It appears that AI applications at this stage are often seen as operational tools rather than strategic assets. To a certain extent, they improve efficiency. Though, they do not fundamentally change decision-making. It is also important to note that many Act-stage tasks can already be handled using basic digital tools. Social media platforms and marketing dashboards offer built-in functionalities at low cost. This may partly explain why the added value of advanced AI may not be clearly perceived. This reduces its impact on adoption intention.

Overall, usefulness across most RACE stages, especially in conversion and engagement, strongly supports AI adoption in digital marketing.

Table 6: Hypotheses Testing

Hypothesis	Relationship	Path Coefficient (O)	p-value	Decision
H1	PUP → ADI	0.184	0.000	Accepted
H2	PUR → ADI	0.132	0.000	Accepted
H3	PUA → ADI	0.004	0.881	Rejected
H4	PUC → ADI	0.237	0.000	Accepted
H5	PUE → ADI	0.345	0.000	Accepted

12. Discussion

The main objective of the current study is critical because it fills a gap in the literature by examining how PU across all five RACE stages influences the intention to adopt AI among DM in Saudi Retail SMEs (Dilami et al., 2021; Papastefanou & Papaioannou, 2024; Patel, 2024; Rautela, 2021). PU is typically studied in a single area, without accounting for differences across marketing activities (Chen & Aklikokou, 2020; Park & Kim, 2023; Wilson et al., 2021). AI tools, however, may be more or less effective depending on the stage. Therefore, PU is not uniform. It varies across the digital marketing cycle. By breaking PU into the five RACE phases, this study offers a more detailed view of where retail SMEs see AI adoption as most valuable.

SMEs often operate with limited resources, so they must focus on where AI provides the most benefit. Knowing which RACE stages are most strongly tied to adoption intention gives practical guidance. For example, if AI is most useful in the Plan or Reach stages, managers and policymakers can target training and investment there. If usefulness in Engage is weaker, vendors and consultants may need to highlight AI's benefits more effectively in that stage. The study also adds new evidence for the local context in Saudi Arabia. Many previous studies focus on large firms in developed economies. (Al Khaldy et al., 2023; Aloufi et al., 2021; Suleiman et al., 2021) or other developing countries (Chatterjee et al., 2021; Giri et al., 2019; Ifekanandu et al., 2023). Their findings may not reflect the realities of SMEs in emerging markets. In Saudi Arabia, SMEs are central to Vision 2030 but often face financial and digital constraints. Finally, the results build the foundation for later analysis. Understanding PU's direct role in shaping adoption helps explain later expectation of performance effects. This makes the objective essential in connecting theoretical ideas with real-world practice. It ensures the study contributes to both academic debates and managerial decision-making.

The PLS-SEM analysis confirms support for H1, H2, H4, and H5, but not for H3. What emerges here is not a simple relationship; PU of AI in the Plan ($\beta = 0.184$, $p < 0.001$) and Reach stages ($\beta = 0.132$, $p < 0.001$) shows a positive, albeit modest, influence on adoption intention. This suggests that AI-enabled planning and targeting functions are valued, but they are not the primary drivers shaping adoption decisions among retail SMEs. At this point, it becomes clear that a different pattern emerges at later stages of the RACE framework. From this perspective, the stronger effects observed in the Convert ($\beta = 0.237$, $p < 0.001$) and Engage stages ($\beta = 0.345$, $p < 0.001$) are particularly revealing. This may partly explain why the results indicate that AI applications linked to revenue generation, customer retention, and long-term engagement play a central role in motivating adoption. Adoption intentions appear to be driven less by operational support and more by perceived strategic payoff. By contrast, PU in the Act stage does not exert a significant effect on adoption intention ($\beta = 0.004$, $p = 0.881$). This may partly explain why the finding deserves attention. AI applications supporting short-term transactional actions—such as clicks or downloads—may be viewed as incremental rather than transformative. For resource-constrained SMEs, such tools may not justify the investment required, especially when their strategic impact is less visible.

From an empirical standpoint, PU was identified as a factor driving AI adoption or AI adoption intention in different contexts. In Romania, Acatrinei (2025) found that AI is reshaping marketing, and its perceived usefulness for efficiency and personalization drives adoption. In Saudi Arabia (Badghish & Soomro, 2024) and Palestine (Salah & Ayyash, 2024), AI adoption intention was found to be strongly influenced by technological, organizational, and environmental factors. Among Bangladeshi professionals, Hasan Emon et al. (2023) found that ChatGPT's adoption intention is affected by performance benefits, building trust, and creating facilitating conditions. Wang et al. (2023) found that PU directly influenced both user attitudes and the intention to use AI. Chen et al. (2025) highlight three key factors that push firms to adopt AI more aggressively: technological opportunism, strong support from top management, and pressure from industry norms. Keni (2020) explored how PU and PEOU influence consumers' intention to repurchase. Joshi et al. (2025) observed that AI's usefulness in terms of innovation, creative content, speed, efficiency, and personalization is a driver of generative AI adoption.

Theoretically, the current results validate the TAM model (Alnajim & Fakieh, 2023; Alqasa & Afaneh, 2022; Susanti & Astuti, 2019; Wang et al., 2023). PU significantly influences users' behavioral intentions to adopt new technologies. This finding has been replicated across studies across contexts (Chatterjee et al., 2021; Srivastava & Raina, 2021; Wang et al., 2023). In the digital marketing context, marketers are more likely to adopt AI applications if they perceive them as helpful in improving marketing effectiveness (Alqasa & Afaneh, 2022).

In short, AI adoption intentions may differ across the five stages of the RACE framework based on the PU at each stage. PU in the Plan, Reach, Convert, and Engage stages has a strong effect on adoption intention. However, PU in the Act stage has no significant effect. This means that AI's value differs across marketing activities.

13. Research Limitations and Implications

This study has several limitations that should be acknowledged. It focuses exclusively on Saudi retail SMEs, which limits the generalizability of the findings to larger firms, other industries, or different cultural settings. Self-reported survey data were used in the current study. This approach may introduce response bias, as participants could overestimate their perceptions of AI usefulness or their intention to adopt it. Variations in familiarity with AI concepts might have influenced how they interpreted and answered the questions, despite any exerted efforts to provide clear definitions. The study follows a cross-sectional design. As a result, it is not possible to observe changes in perceptions or adoption intentions over time, nor can strong causal relationships be established between perceived usefulness and adoption intention. All such issues limit the generalizability of the findings to evolving contexts. These limitations suggest that the results reflect perceived intentions rather than actual behavior. Future research could adopt longitudinal designs to capture how perceptions of AI usefulness evolve and how adoption decisions unfold over time, providing a clearer understanding of causality and temporal dynamics in AI adoption among SMEs.

The study's emphasis on perceived usefulness of AI within the RACE framework also excludes other relevant factors such as cost, organizational readiness, and cultural influences. Lastly, while PLS-SEM effectively explains relationships among selected variables, it does not capture all potential mediators or moderators, suggesting that future research should employ more comprehensive models and theoretical extensions.

The findings add depth to the TAM. They show that usefulness is not uniform but depends on the stage of use. Integrating TAM with the RACE framework creates a stage-based understanding of how AI is adopted in marketing. It also links TAM with Dynamic Capabilities Theory. In this way, perceived usefulness reflects how firms sense AI opportunities, while adoption intention shows how they seize them. For managers in Saudi retail SMEs, the results highlight where AI adds the most value. The Reach and Engage stages show the strongest impact. These stages involve targeting customers and building personalized relationships. Managers should invest more in these areas to get the best results. Plan and Convert also play a role, helping firms use data for strategy and conversion. The Act stage needs more attention, as AI tools there are not yet fully effective or understood. Policymakers can use these findings to design better support programs. Training and funding should focus on showing SMEs how AI improves customer reach and engagement. Awareness programs can help firms apply AI more effectively in the Act stage. Collaboration between SMEs, universities, and technology providers can also promote adoption. This will help build stronger AI-driven marketing practices across Saudi retail SMEs.

Future research should go beyond Saudi retail SMEs. Other sectors and countries should be included to test generalizability. Researchers should use objective data, such as firm records or analytics, to reduce bias. Combining surveys with interviews or case studies can offer deeper insights. PLS-SEM models can be expanded with moderators and mediators. Variables like firm size, marketing innovation, and digital maturity should be tested.

14. Conclusion

The current study examined how the perceived usefulness of AI at each stage of the customer life cycle (RACE framework) affects AI adoption intention in digital marketing among retail SMEs in Saudi Arabia. The research set out to close theoretical, practical, and policy gaps. It focused on how retail SMEs can use AI to boost competitiveness and improve marketing outcomes. The results show that perceived usefulness shapes adoption intention. Testing PU across marketing activities as a whole may not be effective; it should be examined at various stages of the marketing process. The findings confirm that structured approaches, such as the RACE framework, help SMEs apply AI to customer engagement, conversion, and retention. The study adds to theory by linking AI adoption with the RACE framework. It extends both marketing and information systems literature. On the practical side, SME managers gain insights into where AI can add value. For policymakers, the research highlights the need for support through infrastructure, training, and funding to encourage digital adoption. The work has limitations, yet it contributes to understanding AI adoption in Saudi SMEs. It sets the stage for future studies to examine factors such as organizational readiness, culture, and long-term impacts.

References

[1] Ahmed, M. I. A. A. (2023). The Contribution of Modern Technologies of Artificial Intelligence in the Marketing of Sports Tourist Services in the Kingdom of Saudi Arabia. *Journal for ReAttach Therapy and Developmental Diversities*, *6*(1), 665–679.

[2] Alnajim, R. A., & Fakieh, B. (2023). A Tourist-Based Framework for Developing Digital Marketing for Small and Medium-Sized Enterprises in the Tourism Sector in Saudi Arabia. *Data*, *8*(12), 179. https://doi.org/10.3390/data8120179.

[3] Aloufi, H. A., Al Atif, M. A., & Abdul Aziz, A. H. A. (2021). Artificial Intelligence and Its role in Supporting Marketing. *International Multilingual Academic Journal*, *2*(1), Article 1. https://aasrc.org/aasrj/index.php/imaj/article/view/2096.

[4] Al-Tayyar, R. S. D., Abdullah, A. R. B., Rahman, A. A., & Ali, M. H. (2021). Challenges and obstacles facing SMEs in the adoption of e-commerce in developing countries; A case of Saudi Arabia. *Studies of Applied Economics*, *39*(4), Article 4. https://doi.org/10.25115/eea.v39i4.4644.

[5] Basri, W. (2020). Examining the Impact of Artificial Intelligence (AI)-Assisted Social Media Marketing on the Performance of Small and Medium Enterprises: Toward Effective Business Management in the Saudi Arabian Context: *International Journal of Computational Intelligence Systems*, *13*(1), 142. https://doi.org/10.2991/ijcis.d.200127.002.

[6] Ben Khalifa, W. A., Alshorman, B. A., Seddik, W. A. S., Esseket Zahou, A. M., Torky, M. Sh., Mona Fathi Rizk, Wafaa A. Mostafa Hussein, Mohamed H Rabie, & Yousif, M. A. A. B. (2023). The Reality of Using Artificial Intelligence Applications in Developing E-Marketing in the Kingdom of Saudi Arabia. *Migration Letters*, *20*(S3), Article S3. https://doi.org/10.59670/ml.v20iS3.3768

[7] Cambridge.org. (2024, September 11). *Perception*. https://dictionary.cambridge.org/dictionary/english/perception

[8] Chaffey, D. (2024, January 17). *The RACE Framework: A practical digital marketing strategy framework*. Smart Insights. https://www.smartinsights.com/digital-marketing-strategy/race-a-practical-framework-to-improve-your-digital-marketing/

[9] Chaffey, D., & Smith, P. (2022). *Digital Marketing Excellence: Planning, Optimizing and Integrating Online Marketing* (6th ed.). Routledge. https://doi.org/10.4324/9781003009498.

[10] Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, *170*, 120880. https://doi.org/10.1016/j.techfore.2021.120880.

[11] Chen, L., & Aklikokou, A. K. (2020). Determinants of E-government adoption: Testing the mediating effects of perceived usefulness and perceived ease of use. *International Journal of Public Administration*, *43*(10), 850–865. https://doi.org/10.1080/01900692.2019.1660989.

[12] Dam, H. K., Tran, T., Grundy, J., Ghose, A., & Kamei, Y. (2019). Towards Effective AI-Powered Agile Project Management. *2019 IEEE/ACM 41st International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER)*, 41–44. https://doi.org/10.1109/ICSE-NIER.2019.00019.

[13] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340. https://doi.org/10.2307/249008.

[14] Dilami, Z., Hosseini, S., & Ahmadi, H. (2021). Evaluation of the digital marketing Strategy of the Bushehr Province Mining export Companies using RACE model. *Journal of International Business Administration*, *4*(2), 21–41.

[15] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203.

[16] Kar, S. (2023). Impact of Artificial Intelligence on Digital Marketing. *Interantional Journal of Scientific Research in Engineering And Management*, *07*(07). https://doi.org/10.55041/IJSREM25001.

[17] Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology*, *38*(1), 1–19. https://doi.org/10.1108/IJILT-05-2020-0090.

[18] Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). *Applied Linear Statistical Models* (5th ed.). McGraw-Hill/Irwin.

[19] Monsha'at. (2024). *Digital Transformation for SMEs*. https://www.monshaat.gov.sa.

[20] Nevalainen, I. (2020). *Digital marketing development in a B2B context*.

[21] O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, *41*(5), 673–690. https://doi.org/10.1007/s11135-006-9018-6.

[22] Palos-Sanchez, P. R., Saura, J. R., Martin, M. Á. R., & Aguayo-Camacho, M. (2021). Toward a Better Understanding of the Intention to Use mHealth Apps: Exploratory Study. *JMIR mHealth and uHealth*, *9*(9), e27021. https://doi.org/10.2196/27021.

[23] Park, D. Y., & Kim, H. (2023). Determinants of Intentions to Use Digital Mental Healthcare Content among University Students, Faculty, and Staff: Motivation, Perceived Usefulness, Perceived Ease of Use, and Parasocial Interaction with AI Chatbot. *Sustainability*, *15*(1), Article 1. https://doi.org/10.3390/su15010872.

[24] Rautela, S. (2021). Social media for new product launch: A study of social media platforms across the RACE planning framework. *International Journal of Interactive Mobile Technologies*, *15*(5). https://doi.org/10.3991/ijim.v15i05.18147.

[25] Reuters. (2023, May 31). Saudi population at 32.2 million, 63% of Saudis under 30 years old, census shows. *Reuters*. https://www.reuters.com/world/middle-east/saudi-population-322-mln-median-age-29-years-old-general-authority-statistics-2023-05-31/.

[26] Rojalin, K. (2020). Search engine optimization for an international business to business company in the beauty industry: Measuring the results with web analytics. *Jyväskylä University of Applied Sciences*.

[27] Saudi-US. (2024). *SMEs in Saudi Arabia: How the Supreme Economic Council Can Support SME Growth in the Kingdom | SUSTG.com – News, Analysis, and Features on all things Saudi Arabia*. https://www.sustg.com/smes-in-saudi-arabia-supporting-growth-sme/.

[28] Stylidis, K., Wickman, C., & Söderberg, R. (2015). Defining Perceived Quality in the Automotive Industry: An Engineering Approach. *Procedia CIRP*, *36*, 165–170. https://doi.org/10.1016/j.procir.2015.01.076.

[29] Wilson, N., Keni, K., & Tan, P. H. P. (2021). The role of perceived usefulness and perceived ease-of-use toward satisfaction and trust which influence computer consumers' loyalty in China. *Gadjah Mada International Journal of Business*, *23*(3), 262–294. https://doi.org/10.22146/gamaijb.32106.