Marketing professionals' adoption of artificial intelligence and its influence on marketing efficiency

Benchmarking: An International Journal

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Abstract

Purpose – Artificial intelligence (AI) has transformed marketing operations, creating new benchmarks for operational productivity, customer interaction and sales growth. This study investigates factors that affect the adoption of AI among marketing professionals, focusing on developing benchmarking archetypes and assessing the moderating impact of technology resistance (TR).

Design/methodology/approach – Data from 353 marketing professionals across diverse sectors in Sri Lanka was analyzed using a dual-method approach. The UTAUT2 model guided hypotheses tested with PLS-SEM to establish generalizable benchmarks, while fuzzy-set qualitative comparative analysis (fsQCA) was employed to identify distinct adoption archetypes serving as configurational benchmarks.

Findings – All the UTAUT2 factors significantly influence AI adoption, with TR as a substantial barrier. The fsQCA revealed seven distinct benchmarking archetypes, with behavioral intention, effort expectancy, facilitating conditions, hedonic motivation and price value emerging as core conditions for high adoption, while performance expectancy, social influence and habit functioning as peripheral factors.

Practical implications – The research provides diagnostic benchmarking tools that organizations can use to assess their AI readiness, identify implementation pathways aligned with their contextual characteristics, reduce technology resistance and enhance marketing efficiencies.

Originality/value – This study advances benchmarking literature by identifying both generalizable adoption drivers and distinct configurational archetypes for AI implementation in marketing while establishing technology resistance as a critical moderating variable.

Keywords Artificial intelligence, Benchmarking archetypes, Configurational benchmarking, fsQCA, Marketing efficiency, Technology resistances

Paper type Research paper

1. Introduction

Artificial Intelligence (AI) has emerged as the new game-changer for almost all the domains of the modern era, and one of the most prominent ones is marketing, which is currently in the process of being remodeled from traditional strategies to pave a new path for unprecedented advancement in organizational performance. The entry of AI into the marketing processes is positioned to revolutionize operational productivity and promise the refinement of customer interaction for higher satisfaction, which finally adds to sales growth. AI-driven innovations such as chatbots apply the same principle: engaging customers, issuing immediate personalized responses, and simultaneously handling several interactions (Wu and Monfort, 2023). Additionally, the shift toward AI necessitates establishing performance benchmarks and assessing organizational readiness, including assets, capabilities, and commitment (Jöhnk *et al.*, 2021). Further, organizations need to explore ethical and privacy issues related to the use of AI to ensure their customers' trust. Conversely, implementing AI would require a substantial financial outlay and, in some instances, organizational changes, necessitating cautious and detailed planning (Manrai and Gupta, 2023). To truly connect the benefits of AI, organizations must foster a spirit of collaboration and cooperation. Therefore, employees must be prepared to navigate the shifts AI adoption brings (Bhatt and Shah, 2023). Besides, using AI

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in marketing holds immense potential for boosting financial performance with proper strategies and initiatives, opening up the possibility of ushering in a new era of business competitiveness. However, despite these potential benefits, organizations face significant challenges in AI implementation, with industry reports indicating that 70–80% of AI initiatives fail to deliver their expected value (McKinsey and Company, 2021). This high failure rate represents a critical problem for marketing practitioners seeking to leverage AI technologies and highlights the need for robust benchmarking frameworks to guide implementation efforts.

The integration of marketing and AI is restructuring the boundaries of business possibilities, opening doors for enhanced customer experience, sharp decision-making, and improved efficiency. Verma *et al.* (2021) and Bock *et al.* (2020) emphasized the transformative potential of AI in marketing. Indeed, a recent study contended that customers more familiar with robots and AI would be predisposed to supporting AI marketing strategies (Belanche *et al.*, 2019). Thus, understanding perceptions will help business models lacing the relevant marketing approaches involving AI to meet expectations. The successful implementation of AI in marketing depends on understanding organizational readiness, the external environment, and the innovation attributes of AI (Jöhnk *et al.*, 2021; Pillai and Sivathanu, 2020). Therefore, organizations that want to reap the potential benefits of AI in marketing need to research the adoption of AI in marketing and overcome the challenges prevailing in the current business environment. Specifically, understanding the mechanisms of resistance to AI adoption represents a crucial yet understudied aspect of successful implementation strategies.

Our systematic review of the literature reveals four critical gaps in understanding AI adoption in marketing contexts. First, most of the existing research has focused on specific industries, such as B2B marketing (Keegan *et al.*, 2022; Paschen *et al.*, 2019), SMEs (Rani and Sundaram, 2022), or the hospitality and tourism sector (Goel *et al.*, 2022), impeding the development of generalizable benchmarking frameworks that transcends industry boundaries. Second, while the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) provides a robust framework for understanding technology adoption, its application to AI marketing contexts requires theoretical extension. Specifically, this framework does not account for technology resistance (TR) as a moderating variable—a particularly important consideration given AI's potentially disruptive impact on marketing roles and processes. Third, the TR literature has evolved separately from AI adoption research. While resistance has been identified as a critical barrier to technology implementation (Bhattacherjee and Hikmet, 2007; Lapointe and Rivard, 2005), its role in moderating AI adoption factors in marketing remains unexplored. This gap is particularly significant given evidence that AI technologies generate heightened resistance due to perceived threats to professional identity and autonomy (Belanche *et al.*, 2019; Fu *et al.*, 2022). Fourth, conventional variance-based approaches have dominated the literature, neglecting successful AI implementation's complex, configurational nature. This methodological limitation prevents the identification of multiple equifinal pathways that could serve as distinct benchmarking archetypes for adoption that account for contextual variations across marketing environments (Ragin, 2000; Misangyi *et al.*, 2017).

The lack of comprehensive knowledge about the factors affecting the adoption of AI in marketing and the role of TR raises critical questions for establishing effective benchmarking standards. Thus, businesses need to understand how to overcome the resistance factors to maximize the benefits of AI integration. This limited understanding hampers effective decision-making vis-à-vis AI investments, risk management, and strategic formulation. Based on these identified gaps, this study addresses four specific research questions: (1) What factors significantly influence the behavioral intention to adopt AI in marketing, establishing generalizable benchmarks for adoption readiness? (2) How does TR moderate the relationships between these UTAUT 2 factors and behavioral intention, providing standards for assessing implementation barriers? (3) What configurations of factors constitute distinct benchmarking archetypes that lead to successful AI adoption in marketing contexts? (4) How does AI adoption ultimately impact marketing efficiency as measured against performance assessment benchmarks? Addressing these questions is essential for improving organizational decision-making regarding AI investments, risk management, and strategic formulation in marketing contexts.

This study develops and tests an integrated benchmarking model examining how TR moderates AI adoption in marketing and its subsequent impact on marketing efficiency among Sri Lankan firms. Using data from 353 marketing professionals across diverse industries, we test this framework using a multi-method approach that combines partial least squares structural equation modeling (PLS-SEM) with fuzzy-set qualitative comparative analysis (fsQCA), providing complementary benchmarking perspectives: PLS-SEM establishes generalizable benchmarks while fsQCA reveals distinct "adoption archetypes" that serve as configurational benchmarks. By identifying empirically validated benchmarking typologies in AI adoption while testing their relationship to marketing efficiency, this study provides organizations with diagnostic tools to benchmark their AI implementation readiness against industry standards, identify contextually appropriate adoption pathways, and develop targeted strategies to reduce TR, maximize AI integration, and enhance marketing performance for competitive advantage.

2. Literature review

2.1 Empirical findings

AI has become a significant player in marketing, influencing market information, service theories, and customer interactions. This study examines AI adoption through both individual acceptance factors and organizational benchmarking dimensions—specifically technology benchmarking, strategic capability alignment, and performance assessment tools, which will be defined in our conceptual framework. Paschen *et al.* (2019) explain the fundamentals of AI systems and related B2B marketing. Bock *et al.* (2020) look at AI's current and future impact on service theories that deal with the service encounter. Grandinetti (2020) explains aspects of AI applications that sway the business-to-consumer relationship, concentrating on mass customization. Van Esch and Stewart Black (2021) describe the trailblazing effect AI-enabled digital marketing has on content production, lead generation, customer experiences, and social media marketing. The existing body of research details AI's far-reaching influence over marketing practices and strategies. AI-powered algorithms in diversified industries have been proven to increase operational efficiency while reducing errors.

While recent empirical studies have documented AI's applications in marketing, understanding adoption decisions requires grounding in foundational research. McCarthy *et al.* (2006) original conception of AI established the theoretical foundations, while Simon and Laird (2019) work on decision-making with technology shaped organizational adoption perspectives. Rust and Huang (2014) examined how AI transforms marketing through service automation, while Davenport and Ronanki (2018) categorized AI applications into process automation, cognitive insight, and cognitive engagement—providing a framework for understanding what capabilities marketing professionals are actually adopting. These seminal works help clarify the distinct AI constructs being measured in this study. Integrating AI technologies to adopt precision and personalized marketing activities (Yang *et al.*, 2021) will greatly increase marketing effectiveness at a lower cost. Moreover, AI will improve target marketing by effectively identifying customer needs, thus strengthening relationships between marketers and customers (Mishra *et al.*, 2022).

Previous research has identified several factors that impact the adoption of AI in various applications. These factors include familiarity with robots, support from top management, and cost-effectiveness (Belanche *et al.*, 2019); competitive pressure, relative advantage, HR readiness, and vendor support (Pillai and Sivathanu, 2020); technology readiness and service awareness by customers (Flavián *et al.*, 2021); marketing analytics capability and high data maturity (Rahman *et al.*, 2021); complexity from different internal and external technologies, processes, and equipment (Dora *et al.*, 2021); firm size, perceived ease of use, perceived usefulness, and organizational competence (Na *et al.*, 2023); and environmental, technological, and organizational context factors, perceived benefits, organizational readiness, and technical expertise (Qahtani and Alsmairat, 2023). These factors play a critical role in shaping the adoption and usage of AI in marketing strategies. Bag *et al.* (2021) present evidence on how AI technologies boost user engagement, which proves that strategic and operational goals need closer integration with AI initiatives. Reddy *et al.* (2023) investigate adoption barriers for data science by analyzing operational challenges that prevent AI deployment, and these findings directly match AI assessment in marketing contexts.

Performance assessment tools and strategic capability alignment need to figure into marketing operations that implement AI technology. According to Gani *et al.* (2022), organizations must establish two dynamic capabilities, collaboration and organizational agility, to properly link AI systems to marketing objectives. Pillai and Sivathanu's (2020) utilization of the TOE framework demonstrates how IT/ITeS organizations adopt AI by evaluating their management backing, cost-effectiveness, and organizational readiness, which can be applied to marketing teams integrating AI tools into their operations.

2.2 Conceptual framework

Marketing is one of the sectors where AI develops in close correspondence. This has necessitated a strong theoretical framework to help understand the factors related to AI adoption by marketing professionals. Due to this fact, UTAUT2 stands as one of the most applicable models because it includes improved individual-level constructs to aid in technology acceptance (Venkatesh *et al.*, 2012). Although UTAUT2 offers a strong explanatory model for individual technology adoption, benchmarking theory extends our knowledge of organizational dimensions that are important for the implementation of AI. Technology benchmarking offers standardized metrics for evaluating AI implementation success (Bag *et al.*, 2021; Srivastava and Bag, 2023), strategic capability alignment examines how organizational resources must align with adoption intentions (Pillai and Sivathanu, 2020), and performance assessment tools provide frameworks for measuring post-adoption efficiency outcomes (Reddy *et al.*, 2023). The integrated theoretical approach targets essential individual and organizational factors that drive AI adoption success within marketing environments.

In addition to integrating key components of the leading theories of technology adoption, UTAUT2 is theoretically rich because it provides a unique perspective of the multilayer drivers of acceptance and use of technology. Additionally, numerous research studies have found empirical validation of UTAUT2 in terms of different technological contexts, and all those validate the phenomenal success of UTAUT2 in the study of adopting AI. Examples include de Blanes Sebastián *et al.* (2023), Farzin *et al.* (2021), and Suo *et al.* (2022), who have given testimony that various technological contexts prove UTAUT2 to be effective, hence successful, at motivating the adoption of AI systems. For instance, basing their arguments on assessing the model's adaptiveness, works by Foroughi *et al.* (2023), Islam *et al.* (2022) studied the areas of autonomous vehicles to AI-driven recruitment processes. From a benchmarking perspective, strategic capability alignment research demonstrates that successful AI adoption requires organizational readiness beyond individual acceptance factors (Hashem and Aboelmaged, 2023), Gani *et al.* (2022). This complements UTAUT2 by highlighting how facilitating conditions must be assessed against industry benchmarks rather than in isolation. In addition, applicability is greatly supported by the tri-segmented application model that Gansser and Reich (2021) added when discussing using chatbots for coaching. Despite the varied general evidence, it underlines the suitability of UTAUT2 regarding the factors influencing AI adoption in marketing.

The study uses benchmarking theory together with supplementary methodological approaches to study AI adoption. Our research design advances benchmarking literature in three ways. First, marketing professionals' adoption factors introduce domain-specific metrics that capture operational performance improvements from AI implementation, expanding traditional technology benchmarking approaches (Pillai and Sivathanu, 2020). While IT benchmarks focus primarily on technical efficiency, our marketing-centric approach measures success through KPIs such as accuracy of personalization and agility of conversion. Second, our PLS-SEM analysis reveals how individual adoption factors establish generalizable benchmarks for marketing technology implementation, building on Gani *et al.* (2022) work on technology integration capabilities. Third, our fsQCA methodology identifies distinct adoption archetypes that serve as configurational benchmarks against which organizations can assess their AI marketing initiatives. This study aims to fill the gap in benchmarking literature by contextualizing technology adoption benchmarks through marketing professionals' perspectives. In line with the benchmarking focus on operational excellence and industry-based benchmarking frameworks within the context of performance measurement, our dual-methodology approach provides marketing leaders with actionable diagnostics for assessing AI readiness, implementation pathways, and potential performance outcomes.

2.3 Hypothesis development

Performance expectancy (PEX) refers to the degree to which a marketing professional believes that adopting AI will enhance their job performance. It involves judging that the latest technology enables efficient execution, is productive, and saves effort and time in executing activities. From a technology benchmarking standpoint, PEX must be measured against quantifiable industry metrics, with a recent study showing that meaningful improvement in overall user engagement is possible when AI technology is well implemented (Bag *et al.*, 2021). Ramachandran *et al.* (2023) show that qualified staff and management support greatly impact adoption intentions, illustrating how the integration of AI can enhance decision-making capabilities in complex environments. This finding resonates with those that indicate AI deployment leads to improved user experiences, driving repurchase intentions and supporting more effective strategic marketing decisions (Bag *et al.*, 2021). The general findings in this field show a pattern that higher BI for AI adoption could be derived from the perceptions of its usefulness, efficiency, and effectiveness.

H1. PEX influences Behavioural Intention to adopt AI in marketing (BIU).

Effort Expectancy (EEX) is defined as the perceived degree of ease associated with using AI systems in marketing. AI-based systems in professional services can help improve operational efficiency through task automation by enhancing professionals' capabilities to shorten user effort (Spring *et al.*, 2022). EEX stands crucial for the UTAUT2 model because it shapes user adoption decisions through beneficial activity outcomes (Thaker *et al.*, 2022). Bag *et al.* (2021) empirically proved that AI technologies aimed at increasing user experience in digital environments accelerate engagement and conversion rates, highlighting the importance of user-friendly implementations. Pillai and Sivathanu (2020) use the TOE framework to show how organizational features affect technology acceptance with insights into how easy user experience shapes marketing technology decisions. These studies provide evidence for this proposition that EEX impacts the BI of adopting AI.

H2. EEX influences BIU.

Social influence (SIN) represents the extent to which marketing professionals perceive that important others believe they should adopt AI technologies. Trawnih *et al.* (2023) found that the pressure exerted by trading partners-a form of SIN-had a positive relationship with the BI to adopt social commerce among SMEs in Jordan. Indeed, in one study, SIN and BI were significantly related to adopting QR-code mobile payment. Suo *et al.* (2022) pointed out that in this regard, Chu *et al.* (2022) report SIN to be a significant predictor of consumers' intentions toward adopting intelligent elevators in Taiwan. In another study, however, SIN was shown to influence significantly the acceptance of AI applications (Cabrera-Sánchez *et al.*, 2021). With more recency, SIN was reported to use UTAUT2 as a powerful driving force for intentions to adopt new technologies such as autonomous vehicles (Foroughi *et al.*, 2023).

H3. SIN influences BIU.

Facilitating conditions (FCN) refer to the organizational and technical infrastructure that supports the adoption and use of AI technologies surfaced among the central contending predictors of AI adoption (Zuiderwijk *et al.*, 2015). It has been further brought out by other studies that user training, helpdesk support, and provision of other requisite tools are major influencing factors on business and library users' intent for AI adoption (Cabrera-Sánchez *et al.*, 2021; Andrews *et al.*, 2021). These results prove that FCN should be encouraged to promote the adaptation to AI. However, besides ascertaining compatibility with current network systems, Khayer *et al.* (2020) also regarded compatibility as an essential facilitator for cloud-computing adoption among SMEs. Further, Grover *et al.* (2022) emphasized that FCN is an essential contributor towards AI operations management adoption, suggesting that AI-compatible marketing systems would benefit from FCN, provided that certain conditions are met. Strategic capability alignment research further demonstrates that FCN must be benchmarked against organizational readiness frameworks to ensure successful implementation (Pillai and Sivathanu, 2020; Hashem and Aboelmaged, 2023).

H4. FCN influences BIU.

Hedonic motivation (HMT) refers to the pleasure and enjoyment derived from using AI technologies in marketing. Numerous studies have already provided evidence showing that HMT is an important predictor of the intention to adopt AI technology. Some of these empirical studies show the importance of the UTAUT-2 framework of the adoption intent. For example, In their research on autonomous vehicles, Foroughi *et al.* (2023) posited that HMT is important, whereby perceived hedonic value should significantly predict intentions to use AI. In these lines, Thaker *et al.* (2022) considered HMT through UTAUT2 to enhance the explanatory power for BI and usage. This remains aligned with the finding of Chu *et al.* (2022), in which HMT has been identified as an important salient factor for adopting intelligent elevator technology. The findings of Salgado *et al.* (2020) provided evidence that HMT, in effect, enhanced explained variance in acceptance of mobile health. HMT hence inspires the intention to adopt AI-technology-powered mobile payment marketing platforms. Thus, converging evidence from the reviewed studies shows that enjoyment and pleasure perceived to be gained from AI represent important implications for the adoption intentions of these technologies.

H5. HMT influences BIU.

Price-value (PRV) represents the cognitive tradeoff between the perceived benefits of AI applications and their monetary costs and has consistently been evidenced as an important determinant of behavioral intentions (BI) to adopt new technologies within the UTAUT2 framework. Technology benchmarking research demonstrates that this cost-benefit evaluation can be systematically assessed through established metrics in e-commerce contexts, where AI implementation ROI is quantifiably measured against industry standards (Deng and Guo, 2023). Thaker *et al.* (2022) demonstrated that favorable cost-benefit appraisals significantly increased adoption intentions. Further support comes from Almaiah *et al.* (2022), who identified perceived price value as a key determinant of the customer's intention of technology acceptance. Cabrera-Sánchez *et al.* (2021) did provide longitudinal evidence predicting that PRV predicts subsequent technology usage.

H6. PRV influences BIU

Habit (HAB) refers to the extent to which marketing professionals tend to perform behaviors automatically as a result of prior experience with similar technologies. This is one of the determiners of the intention to use new technologies in the UTAUT2 framework that has always received support through evidence. The effect suggested by empirical evidence was that, since it is underpinned in repetition and practiced routine, habit is strong enough to outweigh other variables in determining technology acceptance intentions and behaviors. Consistent with this, Faraj *et al.* (2023) discovered the positive relationships between habit and using different emerging technologies. Concerning AI in particular, Chu *et al.* (2022) found that habit is one of the most potent consumption intention determinants for consumers of intelligent elevators. Also, Andrews *et al.* (2021) revealed how habits significantly influence the acceptance of AI tools among librarians. Furthermore, habit impacts a vast range of technologies, including mobile learning (Nikolopoulou *et al.*, 2021), QR payments (Suo *et al.*, 2022), mobile health (Salgado *et al.*, 2020), internet banking (Thaker *et al.*, 2022), mobile banking (Farzin *et al.*, 2021), and mobile wallets (Faraj *et al.*, 2023).

H7. HAB influences BIU.

Behavioural intention functions as a primary influencing factor of technology usage behavior in the UTAUT model (Venkatesh *et al.*, 2003). BIU stands as the professional marketing commitment to using AI technologies in their marketing applications. Research on dynamic capabilities benchmarking creates organizational assessment frameworks to evaluate the implementation success of intentions by measuring organizational agility for behavior–intention gap closure (Gani *et al.*, 2022). From the perspective of benchmarking, AI implementation demands the existence of individual intentions as well as collective organizational capabilities, which can be compared to industry standards. Other studies have confirmed this pattern in their research findings. Saprikis *et al.* (2022) analyzed mobile banking applications to establish important BI affecting factors while understanding their impact on marketing technology adoption. Multiple research contexts demonstrate that BI produces substantial impacts on technology acceptance through various settings.

H8. BIU influences the actual use behavior of AI in marketing (AU).

Actual use (AU) refers to the observable implementation and utilization of AI technologies within marketing operations. Studies from different contexts and domains reported consistent findings that FCN positively influences AI use behavior in marketing activities (Butarbutar *et al.*, 2022). The findings show that supportive resources, infrastructures, and an enabling environment can promote and encourage individuals to engage in AI technologies actively. Furthermore, the constructs of FCN, HAB, trust, and personal innovation significantly influenced AI adoption and use behavior in organizational settings (Saura *et al.*, 2023). Moreover, HAB significantly influences AI use behavior (Nikolopoulou *et al.*, 2021). The HAB and routines of individuals strongly influence their use behavior when adopting AI technology in marketing-related activities. Other factors that fall under the UTAUT2 model, HMT, have been found to influence behavioral intention and use behavior (Salgado *et al.*, 2020; Wu *et al.*, 2007). So, based on the evidence produced, it might be said that FCN and habit play an indispensable role in the use behavior of AI in the marketing domain.

H9. FCN influences AU

H10. HAB influences AU

The resource-based view (RBV) functions as the core theoretical consideration when businesses implement AI to enhance MKE. The term marketing efficiency (MKE) is defined as using AI to optimize marketing performance by improving the way resources are used. MKE is operationalized by means of campaign responsiveness (Tammela *et al.*, 2013), operational streamlining (Thien *et al.*, 2023), ROI, cost efficiency (Singh and Gundimeda, 2021), and team productivity, validated through benchmarking studies on various cases of technology adoption. RBV principles indicate that the sources of competitive advantage and superior performance lie in firms that have rare, valuable and difficult-to-imitate resources (Barney, 1991). Although RBV explains why AI capabilities create competitive advantage, performance assessment benchmarking is also a methodological framework for systematically measuring these advantages across organizations and industries (Ramachandran *et al.*, 2023; Kumar and Singh, 2019). The empirical data confirms that the use of AI leads to better marketing efficiency as it helps optimize data-backed operations in areas of pricing, promotions, recommendations and customer engagement strategy (Mishra *et al.*, 2022). Seminal studies directly studying the connection between AI adoption and MKE examined AI's role in personalization strategies and customer engagement metrics (Kumar *et al.*, 2019), as well as enhancements in marketing tasks achieved by human-AI cooperation (Paschen *et al.*, 2020). Finally, these studies provide empirical support to the relationship between AI adoption and marketing performance improvements, as suggested in our model.

H11. AU enhances MKE.

Understanding resistance to technological innovation is critical when examining AI adoption. Implementation barrier benchmarking research identifies resistance factors that impede adoption across contexts, enabling systematic assessment against industry benchmarks to develop mitigation strategies (Reddy *et al.*, 2023). Lapointe and Rivard (2005) developed a multilevel resistance model relevant to understanding marketing teams' responses to AI adoption initiatives. This resistance perspective complements adoption models and offers insights into the barriers marketing professionals face when considering AI technologies. If a new information system is installed, users decide whether to adopt or resist it based on assessment (Joshi, 2005). TR refers to marketing professionals' opposition or reluctance toward adopting AI technologies. Oreg (2003) foundational work established the psychological dimensions that predict which professionals might resist technological change regardless of potential benefits. It is a serious barrier to diffusion and success in implementing any innovation (Talwar *et al.*, 2020; Fu *et al.*, 2022). In the context of AI specifically, Longoni and Cian (2022) demonstrated that resistance is heightened when it appears to replace human judgment in creative or strategic marketing tasks. For instance, while Talwar *et al.* (2020) observed that the key point to adoption is addressing resistance, Fu *et al.* (2022) noted that—understanding and overcoming resistance can help facilitate technology diffusion. Literature shows some drivers as fear of change, unfamiliarity, work process disruptions, and image and tradition concerns (O'Shaughnessy *et al.*, 2021). Based on the above arguments, we can propose the following hypotheses:

H12. TR negatively affects BIU.

H13a-H13g. TR moderates the relationships between PEX, EEX, SIN, FCN, HMT, PRV, HAB, and BIU.

Based on the above-proposed hypotheses, a conceptual framework is formulated, as shown in Figure 1.

3. Research methodology

3.1 Sampling strategy and data collection

The target population includes marketing professionals within all sections where AI technology can be plausibly implemented. The selection of respondents was carried out by using purposive sampling. Purposive sampling was necessary, given the specialized knowledge required to evaluate AI marketing technologies meaningfully (Patton, 2002; Mohamed Riyath and Inun Jariya, 2024). Initial respondents were identified through professional marketing associations in Sri Lanka and key informants at leading companies who provided access to qualified professionals across various industries. This approach

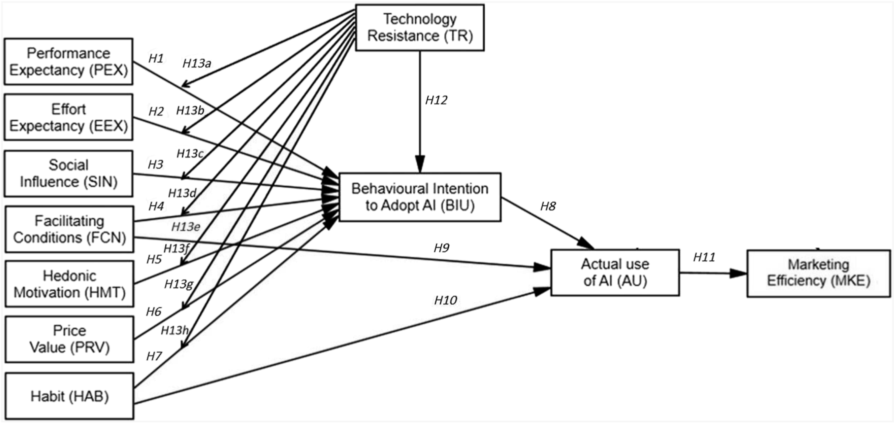

Figure 1. Conceptual framework. Source: Authors' own work

ensured diversity in our initial recruitment before expanding to the full sample. An attempt has been made to ensure that a sample is chosen appropriately to represent the segments where AI integration was plausible for representation. The sampling frame was restricted to include only marketing professionals with direct experience with at least two AI marketing applications and a minimum of one year of marketing technology experience. The respondents' identification included sending SMS-based marketing campaigns, advertising over the social media platform, using CRM technologies in large companies, and excelling as a reputed seller on the e-commerce platform. Respondents were also taken from telecommunication, e-commerce, finance, media, technology start-ups, and marketing agency individuals. This process ultimately resulted in 364 responses from an initial pool of 527 eligible professionals (69.1% response rate), yielding a final sample of 353 respondents after data cleaning. Non-response bias was assessed through wave analysis comparing early and late respondents, revealing no significant differences ($p > 0.05$). Further, a team of five research assistants was recruited for this study to ensure efficient data collection. Data collection was conducted exclusively through in-person meetings by these well-trained research assistants, which allowed verification of respondent qualifications in real-time and ensured data quality. To encourage thoughtful participation, we promised to share the study's findings with respondents.

3.2 Instrument development and validation

A questionnaire was administered to collect the data in this study. All UTAUT2 constructs were adapted from Venkatesh *et al.* (2012), with wording modified to reference AI marketing applications specifically. TR and marketing efficiency measures were new custom-developed following DeVellis and Thorpe (2021) guidelines. Given that the instrument's validity is one of the most essential aspects, five professionals and five professors in the field of Marketing ensure the questionnaire's face and content validity. After validation, additional experts were requested to analyze the scale items' clarity, relevance, and comprehensive nature. The consolidated final version comprises two sections, the first being MCQs aimed at collecting demographic information. The demographic data collected was analyzed using SPSS to gain insights into the respondents' profiles. The second section of the questionnaire measured respondents' perceptions of the respective indicators for the constructs under study. A 7-point Likert scale that used "strongly disagree" (1) to "strongly agree" (7) measured the agreement of the respondents with the statements. This scale was employed following established practices in technology adoption research (Venkatesh *et al.*, 2012; Thaker *et al.*, 2022) as it provides finer discrimination between response options compared to 5-point scales, facilitating more precise measurement of complex psychological constructs (Finstad, 2010).

The potential common method bias in the study was assessed using the one-factor method. It involves extracting a single factor from the questionnaire items and testing if it explains a large variance in the constructs. Responses with >10% missing data were excluded ($n = 4$). For minor missing values, Expectation-Maximization (EM) imputation was applied. Potential outliers were identified by examining standard deviations of respondent scores, with seven cases removed after qualitative review.

3.3 PLS-SEM analysis procedure

A two-stage data analysis was conducted. The first stage checks construct validity and reliability. Internal consistency and convergent validity were evaluated using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) (Hair *et al.*, 2017). This study checked the discriminant validity using the Fornell–Larcker criterion and Heterotrait-Monotrait (HTMT) ratio. Stage Two runs the hypothesized model by PLS-SEM through Partial Least Square Structural Equation Modeling. A bootstrap of 5,000 subsamples was taken to test the significance of path coefficients. The SRMR (Standardized Root Mean Square Residual), NFI (Normed Fit Index), and rms Theta are used to check the model fit. It gives insight from these indices into the suitability of the proposed model (Henseler *et al.*, 2015).

3.4 fsQCA implementation

To strengthen our research design, we tended to combine the PLS-SEM approach with advanced analytical techniques. Thus, we further infuse the Fuzzy Set Qualitative Comparative Analysis (fsQCA) methodology into the process as a valuable addition to our existing framework. The fsQCA is used to look into configurations of factors leading to a high level of outcome (Ragin, 2000). It accommodates the complex nature of causality, characterized by causal complexity, equifinality, and asymmetry of relationships among the conditions and the outcomes. fsQCA is one of the case-oriented configurational approaches and is highly applicable, particularly in those cases of representation of causality when it is complex (Misangyi *et al.*, 2017). In this method, the fsQCA methodology allowed a robust establishment of the combination conditions related to high degrees of adoption of AI marketing technologies at the highest level and brought actionable insights for the marketing managers. It includes calibrating variables to the set memberships, constructing truth tables summarizing configurations, and deriving simplified combinatorial conditions connected to an outcome using Boolean algebra (Greckhamer *et al.*, 2018). For fsQCA, survey data on adoption drivers was first normalized into scores from 0 to 1 (Sukhov *et al.*, 2023). The values of calibration thresholds were defined based on the theory of data distribution, such as 1 for full membership, 0.5 for crossover, and 0 for full non-membership in the set of high AI adoption intention (Rasoolimanesh *et al.*, 2023; Ragin, 2000). A direct-designed set of cases that obtain scores for the membership of sets by their relative standing on the factors (Pappas and Woodside, 2021). To ensure consistency in calibration, percentiles (fully in >90%, the crossover point 50%, fully out <10%) of data distribution were used as external criteria to calibrate the scores of the latent variables (Sukhov *et al.*, 2023). This was followed by an analysis using a truth table, which indicated the configurations of the conditions that predict high AU. Solutions were derived using the Quine-McCluskey algorithmic minimization and derived from complex, parsimonious, and intermediate solutions (Ragin, 2000; Pappas and Woodside, 2021). Further attempts have been made to enhance the robustness with a change by applying a frequency threshold of three cases and a consistency cut-off of 0.9 (Pappas and Woodside, 2021; Rasoolimanesh *et al.*, 2023).

3.5 fsQCA predictive validity testing

Testing out-of-sample data is performed to assess the predictive power, the external validity and generalization of the results. The whole sample is randomly split into two subsets (Greckhamer *et al.*, 2018; Sukhov *et al.*, 2023; Pappas and Woodside, 2021). From this subsample, solutions are derived and tested for their predictive accuracy in being a member of the outcome set against the second holdout sample. Consistency and coverage scores were calculated to assess the predictive validity of the initial solution (Pappas and Woodside, 2021; Sukhov *et al.*, 2023). It sought to verify the properties of relevancy and stability for the extracted configurations concerning new data. A configuration chart was also built to examine the complex, parsimonious, and intermediate solutions generated through the fsQCA (Fiss, 2011). This visual representation delineates the core configurations of conditions consistently associated with a high level of AU. The chart provides a synoptic summary of the combinatorial recipes identified and labeled as sufficient for the outcome based on the analysis.

3.6 Methodological integration for benchmarking

This study employs complementary methodological approaches that create a robust benchmarking framework for AI adoption. PLS-SEM establishes generalizable performance benchmarks through linear, symmetrical relationships, revealing which UTAUT2 factors consistently predict adoption success across contexts. Conversely, fsQCA uncovers distinct “adoption archetypes” or “readiness profiles” - specific configurational benchmarks representing multiple equifinal pathways to successful implementation (Ragin, 2000; Misangyi *et al.*, 2017; Del Giudice *et al.*, 2018). This approach contrasts PLS-SEM’s linear analysis of individual adoption drivers (e.g. EEX → BIU) with fsQCA’s identification of synergistic condition combinations (e.g. EEX + FCN + HAB) that could define adoption archetypes. This illustrates how the methods serve complementary benchmarking functions: while PLS-SEM might identify factors like “ease-of-use” as standalone predictors of adoption, fsQCA can reveal how such factors might only drive success when combined with other elements—potentially defining distinctive adoption archetypes. Importantly, the identification of multiple viable pathways allows organizations to benchmark against diverse strategies rather than a single “best” approach, acknowledging that optimal implementation approaches vary by organizational context. This methodological integration enables practitioners to evaluate their organization against both industry-standard performance indicators and specific capability benchmarks aligned with their unique characteristics, providing empirically validated reference points to assess AI implementation readiness and develop targeted improvement strategies.

4. Findings and discussion

4.1 Descriptive study

The demographic profile of the respondents (Table 1) provides an overall view of the sample, expressing the diverse cross-section of marketing professionals in Sri Lanka. The gender distribution is male-dominant, where males represented 71.1% ($n = 251$) and 28.9% ($n = 102$) represented females. Most of the respondents (70%, $n = 247$) are 31–50 years old, thus ensuring that experienced professional inputs are brought in. Educational qualification is at the degree level (40.2%, $n = 142$) and postgraduate (29.7%, $n = 105$), showing a highly educated sample. The educational background is varied, with significant representation from IT/Engineering (39.1%, $n = 138$) and Business (27.2%, $n = 96$), aligning with the study’s focus on technology and marketing. In addition to diversity, degrees were obtained from foreign (45.6%, $n = 161$) and local (54.4%, $n = 192$) institutions. The distribution of the working industry focuses on sectors relative to the adoption of AI, such as Retail (31.2%, $n = 110$) and technology (12.2%, $n = 43$). This ensures that the respondents cut across a wide spectrum of industry perspectives, including those from finance (13.0%, $n = 46$) and entertainment (16.7%, $n = 59$).

4.2 Stage one: measurement model

Table 2, Panel A shows the reliability and validity of the under-investigation constructs in the form of Cronbach’s Alpha, Composite Reliability (CR), and Average Variance Extracted

Table 1. Descriptive statistics of demographic profile of respondents

		Count	N %
Gender	Female	102	28.9
	Male	251	71.1
Age	Below 30	58	16.4
	31–40	133	37.7
	41–50	114	32.3
	Above 50	48	13.6
Education level	A/L / Diploma	44	12.5
	Degree	142	40.2
	Postgraduate	105	29.7
	Professional Qualification	62	17.6
Educational background	Business	96	27.2
	IT / Engineering	138	39.1
	Science	74	21.0
	Social Science / Language	45	12.7
Degree offered by	Foreign	161	45.6
	Local	192	54.4
Working industry	Technology	43	12.2
	Retail	110	31.2
	Finance	46	13.0
	Entertainment	59	16.7
	Other	95	26.9

Source(s): Authors' own work

(AVE). Based on this, Cronbach's Alpha had a value that falls between 0.767 and 0.953, and this gives an excellent internal consistency ($\alpha > 0.9$) for AU, EEX, FCN, HAB, HMT, and TRS; good consistency ($0.8 < \alpha < 0.9$) for MKE, PEX, and SIN, while BIU reflects acceptable consistency (0.767). Composite reliability values were uniformly high, exceeding 0.9 for all constructs except BIU (0.852). The notably high Cronbach's Alpha and CR values can be attributed to several factors: (1) the homogeneity of our sample in terms of professional experience and educational background, leading to more consistent response patterns; (2) the rigorous scale adaptation process that enhanced item clarity; and (3) the pre-qualification of respondents ensuring all participants had sufficient knowledge to provide informed responses about AI marketing technologies.

The AVE values gave a clue for the convergent validity: AU, EEX, FCN, HMT, HAB, PEX, SIN and TRS were strong (AVE >0.7), and BIU, MKE, and PRV were at an acceptable level (0.5 < AVE <0.7). The statistical measures collectively affirm the constructs' internal consistency and convergent validity. Table 2, Panel B, below, provides evidence of how the discriminant validity was tested between the constructs using the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker Criterion. Most values between the constructs in the matrix were significantly less than 0.85, giving good evidence across the constructs in the study for discriminant validity. However, there were high values with several pairs, such as AU and BIU (0.686), and BIU and TRS (0.685), which could call for distinctiveness. From the Fornell-Larcker Criterion matrix, the diagonal values of the square root of AVE for each construct were generally higher than the corresponding off-diagonal values. This pattern, in which the discriminant validity of the constructs is supported, suggests that the constructs have more variance in common with the indicators than with each other.

4.3 Stage two: structural equation model

The structural equation model analysis results, presented in Table 3 and Figure 2, exhibit quite reasonable empirical substantiation toward several hypothesized relationships in the research

Table 2. Measurement model

Panel A: Construct reliability and convergent validity

Construct	Items	Operationalization	Item loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
AU	AU1	Frequency of use	0.870	0.917	0.938	0.752
	AU2	Integration level	0.850			
	AU3	Decision reliance	0.849			
	AU4	Daily usage rate	0.856			
	AU5	Standardization level	0.910			
BIU	BIU1	Plan to adopt	0.847	0.767	0.852	0.593
	BIU2	Intention strength	0.842			
	BIU3	Adoption likelihood	0.625			
	BIU5	Aim clarity	0.745			
EEX	EEX1	Learning ease	0.857	0.905	0.933	0.777
	EEX2	User-friendliness	0.890			
	EEX3	Operation ease	0.878			
	EEX4	Interaction ease	0.901			
FCN	FCN1	Resource availability	0.876	0.915	0.937	0.747
	FCN2	Support access	0.856			
	FCN3	System compatibility	0.836			
	FCN4	Org. support	0.890			
	FCN5	Training access	0.864			
HAB	HAB1	Routine use	0.840	0.901	0.927	0.719
	HAB2	Workflow fit	0.865			
	HAB3	Consistency intent	0.760			
	HAB4	Habit strength	0.838			
	HAB5	Regular use	0.930			
HMT	HMT1	Perceived fun	0.760	0.911	0.933	0.737
	HMT2	Enjoyment level	0.916			
	HMT3	Interest level	0.851			
	HMT5	Excitement level	0.847			
	HMT6	Pleasure level	0.909			
MKE	MKE1	Campaign responsiveness	0.837	0.888	0.918	0.692
	MKE3	ROI increase	0.794			
	MKE4	Cost efficiency	0.908			
	MKE5	Team productivity	0.833			
	MKE6	Process efficiency	0.782			
PEX	PEX3	Result improvement	0.923	0.895	0.927	0.762
	PEX4	Competitive edge	0.898			
	PEX5	Efficiency gain	0.884			
	PEX6	Productivity perception	0.778			
PRV	PRV1	Cost-benefit	0.831	0.877	0.91	0.67
	PRV2	Value perception	0.812			
	PRV3	Cost-effectiveness	0.821			
	PRV4	ROI potential	0.835			
	PRV5	Savings level	0.792			
SIN	SIN1	Peer influence	0.869	0.901	0.927	0.716
	SIN2	Colleague view	0.859			
	SIN3	Expert advice	0.828			
	SIN4	Opinion value	0.825			
	SIN5	Org. acceptance	0.849			

(*continued*)

Table 2. Continued

Panel A: Construct reliability and convergent validity

Construct	Items	Operationalization	Item loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
TRS	TRS1	Usage hesitation	0.917	0.953	0.964	0.841
	TRS2	Tech skepticism	0.918			
	TRS3	Integration resistance	0.915			
	TRS4	Discomfort level	0.925			
	TRS5	Learning reluctance	0.911			

Note(s): Missing item numbers (e.g. BIU4, HMT4, MKE2, PEX1, PEX2) were excluded during analysis due to low loadings
Source(s): Authors' own work

Panel B: Discriminant validity

	AU	BIU	EEX	FCN	HAB	HMT	MKE	PEX	PRV	SIN	TRS
Heterotrait-monotrait ratio (HTMT) – Matrix											
AU											
BIU	0.686										
EEX	0.132	0.362									
FCN	0.488	0.430	0.105								
HAB	0.450	0.474	0.142	0.242							
HMT	0.079	0.310	0.133	0.226	0.213						
MKE	0.563	0.397	0.175	0.107	0.150	0.072					
PEX	0.134	0.311	0.255	0.221	0.250	0.254	0.153				
PRV	0.212	0.459	0.173	0.129	0.128	0.164	0.223	0.173			
SIN	0.137	0.324	0.317	0.094	0.127	0.067	0.148	0.152	0.150		
TRS	0.395	0.685	0.069	0.171	0.124	0.078	0.231	0.071	0.179	0.047	
Fornell-Larcker criterion											
AU	0.867										
BIU	0.585	0.770									
EEX	0.122	0.305	0.882								
FCN	0.449	0.371	0.098	0.864							
HAB	0.412	0.403	0.134	0.223	0.848						
HMT	0.069	0.272	0.125	0.215	0.195	0.859					
MKE	0.511	0.329	0.154	0.101	0.135	0.063	0.832				
PEX	0.126	0.265	0.227	0.206	0.229	0.232	0.136	0.873			
PRV	0.192	0.379	0.153	0.118	0.116	0.154	0.193	0.156	0.818		
SIN	0.124	0.275	0.287	0.085	0.117	0.051	0.132	0.139	0.130	0.846	
TRS	−0.370	−0.592	−0.061	−0.160	−0.118	−0.071	−0.211	0.064	−0.167	−0.045	0.917

Source(s): Authors' own work

model. The results from the structural model lend substantial empirical support to the positive effect of PEX on BIU, where it yields a positive substantial standardized path coefficient of 0.126 ($p < 0.001$). The statistical significance indicates that PEX has a predictive relationship with AI adoption intentions. This finding corroborates prior research by Ramachandran *et al.* (2023) and underscores PEX as a key driver of technology acceptance, further highlighting the salience of perceptions of efficiency and effectiveness gains (Thaker *et al.*, 2022; Bag *et al.*, 2021). In this case, therefore, this underscores the importance of clear communication, which must be affected with possible tangible proof of how AI brings benefits in increasing productivity, marketing outcomes, and competitive advantages to marketing managers. Compelling cases for adopters of the performance value proposition of these technologies is

Table 3. SEM path analysis

Panel A: Hypothesis test

Hypothesis	Relationship	Path coefficient	STDEV	T-statistics	*P*-values
H1	PEX → BIU	0.126	0.035	3.616	0.000
H2	EEX → BIU	0.109	0.033	3.294	0.001
H3	SIN → BIU	0.139	0.034	4.06	0.000
H4	FCN → BIU	0.147	0.036	4.075	0.000
H5	HMT → BIU	0.093	0.036	2.618	0.009
H6	PRV → BIU	0.182	0.034	5.429	0.000
H7	HAB → BIU	0.212	0.037	5.781	0.000
H8	BIU → AU	0.415	0.046	9.117	0.000
H9	FCN → AU	0.253	0.041	6.144	0.000
H10	HAB → AU	0.189	0.047	3.978	0.000
H11	AU → MKE	0.511	0.035	14.439	0.000
H12	TRS → BIU	−0.549	0.035	15.629	0.000
H13a	TRS × PEX → BIU	−0.015	0.035	0.438	0.661
H13b	TRS × EEX → BIU	−0.082	0.035	2.335	0.020
H13c	TRS × SIN → BIU	0.028	0.044	0.629	0.529
H13d	TRS × FCN → BIU	−0.076	0.037	2.056	0.040
H13e	TRS × HMT → BIU	0.039	0.033	1.162	0.245
H13f	TRS × PRV → BIU	−0.028	0.033	0.861	0.389
H13g	TRS × HAB → BIU	−0.096	0.033	2.874	0.004

Panel B: Model fit

	R-square	R-square adjusted	SSO	SSE	Q^2 (=1-SSE/SSO)
BIU	0.661	0.646	1168.000	564.722	0.517
AU	0.434	0.429	1460.000	977.502	0.330
MKE	0.261	0.259	1460.000	1229.217	0.158

Note(s): SRMR: 0.049; d_ULS: 3.972; d_G: 1.092; Chi-square: 2172.422; NFI: 0.855
Source(s): Authors' own work

essential in showing, quantitatively, that AI can optimize workflows, improve marketing productivity, increase sales, and support competitive positioning.

The finding reveals that EEX positively influences BIU, with the standardized path coefficient at 0.109 ($p = 0.001$), meaning that the statistical significance is at a strong predictive relationship level. These align with previous findings, that continue to highlight EEX as a core driver of adoption intention with mitigating uncertainties (Thaker *et al.*, 2022; Bag *et al.*, 2021; Spring *et al.*, 2022). This points to an indispensable duty of marketing managers: reducing perceptions of complexity and enhancing the usability of the AI system. User-centered designs with intuitive interfaces, comprehensive training programs on system functionality, and responsive technical support can proactively address EEX perceptions. It would hugely lower the concerns about the level of effort and difficulties, positively affecting attitudes towards adopting AI technologies by reducing friction in usability and confusion.

The findings showed a statistically significant positive relationship between SIN and BIU, with a large standardized path coefficient value of 0.139 ($p < 0.001$). Therefore, the high significance level and large coefficient can give very good empirical support to SIN as a significant determinant that forms individual intentions to adopt AI. This finding corroborates prior UTAUT2-based research by Chu *et al.* (2022) and Trawnih *et al.* (2023) identifying SIN

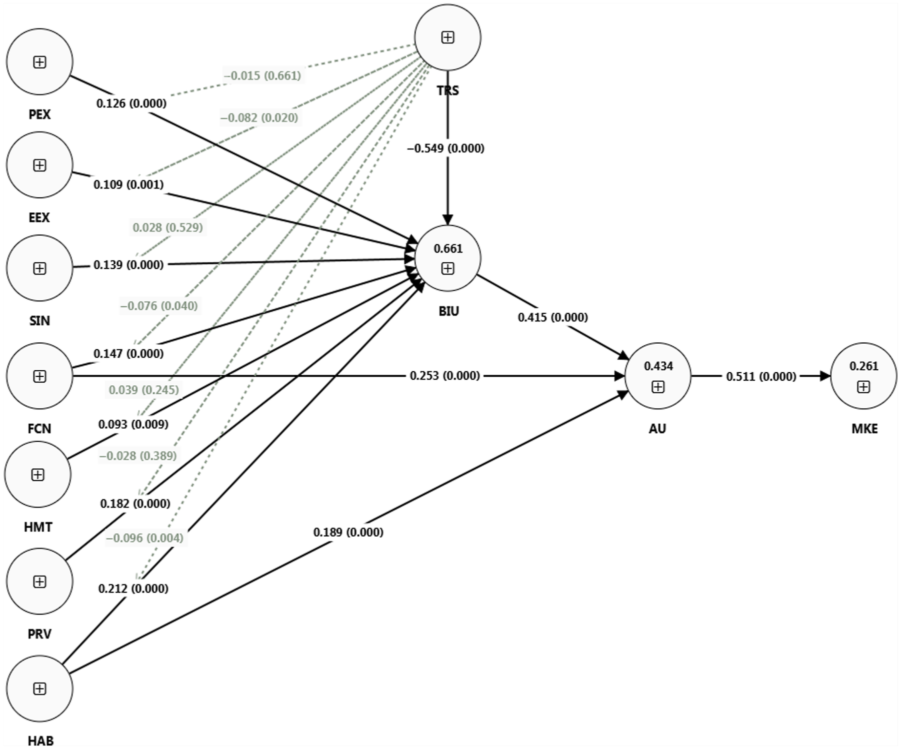

Figure 2. SEM path model. Source: Authors' own work

as a pivotal determinant, although its magnitude may be context-dependent (Cabrera-Sánchez *et al.*, 2021). This finding points out the need for marketing managers to continuously leverage credible referents, such as opinion leaders, experts, and peers, to provide salient subjective norms and vicarious experiences around AI adoption. Testimonials, communities of practice, and social networking are among the strategies that may enable potential adopters to see other people using AI technologies successfully. Social opportunities for learning and reinforcement from respected referents have a powerful impact on forming intentions toward systems for accepting AI.

More robust empirical support for the positive impact of HMT on BIU is shown with a value of 0.093 ($p = 0.009$) of a standardized path coefficient. The strong statistical significance confirmed the findings of previous studies grounded in UTAUT2, where perceptions of pleasure and enjoyment are considered critical drivers of technology acceptance (Chu *et al.*, 2022; Foroughi *et al.*, 2023; Luyao *et al.*, 2022). This highlights the importance of emphasizing AI technologies' inherent fun, enjoyment, and emotional benefits for marketing managers. Communications and campaigns that show novelty, coolness, or amusement of AI systems can be attractive from internal motivations. Potential adopters' exposure to immersive and entertaining AI applications can generate positive perceptions.

The substantial standardized path coefficient of 0.182 ($p < 0.001$) indicates a positive impact of PRV on BIU. The test's significant coefficient yields robust statistical support for the argument that favorable value-cost evaluations significantly influence adoption intentions. This aligns with past research, which identified perceived value relative to cost as having the highest relevance for technology acceptance (Almaiah *et al.*, 2022; Deng and

Guo, 2023). For marketing managers, this underscores the importance of demonstrating quantified ROI and analyses showing the benefits of AI exceed expenses. Cost-benefit analysis, return on investment models, and piloting can provide persuasive evidence of economic value propositions. Results indicate that the positive intention to adopt AI technologies emerges in marketing managers' efforts to promote favorable price value perceptions.

The result, therefore, represents clear and strong empirical evidence for a substantial positive effect of FCN on BIU, evidenced by the magnitude of the standardized path coefficient of 0.147 ($p < 0.001$). A strong predictive relationship accords with research done to receive support in favor of the influence the needed resources and infrastructures have on technology adoption intentions (Pillai and Sivathanu, 2020; Hashem and Aboelmaged, 2023). Furthermore, the empirical support revealed that FCN positively affected AU, with the standardized path coefficient being substantial at 0.253 ($p < 0.001$). This is in bounds with earlier research work that had alluded to the central role of resource availability and an enabling environment in enhancing the intensity of engagement with adopted AI technologies (Butarbutar *et al.*, 2022). The findings suggest that marketing managers must continue providing ongoing technical support, training, and infrastructure maintenance even after initial adoption to ensure sustained usage. Optimizing FCN along with the AI lifecycle will be one of the driving factors for successful adoption outcomes.

Persuasive empirical evidence emerges for the significant positive effect of HAB on BIU, as indicated by the standardized path coefficient of 0.212 ($p < 0.001$). This finding aligns with UTAUT2-based research, where habit was predictive of pronounced influence over the decision to adopt the technology compared to the other determinants, given its bases in well-ingrained behaviors and routines (Faraj *et al.*, 2023; Nikolopoulou *et al.*, 2021; Suo *et al.*, 2022). Further, HAB significantly positively affected AU at 0.189 ($p < 0.001$). Previous research confirms that the role of habit in continued usage among applications is, in fact, an important one (Nikolopoulou *et al.*, 2021). For marketing managers, the results suggest that leveraging well-established routines and workflows can strongly promote habitual engagement with AI systems over time. Seamless integration with ingrained processes ensures habits effectively drive persistent AI usage.

The findings from this study do provide strong empirical validation for the significant positive effect of BIU on AU, with a standardized path coefficient as large as 0.415 ($p < 0.001$). This aligns with the conceptualization in UTAUT that the intention to engage with technology is a proximal driver of actual adoption and use (Venkatesh *et al.*, 2003). The strong predictive relationship corroborates the broader technology acceptance literature evidencing intention's pivotal role in shaping usage behaviors across contexts (Saprikis *et al.*, 2022; Gani *et al.*, 2022). The findings underscore cultivating positive intentions toward AI technologies as a crucial prerequisite for ensuring actual adoption and deployment. Nurturing acceptance through perceived benefits, SIN, and facilitation is important for the initial "buy-in" stage to drive continuous active usage and integration of AI capabilities within marketing practices.

The study establishes firm empirical proof of the positive relationship ($\beta = 0.511$, $p < 0.001$) between AU and MKE while confirming AI capabilities as strategic resources that bring competitive advantages (Barney, 1991; Mishra *et al.*, 2022). The strong relationship confirms that the adoption of AI improves MKE along four aspects crucial for our study goals. AI-enabled automation in cost management streamlines labor costs through data collection and segmentation automation, which allocates human resources for strategic functions (Pillai and Sivathanu, 2020). Real-time data processing done by AI systems improves campaign responsiveness, allowing marketers to adapt their strategies based on detected shifts in consumer behavior (Bag *et al.*, 2021). AI personalization technology builds marketing approaches that enhance customer engagement rates and achieve better satisfaction results (Kumar *et al.*, 2019). At the same time, AI analytics boost ROI measurement precision to monitor marketing returns better (Basu and Bhola, 2021). Together, the defined efficiency dimensions fulfill our research purpose of understanding how AI implementation changes marketing operations to produce value. The tested relationship supports Paschen *et al.* (2020) finding about the efficiency benefits of human-AI teamwork since effective deployments yield measurable performance enhancements across all measured dimensions despite difficulty with implementation. The empirical analysis directly addresses the fourth research question through its demonstration of concrete relationships between AI implementation and MKE performance, which helps advance our research goal of creating assessment frameworks for implementation success.

The empirical evidence supports a negative significant relationship between TR and BIU ($\beta = -0.549$, $p < 0.001$). This result corresponds with existing literature that recognizes TR as one of the major obstacles to successful technology utilization (Reddy *et al.*, 2023; O'Shaughnessy *et al.*, 2021). Resistance often originates from the fear of change, unfamiliarity with the new systems, disruptions to established processes, and eliminating these sources of resistance is an essential enabler for user AI adoption and the diffusion of new technologies among marketing professionals (Talwar *et al.*, 2020; Fu *et al.*, 2022).

4.3.1 Moderating effect. Furthermore, investigating the moderating effects of TR toward BIU in marketing shows significant and nonsignificant interaction. Specifically, TR significantly moderates the relationship between EEX and BI to adopt AI ($\beta = -0.082$, $p = 0.020$, $f^2 = 0.0158$), implying that resistance might slightly dampen the effects of EEX on the adoption intent of AI. TR moderates the relationship between FCN and BI ($\beta = -0.076$, $p = 0.040$, $f^2 = 0.0128$) in the sense that resistance plays a role in determining the influence of FCN on AI adoption. Most importantly, it was found that the TR variable significantly moderates the relationship between the latent variable habit and BI ($\beta = -0.096$, $p = 0.004$, $f^2 = 0.0128$). The significant moderation between TR and EEX, FCN, and habit aligns with existing literature that identifies TR as a complex barrier hindering technological innovations (Fu *et al.*, 2022; Longoni and Cian, 2022; Talwar *et al.*, 2020). The specific contours and boundaries of resistance discovered in this study include cultural barriers and structures of the organization, which resonate with previous studies that have set multi-faceted structures of TR in place by Lapointe and Rivard (2005) and Oreg (2003). Again, the observed conceptual interactions will resonate with the arguments of Talwar *et al.* (2020) regarding the need to understand and strategically address TR when promoting AI adoption.

4.3.2 PLS-SEM model fit. The adjusted R Square and Q^2 values explain the model's efficacy in explaining and predicting marketing professionals' adoption variables. The above is shown in Table 3, Panel B. Specifically, the adjusted R Square values indicate that the model explains 66.1% of BIU, 43.4.9% of AU, and 26.1% of MKE. Correspondingly, the Q^2 values reveal predictive relevance of 51.7% for BIU, 33% for AU, and 15.8% for MKE. These combined statistics indicate that the model is strong in predicting or explaining BIU and AU, but there is still room for more improvement in capturing MKE (Nitzl *et al.*, 2016). The model fit statistics for the study on AI adoption in marketing were assessed using several indices. The SRMR value of 0.049 falls below the commonly accepted threshold of 0.08, indicating a good fit between the observed and predicted covariance matrices (Hu and Bentler, 1999). The value of d_ULS at 3.972 and d_G at 1.092 also supported the fit. However, the Chi-Square statistic of 2172.422, though large, is sensitive to sample size (Bollen, 1989). The Normed Fit Index (NFI) value at 0.855 has fallen slightly below the preferred cut-off of 0.9 but still exhibited an acceptable fit (Bentler and Bonett, 1980). The statistics, therefore, indicate evidence of the data being reasonably represented by the model estimates and contribute to supporting the construct validity of the constructs on the adoption of AI in marketing.

4.4 fsQCA analysis

4.4.1 Calibration and predictive validity assessment. Table 4, Panel A includes the calibration thresholds that are insightful into the differences in commitment levels of the latent variables to

Table 4. FsQCA

Panel A: Calibration threshold values for latent variables

	AU	BIU	EEX	FCN	HAB	HMT	PEX	PRV	SIN	TRS
Fully in >90%	0.713	0.762	0.873	0.816	0.771	0.783	0.842	0.852	0.804	0.827
Crossover point = 50%	0.464	0.538	0.583	0.569	0.537	0.537	0.522	0.603	0.497	0.273
Fully out <10%	0.210	0.289	0.278	0.303	0.307	0.304	0.210	0.334	0.194	0.103

Panel B: FsQCA model predictive validity test

Models	First subsample		Holdout sample (based on XY plot)	
	Coverage	Consistency	Coverage	Consistency
M2(Comprehensive adopters): BIU*EEX*FCN*HMT*PEX*PRV*~SIN*~TRS	0.1633	0.8787	0.1831	0.9438
M3(Experience pioneers): BIU*EEX*FCN*~HAB*HMT*~PEX*PRV*SIN	0.1309	0.9323	0.1533	0.8732
M4(Efficiency champions): BIU*EEX*FCN*HAB*HMT*PEX*PRV*~TRS	0.2239	0.9026	0.2324	0.9431

Source(s): Authors' own work

accept the use of AI in marketing; these thresholds establish standardized benchmarking parameters that provide an in-depth perspective on the adoption intent spectrum. A rigorous predictive validity assessment was conducted to evaluate the generalizability and stability of the adoption benchmark configurations identified through Truth Table Analysis (TTA). Three high-performing models (M2, M3, and M4) were selected based on raw coverage value and exceeding a consistency threshold of 0.8 on the first subsample of the data. These validated models underpin the seven AI adoption archetypes in Table 5, transforming statistical configurations into actionable benchmarking profiles. The holdout sample tested the predictive power of these models. Table 4, Panel B indicates that each of the three models illustrated strong consistency, the key criterion of predictive validity, when applied to the first subsample data. For instance, M4, where a high consistency of 0.9026 is maintained with a coverage value of 0.2239, reflects the robustness of the "Comprehensive Adopters" archetype as a benchmarking standard. Another technique used to assess the models' consistency and raw coverage is the XY plot shown in Figure 3, which validates the results in Table 4 using the holdout sample. Model M4's coverage and consistency on the holdout sample are 0.2324 and 0.9431, respectively. This implies that the configurations captured meaningfully distinct benchmarking archetypes representing viable pathways to high adoption. The present analysis yields that the TTA-derived benchmarking models are generalizable and give consistent, valid predictions even if they are used with a new data set. The predictive strength of the configurations is also verified using the holdout sample. This underlines the external validity of the modeling approach, which reveals complex combinations of conditions that regularly result in strong adoption intentions across diverse datasets in the marketing domain.

4.4.2 Core and peripheral conditions for AI adoption. fsQCA utilizes set-theoretic logic to determine combinations of the conditions that necessarily result in an outcome (Ragin, 2000). A significant pattern emerges when scrutinizing the configuration of conditions corresponding to the presence and absence of actual use (AU). Table 5 synthesizes the fsQCA-derived models into readiness profiles, enabling organizations to benchmark their AI adoption capabilities against empirically validated pathways. Table 5 shows that when AU is present across seven solutions (coverage: 0.366, consistency: 0.872), BIU, EEX, FCN, HMT and PRV most frequently appear, emerging in 6, 5, 5, 5, and 5 solutions, respectively. This repeated

Table 5. AI adoption archetypes: benchmarking configurations leading to actual use (AU)

Configurations/ Archetype	Archetype label/Readiness profile	BIU	EEX	FCN	HAB	HMT	PEX	PRV	SIN	TRS	Raw coverage	Consistency
1	Strategic Implementers	⊗	●	●	⊗	⊗	•	●	⊗		0.123	0.907
2	Comprehensive Adopters	●	●	●		●	•	●	⊗	⊗	0.173	0.912
3	Experience Pioneers	●	●	●	⊗	●	⊗	●	•		0.143	0.900
4	Efficiency Champions	●	●	●	•	●	•	●		⊗	0.225	0.927
5	User-Centric Innovators	●	⊗	⊗	•	⊗	⊗	●	⊗	⊗	0.138	0.910
6	Value-Driven Practitioners	●	⊗	⊗	•	●	⊗	⊗	•	⊗	0.124	0.903
7	Digital Leaders	●	●	●	•	●	⊗	⊗	⊗	⊗	0.139	0.930

Note(s): Solution coverage: 0.366; solution consistency: 0.872
Filled black circles (●) denote the presence of a condition in a configuration, while crossed-out circles (⊗) denote the absence of a condition in a configuration. Large circles denote core while small circles denote peripheral condition
These archetypes represent standardized readiness profiles for organizations to benchmark their AI adoption capabilities
Source(s): Authors' own work

Figure 3. FsQCA XY plot. Source: Authors’ own work

co-occurrence indicates that these conditions strongly combine to drive professionals’ adoption of AI technologies. It is grounded on the frequency and consistency of conditions permanently tied to the emergence of the outcome; BIU, EEX, FCN, HMT, and PRV can be robustly classified as core conditions or factors whose presence holds a consistent association with shaping AU. In contrast, HAB, PEX, and SIN are identified as peripheral conditions (factors), demonstrating weaker, more inconsistent relationships in fewer solutions.

4.4.3 Benchmarking archetypes and strategic implications. The “Comprehensive Adopters” archetype (high BIU, EEX, FCN, HMT, PRV) mirrors Model M2’s configuration, which achieved 0.912 consistency (highly reliable pathways), indicating its reliability as a benchmark for organizations with strong intentions and infrastructure. The core role of EEX reiterates ease-of-use perception as central to technology adoption from the UTAUT 2 model. The centrality of FCN also echoes research evidence that indicates resource infrastructure has a central role in assimilation. From a strategic perspective, these findings imply that marketing practitioners should intervene strategically on the set of core conditions to encourage the adoption of AI. The set of archetypes provides distinct readiness profiles

(Del Giudice *et al.*, 2018) that organizations can use to measure their AI implementation progress. Organizations with the "Efficiency Champions" profile maintain advanced infrastructure and positive behavioral inclination but should receive extra training to resolve challenges related to addressing evolving operational challenges. Organizations under the "Digital Leaders" profile have all the necessary preconditions for AI adoption, yet they require targeted behavioral intervention for their technology assets to generate enduring system usage. The archetypes are standardized benchmarks - they allow organizations to know where they stand in terms of AI adoption relative to empirically documented benchmarks of such pathways.

4.4.4 Managerial application: AI Readiness Matrix. To translate our theoretical findings into actionable managerial guidance, we developed an AI Readiness Matrix (Table 6) that categorizes the seven adoption archetypes into three strategic themes: Technical Excellence, User-Centricity, and Strategic Alignment. This diagnostic framework allows marketing leaders to (1) identify their organization's current readiness profile, (2) recognize the inherent strengths and limitations of their profile, and (3) implement targeted interventions to enhance AI adoption outcomes. The matrix provides specific action steps customized for each profile, transforming our configurational findings into practical implementation roadmaps. For example, organizations exhibiting the "Digital Leaders" profile should prioritize employee training and adoption incentives, while "Experience Pioneers" should focus on infrastructure upgrades and systematic user feedback collection. This application-oriented extension of our fsQCA results directly addresses the benchmarking needs of marketing professionals navigating AI implementation challenges.

Table 6. AI readiness matrix for managers

Identify your profile → Take action				
Theme	Readiness profile	Who are they	Key strengths	Immediate actions
Technical excellence	Digital Leaders	Strong tech infrastructure, needs stronger user engagement	Cutting-edge tools; Strong IT infrastructure	Train employees to use tools effectively; Create incentives for AI adoption
	Efficiency Champions	Focused on cost-saving, needs simplified workflows	Cost-saving systems; Streamlined processes	Simplify workflows with AI; Provide hands-on workshops
User-centricity	Experience Pioneers	Prioritize user experience, but lack technical scale	User-friendly designs; High customer satisfaction	Upgrade IT to scale solutions; Gather user feedback monthly
	User-Centric Innovators	Creative solutions, but inconsistent tool usage	Creative problem-solving; Agile teams	Standardize AI tools across teams; Align AI with company goals
Strategic alignment	Strategic Implementers	Leadership-driven vision, but uneven team adoption	Leadership vision; Clear AI roadmap	Run pilot projects for quick wins; Communicate benefits to teams
	Value-Driven Practitioners	Data-driven decisions, but poor cross-team collaboration	Data-driven decisions; ROI-focused	Foster cross-team AI collaboration; Invest in analytics training
	Comprehensive Adopters	Advanced in AI adoption, but risk of complacency	Advanced AI integration; Mature workflows	Audit systems quarterly; Stay updated on AI trends

Source(s): Authors' own work

5. Conclusion, theoretical contributions and practical implications

5.1 Conclusion

The study takes an integrated benchmarking approach using both PLS-SEM and fsQCA to determine the factors leading to the adoption of AI among marketing professionals across diverse industry contexts. The results depicted that PEX, EEX, SIN, HMT, PRV, FCN, and HAB positively influence the intention to adopt AI for marketing, with TR functioning as a significant negative factor. The study revealed significant and nonsignificant moderation effects, particularly emphasizing TR's role in shaping the relationship between AI adoption factors. It unfolds the significant moderation of TR on HAB, EEX, and FCN in adopting AI, demonstrating how resistance selectively impacts certain adoption pathways. Particularly, the fsQCA showed configurations of conditions, core and peripheral, leading to consistently strong AI adoption intentions and identified seven distinct "adoption archetypes" that serve as configurational benchmarks representing multiple equifinal pathways to successful implementation. In these core conditions that consistently associated themselves with shaping marketing professionals' AI adoption intention, BIU, EEX, FCN, HMT, and PRV emerged. In contrast, HAB, PEX, and SIN exhibited weaker and more inconsistent relationships in these configurations. This integration of variance-based and configurational approaches represents a methodological contribution to benchmarking literature, revealing how different factors can combine in various ways to achieve high adoption outcomes.

Our findings further establish a substantial positive relationship between AI adoption and marketing efficiency across four key performance dimensions: cost management, campaign responsiveness, customer engagement, and ROI precision. This empirical validation confirms that when marketing professionals successfully implement AI technologies in alignment with the identified benchmarking standards, organizations achieve significant performance improvements in their marketing operations. This relationship supports the resource-based view that AI capabilities function as strategic resources conferring competitive advantages through improved efficiency, effectiveness, and customer engagement. The benchmarking typologies established in this study provide organizations with standardized reference points for assessing their AI implementation readiness, identifying contextually appropriate adoption pathways, and developing targeted strategies to overcome resistance barriers. By benchmarking against both generalizable performance standards (derived from PLS-SEM) and specific capability profiles (identified through fsQCA), marketing departments can develop more effective technology implementation roadmaps tailored to their unique characteristics and constraints.

5.2 Theoretical contributions

This study advances benchmarking and technology adoption literature in marketing AI contexts in four key ways: First, we extend UTAUT2 by empirically validating TR as a critical moderator affecting adoption pathways. The significant moderation of TR on effort expectancy, facilitating conditions, and habit provides a complete theoretical framework that integrates both acceptance and resistance perspectives—answering calls for comprehensive benchmarking models that capture implementation complexity. Second, our methodological innovation combining variance-based (PLS-SEM) and configuration-based (fsQCA) approaches reveals both direct effects and equifinal adoption pathways. This identifies core conditions (BI, EEX, FCN, HMT, PRV) versus peripheral factors (HAB, PEX, SIN), advancing understanding of causal complexity in technology adoption that aligns with neo-configurational theory and establishes empirically-validated benchmarking archetypes for AI implementation. Third, we strengthen the Resource-Based View (RBV) theory in marketing technology by empirically establishing the AI adoption-marketing efficiency link using performance assessment benchmarks. This validates that AI technologies function as strategic resources conferring competitive advantage—substantiating RBV's central proposition regarding valuable, rare, and inimitable resources while providing quantifiable benchmarking standards for measuring performance improvements. Fourth, our cross-industry approach yields generalizable findings on fundamental AI adoption mechanisms—transcending the contextual limitations of prior sector-specific research (B2B, SMEs, hospitality). This provides theoretical foundations for a standardized benchmarking framework of marketing technology implementation across diverse organizational contexts that enables meaningful cross-industry comparisons and performance assessment. Fifth, we contribute to benchmarking theory by integrating individual-level technology acceptance factors with organizational capability metrics to create a multi-level assessment framework. This addresses the noted gap in benchmarking literature between individual adoption behaviors and organizational performance outcomes, offering a more comprehensive theoretical model for technology benchmarking than previously available.

5.3 Practical implications

Our findings offer five evidence-based imperatives for marketing organizations implementing AI technologies: First, the significant negative effect of resistance on adoption intention underscores the necessity of addressing psychological and organizational barriers through participatory implementation strategies. Organizations must develop resistance mitigation protocols that specifically target the moderating effects we identified on effort expectancy, facilitating conditions, and habit formation. Second, our fsQCA results reveal that successful AI implementation requires specific configurational recipes centered on behavioral intention, effort expectancy, facilitating conditions, hedonic motivation, and price value. These core conditions must be systematically cultivated through human-centered design principles, infrastructure development, and value-driven implementation frameworks. Third, the identification of multiple sufficient causal recipes suggests that successful AI integration follows contextually dependent pathways rather than universal models. Marketing executives should develop organizational diagnostic tools to identify contextual alignments with specific causal configurations before implementation. Fourth, the robust empirical relationship between AI use and marketing efficiency across four key dimensions provides quantifiable justification for strategic investment. Organizations should implement measurement frameworks capturing efficiency gains in: (1) cost management through tracking resource reallocation from automated tasks to strategic initiatives; (2) campaign responsiveness by establishing AI-driven feedback loops for dynamic market adjustments; (3) customer engagement by measuring personalization effectiveness through conversion metrics; and (4) ROI precision, using advanced attribution modeling to quantify marketing performance improvements. Fifth, the influence of facilitating conditions on both intention and usage behavior highlights the necessity of breaking down functional silos. Marketing organizations must restructure governance mechanisms to ensure technological infrastructure aligns with strategic marketing objectives through formalized integration processes.

5.4 Limitations and direction for future research

Our study has some limitations that present opportunities for future research. While our fsQCA analysis identified configurational pathways to AI adoption, the calibration thresholds employed require validation through sensitivity analyses. Our operationalization of TR as a unidimensional construct fails to capture its multifaceted nature—future studies should develop taxonomies distinguishing between passive, active, and innovation-specific resistance forms. Additionally, our generalized approach to AI technologies may obscure variation in adoption mechanisms across specific marketing applications; research examining configurational differences between predictive analytics, customer segmentation, and generative AI implementations would enhance understanding of context-specific adoption patterns. The complexity of contextual influences on AI adoption, which might not be fully captured quantitatively, necessitates in-depth case studies to better understand organizational dynamics. These qualitative methodologies could reveal different dimensions of TR and explore cultural, psychological, and organizational barriers. Our model also omitted potentially significant organizational conditions (data maturity, marketing-IT integration) that might constitute essential elements in certain adoption configurations. Furthermore, while our study provides valuable behavioral insights at the individual marketing professional level, its focus on individual-level analysis limits its applicability for organizational benchmarking. Future research could extend benchmarking efforts to the organizational level, enabling firms to compare their AI adoption maturity and marketing performance outcomes against industry peers. Finally, multi-group analysis could identify differences in adoption factors across demographic segments and industries, providing insight into the context-specific functioning of predictors and addressing generalizability constraints across diverse organizational settings.

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