Chatbot Acceptance in Marketing: Literature Review

Nadia Sfar

Lecturer at the Faculty of Economics and Management of Mahdia University of Monastir, Tunisia

DOI: https://doi.org/10.47772/IJRISS.2025.914MG00245

Received: 12 December 2025; Accepted: 20 December 2025; Published: 25 December 2025

ABSTRACT

The digital transformation of consumer behavior and service delivery has accelerated the adoption of AI-powered chatbots in marketing. This paper synthesizes existing literature to examine the diverse applications of chatbots across key marketing domains, including advertising, mobile commerce, e-services, and branding, where they enhance engagement, service quality, and personalized customer experiences. A central focus is the pervasive use of the Technology Acceptance Model (TAM) as the primary theoretical framework for studying chatbot adoption. While acknowledging TAM's robust analytical utility, the review concurrently identifies and discusses its critical limitations, such as technological narrowness, structural oversimplification, and methodological constraints.

Keywords: Chatbot Adoption, Technology Acceptance, AI, TAM model, Marketing

INTRODUCTION

The digital transformation of consumer behavior has deeply reshaped the way with which services are delivered. As internet users now average 2.5 hours per day on social networks (Kemp, 2022), brands are increasingly adopting digital platforms to address changing customer needs. This transition is supported by sophisticated virtual agents, which provide real-time, personalized service and help merge traditional in-person interactions with digital expectations (Hagberg et al., 2016). Today's consumers show a growing preference for digital channels, valuing their greater accessibility, cost savings, and efficiency over offline options (Escobar, 2016).

Marketing has been one of the first domains affected by AI's transformative impact, leading to numerous developments (Chintalapati, 2022; Kumar et al., 2024). Brands are increasingly leveraging AI-powered chatbots equipped with Natural Language Understanding (NLU) and Machine Learning (ML), to strengthen consumer engagement and streamline interactions, interpret his feedback and anticipate his needs, foster more natural communication, offer real-time assistance, and deliver tailored promotional messages (Lim et al., 2022; Ford et al., 2023).

The present paper examines several applications of chatbots identified in marketing literature. Particular attention is given to the Technology Acceptance Model (TAM), as it serves as the primary theoretical lens through which chatbot adoption is studied in this field.

1.METHODOLOGY

This article employs a narrative (semi-systematic) review methodology (Snyder, 2019), appropriate for synthesizing literature across interdisciplinary fields and capturing the evolving landscape of chatbot marketing. Our analysis focused on peer-reviewed articles published between 2015 and 2024, sourced from major databases including Scopus, Web of Science, and EBSCO Business Source Complete. Search terms included combinations of 'chatbot,' 'AI,' 'marketing,' 'adoption,' 'TAM,' and 'Generative AI.' Inclusion criteria prioritized empirical studies and conceptual papers in leading marketing, business, and information systems journals. While not a fully systematic review with formal meta-analysis, this approach allows for thematic synthesis and identification of dominant theoretical trajectories and emerging gaps

II. LITERATURE REVIEW

This review synthesizes literature on marketing chatbots through three interconnected thematic lenses: (1) Functional Applications (advertising, m-commerce, e-service, branding), (2) Theoretical Foundations (dominant vs. alternative models), and (3) Technological Evolution (from rule-based to GenAI-powered chatbots). This structure allows us to not only catalog applications but also analyze comparative drivers, theoretical adequacy, and evolutionary trajectories.

According to Alsharhan et al. (2024)' systematic review, studies in the marketing domain (around 20 studies) have explored chatbot applications across various areas, including advertising, mobile marketing, mobile advertising, and branding, targeting different consumer segments.

In recent years, academic research on AI advertising has grown significantly, providing valuable insights into chatbots potential applications (Neumann et al., 2019), core functions (Campbell et al., 2021; Wu et al., 2021), defining features (Lee & Cho, 2019; Van den Broeck et al., 2019; Smith, 2020; Kietzmann et al., 2021), and associated challenges (Palos-Sanchez et al., 2019; Watts & Adriano, 2021). Among these, Van den Broeck et al. (2019) specifically investigated the effectiveness of chatbot-delivered advertising. Their study focused on how consumers perceive the relevance and intrusiveness of chatbot ads, revealing that these factors significantly shape evaluations through perceived usefulness and helpfulness. Notably, their findings emphasize that message acceptance plays a mediating role between users' perception of intrusiveness and their assessment of chatbot advertising's utility and potential influence on patronage behavior (Ford et al., 2023).

The proliferation of mobile technologies in managerial applications has increased scholarly attention to mobile marketing (Shankar & Balasubramanian, 2009; Venkatesh et al., 2012), mobile advertising (Andrews et al., 2015; Bart et al., 2014), and mobile commerce (Shankar et al., 2016) – terms often used interchangeably in the literature despite their conceptual nuances (Leppäniemi & Karjaluoto, 2005). The rise of mobile commerce (m-commerce) has accelerated messaging-enabled platforms, fostering conversational commerce – AI-driven chatbots that redefine B2C interactions (de Cosmo et al., 2021). Empirical studies demonstrate the impact of these AI-driven entities in enhancing customer experience through real-time engagement and personalized decision support (Sestino et al., 2020), with context-aware messaging critically shaping consumer attitudes and behaviors (Go & Sundar, 2019). Recent work further specifies adoption drivers, including compliance-boosting chatbot features (Adam et al., 2021) and smartphone-specific utility perceptions (Kasilingam, 2020), reflecting growing academic interest in this domain (Sharma et al., 2024).

Chatbots are increasingly developing in e-service as well, representing a promising opportunity to improve customer service quality and performance (Misischia et al., 2022). The literature identifies five customer-related functions of chatbot, presented as five chatbots' marketing efforts. These are interaction, entertainment, trendiness, customization and problem-solving (Chung et al., 2020). Misischia et al. (2022) divided these five functions in two major categories: "improvement of service performance" which includes interaction, entertainment and problem-solving, and "fulfillment of customer's expectations" which encompasses trendiness, customization. These categories represent the core objectives of chatbot implementation in marketing.

Branding has been also identified as a critical application area for chatbots in marketing (Alsharhan et al., 2024).
In fact, the rapid adoption of brand chatbots on social networking platforms has transformed direct consumer brand communication (Appel et al., 2020), enhancing research attention to chatbots branding implications (Chung et al., 2020; Zarouali et al., 2018). Research reveals that the more a consumer perception of chatbot as helpfulness and utility, the less is his feeling of intrusiveness toward chatbot-initiated advertising messages. Moreover, Kull et al. (2021) establish that initial chatbot messages employing a warm (versus competent) tone effectively diminish self-brand distance and subsequently increase behavioral brand engagement. Further,

Cheng and Jiang (2021) provide empirical evidence that chatbot marketing enhances consumer-brand relationships through three dimensions of communication quality - credibility, accuracy, and competence - which collectively generate favorable brand responses. Additionally, scholars have examined the impact of chatbots on customer relationship management (CRM). Lee and Li (2023) analyze how AI chatbot affordances influence customer perceptions and brand loyalty, whereas Youn and Jin (2021) explore how different types of customer – AI chatbot relationships affect consumer relationship quality.

The significance of using chatbots is particularly evident in luxury fashion branding, where chatbots' ability to deliver personalized engagement aligns with the sector's emphasis on exclusivity and customer-centric experiences (Zeng et al., 2023). Leading luxury brands like Burberry, Gucci, and Louis Vuitton exemplify effective chatbot implementations that enhance customer interactions (Chung et al., 2020; Lee & Choi, 2017; Zeng et al., 2023), while early adopters like Tommy Hilfiger demonstrate advanced applications for query resolution (Rossi, 2020) and Sephora/Estée Lauder showcase personalized recommendation systems (Landim et al., 2022).

Empirical studies in luxury branding highlight chatbots' capacity to provide tailored information (Sangar, 2012), enhance customer personalized shopping experience (Chung et al., 2020; Zeng et al., 2023), and improve satisfaction through time-efficient content delivery and preference memory (Landim et al., 2022). This shift positions AI-driven chatbots as transformative tools that bridge luxury brands' traditional service ethos with digital commerce demands. Nevertheless, while studies recognize chatbots value in luxury brand engagement, critical gaps persist between technological potential and practical implementation: chatbots remain underutilized relative to their capabilities in bridging luxury brands' traditional service ethos with digital commerce demands (Pantano & Pizzi, 2020; Zeng et al., 2023).

Furthermore, there is a significant impact of Generative AI (GenAI) on business processes, including the marketing sector where (GenAI) offers diverse applications (Chan and Choi, 2025). The integration of Generative AI (GenAI) into marketing strategies and decision-making holds great potential for both businesses and consumers. It can assist in content creation (such as blog posts and emails, generate visual assets for advertisements and virtual try-ons), respond to consumer inquiries, support sentiment analysis, identify consumer behavior patterns, and enhance personalization through product recommendations (Gill, 2023). However, despite its growing relevance, research on the impact of GenAI-powered chatbots in marketing strategies and consumer behavior is still scarce in leading business and marketing journals. Within the marketing field, GenAI is expected to redefine customer experiences, shape attitudes and behaviors, and influence customer relationship management. Given this shift, it is essential for marketers to gain a deep understanding of how consumers interact with a technology and how these interactions drive decision-making before fully adopting GenAI solutions (Chan & Choi, 2025). Peres et al. (2023) explore the implications of Generative AI (GenAI) across various domains, including marketing. They emphasize the importance of understanding how GenAI can enhance marketing activities while also identifying its potential challenges.

One of the most significant ways GenAI is transforming digital marketing is through personalized content creation. By leveraging advanced AI models, businesses can tailor marketing messages to individual consumers, improving engagement and effectiveness (Chan & Choi, 2025). A prime example of this is ChatGPT, which has gained widespread recognition due to its generative pre-trained transformer (GPT) architecture and impressive capabilities. Built on Large Language Models (LLMs), ChatGPT utilizes deep learning techniques and extensive training on vast amounts of internet data to generate human-like responses (Hermann & Puntoni, 2024). In practice, ChatGPT is being increasingly integrated into marketing strategies. Tafesse and Wien (2024) examine real-world applications of ChatGPT in marketing by analyzing user engagement on social media. Using webscraping techniques to collect tweets related to ChatGPT and marketing, they identify key themes, including its role in content marketing and digital marketing.

Beyond its applications in marketing field, researchers have also explored factors influencing consumer adoption of GenAI technology. For instance, Gude (2023) investigates the critical determinants shaping consumers' willingness to use ChatGPT, while Abdelkader (2023) finds that a positive customer experience with ChatGPT enhances consumer satisfaction with digital marketing. Moreover, Hoffmann et al. (2024)

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XIV November 2025 | Special Issue on Management

highlight ChatGPT's potential in facilitating scale development in consumer behavior research. These studies underscore the evolving role of GenAI in reshaping consumer interactions and brand engagement in the digital era.

As synthesized in Table 1, chatbot applications span key marketing domains with distinct functions, drivers, and outcomes.

Table 1: Comparative Analysis of Chatbot Applications Across Marketing Domains

Marketing Domain	Primary Functions & Objectives	Key Adoption Drivers	Measured Outcomes	Illustrative Studies
Advertising	Deliver targeted ads, assess message relevance/intrusiveness, mediate patronage behavior	Perceived usefulness, perceived helpfulness, low intrusiveness, message acceptance	Ad evaluation, utility perception, patronage intention	Van den Broeck et al. (2019); Ford et al. (2023); Lee & Cho (2019)
Mobile Commerce (mCommerce)	Enable conversational commerce, provide real-time engagement, offer personalized decision support	Context-aware messaging, complianceboosting features, smartphone-specific utility	Customer experience, consumer attitudes/behaviors, adoption rates	Sestino et al. (2020); Go & Sundar (2019); Adam et al. (2021); Kasilingam (2020)
E-Services	Improve service quality/performance via interaction, entertainment, trendiness, customization, problem-solving	Service performance improvement (interaction, entertainment, problem-solving), fulfillment of customer expectations (trendiness, customization)	Service quality, customer satisfaction, operational performance	Misischia et al. (2022); Chung et al. (2020)
Branding	Transform direct consumer-brand communication, enhance brand engagement, improve CRM	Perceived helpfulness/utility, warm vs. competent tone, communication quality (credibility, accuracy, competence)	Reduced self-brand distance, behavioral brand engagement, brand loyalty, relationship quality	Appel et al. (2020); Kull et al. (2021); Cheng & Jiang (2021); Lee & Li (2023)

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XIV November 2025 | Special Issue on Management

Luxury Fashion Branding	Deliver personalized engagement, provide tailored information, enhance exclusive shopping experiences	Alignment with exclusivity, customer-centricity, personalized shopping experience, timeefficient content delivery	Customer satisfaction, personalized experience quality, brand-customer relationship strength	Zeng et al. (2023); Chung et al. (2020); Landim et al. (2022); Sangar (2012)
Generative AI (GenAI) Applications	Content creation, sentiment analysis, behavior pattern identification, hyperpersonalization, research facilitation	Advanced personalization, human-like interaction (GPT/LLM capabilities), positive user experience, research utility	Consumer engagement, satisfaction with digital marketing, scale development in research	Chan & Choi (2025); Tafesse & Wien (2024); Gude (2023); Hoffmann et al. (2024)

III. TECHNOLOGY ACCEPTANCE MODEL (TAM)

Existing marketing literature on chatbot adoption has largely centered on applying and extending the Technology Acceptance Model (TAM) framework (Naude, 2019; Linh & Wu, 2023; Alsharhan et al., 2024). Introduced by Fred D. Davis in 1986 and built on the Theory of Reasoned Action (Fishbein, 1979), (TAM) has emerged as a robust analytical framework for predicting and explaining technology adoption decisions (Savari et al., 2021). This influential model has been widely applied in research to examine user acceptance of emerging digital technologies and new e-services across diverse contexts (Davis, 1989; Davis and Venkatesh, 1996). It provided a psychological framework to understand human behavior; a perspective which was notably absent from the Information Systems (IS) literature at the time (Davis, 1989; Davis, 1993). While foundational theories of technology acceptance originated in the 1970s (Fishbein & Ajzen, 1975), (TAM) subsequently formalized these concepts, establishing itself as a seminal theoretical foundation for information systems research.

The (TAM) model was developed with several objectives: to predict user behavior through identifiable psychological mechanisms, and to guide implementation strategies by identifying pre-adoption facilitators (Rondan-Cataluña et al., 2015; Marikyan & Papagiannidis, 2023). Based on evidence in previous studies (e.g. Johnson and Payne, 1985; Payne, 1982; Robey, 1979), TAM postulates two core cognitive determinants of acceptance: perceived usefulness (PU) and perceived ease of use (PEOU) (Marikyan & Papagiannidis, 2023). These constructs represent fundamental belief dimensions that shape behavioral intentions toward information technologies (Davis, 1989). Formally, TAM posits that technology adoption decisions derive from a cost-benefit evaluation where PU reflects anticipated system benefits and PEOU captures expected usage effort (Davis, 1989).

PU reflects an individual's belief that a technology enhances task performance. This concept draws from Bandura's (1982) notion of outcome judgment, which emphasizing the expectation of a positive result as a driver of behavior, and has been operationalized based on empirical findings that link performance expectancy to system usage (Robey, 1979). On the other hand, PEOU captures the belief that system usage requires minimal effort (Davis, 1989), grounded in self-efficacy theory which emphasizes capability judgments (Bandura, 1982; Davis, 1989). Both constructs function as behavioral antecedents, where adoption decisions involve: (1) assessing performance enhancement potential (PU), and (2) evaluating required usage effort (PEOU) (Hill et al., 1987).

The Technology Acceptance Model (TAM) posits that technology adoption follows three hierarchically organized stages: (1) external factors (e.g., system design characteristics) creating user perceptions, (2)

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue XIV November 2025 | Special Issue on Management

cognitive evaluations (perceived usefulness [PU] and perceived ease of use [PEOU]), which subsequently shape (3) affective responses (attitudes and behavioral intentions), ultimately leading to technology usage (Davis, 1989, 1993). While perceived usefulness directly affects usage, ease of use only matters if it makes the technology seem more useful. Essentially, people adopt technologies they find both helpful and easy to use (Davis, 1989, 1993). Thus, TAM conceptualizes technology acceptance as an affectively-mediated cognitive evaluation process, where ease-of-use perceptions determine whether users ever recognize the technology's usefulness.

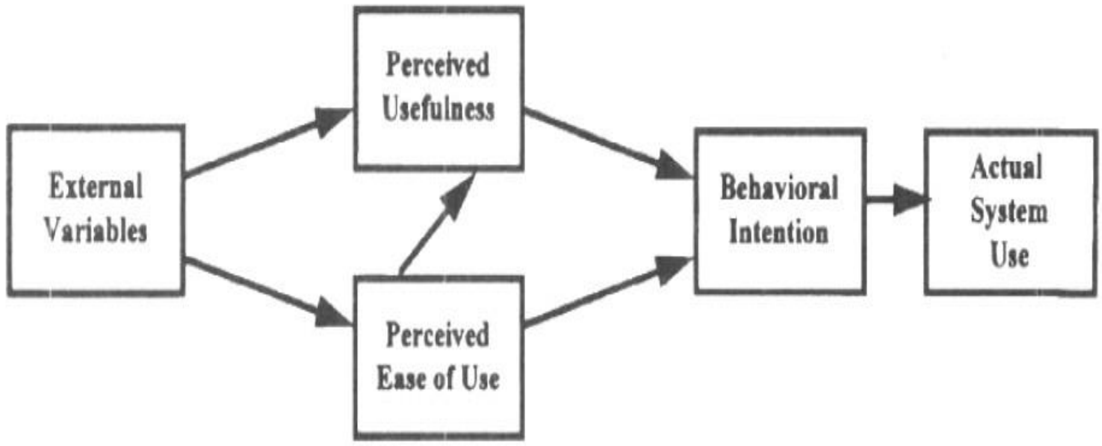

Figure 1. The Technology Acceptance Model
Source: Davis (1989)

Despite its enduring relevance, the Technology Acceptance Model (TAM) has faced increasing criticism for its conceptual limitations across three key dimensions. First, its narrow technological focus overlooks critical nontechnological factors, including individual differences (Marikyan & Papagiannidis, 2024) and organizational contexts like workflow integration (Holden & Karsh, 2010). Second, its oversimplified structure reduces adoption to three static constructs (PU, PEOU, intention), ignoring both actual usage patterns (Shachak et al, 2015) and emerging technology complexities like AI transparency (Shin, 2021) or human-AI reciprocity (Wirtz et al., 2023). Third, its methodological rigidity manifests in basic usage metrics such as frequency or duration, failing to distinguish between requisite use and value-adding use (Mclean et al., 2011) and an assumption of linear intention-behavior linkages – which traces back to Fishbein and Ajzen’s 1975 Theory of Reasoned Action - failing to capture adoption as a dynamic process (Rogers, 2003). While TAM’s parsimony enabled rapid assessments (Venkatesh & Bala, 2008), these limitations constrain its relevance for contemporary digital ecosystems despite its over 12,000 citations (Shachak et al., 2019).

Theoretical Model	Core Constructs	Application in Chatbot Studies	Key Insights for Chatbots	Limitations for Chatbot Context
Technology Acceptance Model (TAM)	Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude,	Dominant framework for predicting initial chatbot adoption decisions; used across	Establishes baseline utility-effort evaluation; parsimonious for early-stage adoption studies	Technological Narrowness: Ignores non-technological factors (individual differences, organizational context) Structural Oversimplification: Reduces adoption to static constructs; ignores actual usage patterns and AI-specific
Theoretical Model	Core Constructs	Application in Chatbot Studies	Key Insights for Chatbots	Limitations for Chatbot Context

	Behavioral Intention	marketing domains		complexities (transparency, reciprocity) 3. Methodological Constraints: Relies on basic usage metrics; assumes linear intention-behavior linkage

To address TAM's limitations, scholars have begun to apply or call for more nuanced frameworks. The Unified Theory of Acceptance and Use of Technology (UTAUT2) introduces hedonic motivation and habit, crucial for engaging consumer technologies (Venkatesh et al., 2012). The Service-Scape or SERVQUAL models help evaluate chatbots as digital service agents, emphasizing reliability and empathy (Parasuraman et al., 1988). Furthermore, theories of anthropomorphism (Blut et al., 2021) and human-computer interaction (HCI) are essential for understanding how chatbot design (e.g., warmth, competence) influences trust and relationship quality, moving beyond mere utility.

CONCLUSION

The marketing literature demonstrates extensive chatbot applications across key domains including advertising, mobile marketing, and branding (Alsharhan et al., 2024). Research in AI advertising provides critical insights into chatbot functionalities and implementation challenges (Ford et al., 2023), while mobile commerce studies highlight their positive impact on customer perceptions (Sharma et al., 2024). Particularly in e-service contexts, chatbots have emerged as valuable tools for improving service quality and operational performance (Misischia et al., 2022). The proliferation of brand chatbots on social media platforms has further stimulated research into their branding implications (Chung et al., 2020; Zarouali et al., 2018), with notable success in luxury sectors where they facilitate personalized shopping experiences (Chung et al., 2020; Zeng et al., 2023), deliver tailored information (Sangar, 2012), and boost satisfaction (Landim et al., 2022). These developments coincide with the broader emergence of Generative AI (GenAI) and its diverse marketing applications (Chan & Choi, 2025).

The Technology Acceptance Model (TAM) remains the predominant theoretical framework for studying chatbot adoption in marketing (Alsharhan et al., 2024), valued for its robust analytical approach to technology adoption decisions (Savari et al., 2021). However, contemporary scholarship has identified important limitations, including its narrow technological focus (Marikyan & Papagiannidis, 2024), structural oversimplification (Shachak et al., 2015), and methodological constraints (McLean et al., 2011).

REFERENCES

1 Alsharhan, A., Al-Emran, M., & Shaalan, K. (2024). Chatbot adoption: A multiperspective systematic review and future research agenda. IEEE Transactions on Engineering Management, 71, 10232-10244. Doi:10.1109/TEM.2023.3298360.
2 Andrews, M., Luo, X., Fang, Z., & Ghose, A. (2016). Mobile Ad Effectiveness : Hyper-Contextual
3 Targeting with Crowdedness. Marketing Science, 35(2), 218-233. https://doi.org/10.1287/mksc.2015.0905 3. Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
4 Bart, Y., Stephen, A. T., & Sarvary, M. (2014). Which Products Are Best Suited to Mobile Advertising? A Field Study of Mobile Display Advertising Effects on Consumer Attitudes and Intentions. Journal of Marketing Research, 51(3), 270-285. https://doi.org/10.1509/jmr.13.0503
5 Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. J., & Mavrommatis, A. (2020). From data to action : How marketers can leverage AI. Business horizons, 63(2), 227-243. https://doi.org/10.1016/j.bushor.2019.12.002
6 Chintalapati, S., & Pandey, S. K. (2022). Artificial intelligence in marketing : A systematic literature review. International Journal of Market Research, 64(1), 38-68.
7 Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. Journal of Business Research, 117, 587–595.

8 Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: Theory and results [Doctoral dissertation, Massachusetts Institute of Technology]. MIT Sloan School of Management.
9 Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. Management Science, 35(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982
10 Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology, 22(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x
11 De Cosmo, L. M., Piper, L., & Di Vittorio, A. (2021). The role of attitude toward chatbots and privacy concern on the relationship between attitude toward mobile advertising and behavioral intent to use chatbots. Italian Journal of Marketing, 2021(1-2), 83-102. https://doi.org/10.1007/s43039-021-00020-1
12 Escobar, A. (2016). The impact of the digital revolution in the development of market and communication strategies for the luxury sector (fashion luxury). Central European Business Review, 5(2), 17
13 Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior : An introduction to theory and research. https://philpapers.org/rec/FISBAI?all_versions=1
14 Ford, J., Jain, V., Wadhwani, K., & Gupta, D. G. (2023). AI advertising : An overview and guidelines. Journal of Business Research, 166, 114124. https://doi.org/10.1016/j.jbusres.2023.114124
15 Hagberg, J., Sundstrom, M., & Egels-Zanden, N. (2016). The digitalization of retailing: An exploratory framework. International Journal of Retail & Distribution Management, 44(7), 694–712.
16 Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. Journal of Biomedical Informatics, 43(1), 159-172. https://doi.org/10.1016/j.jbi.2009.07.002
17 Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. Technology in Society, 62, 101280.
18 Kemp, S. (2022). Digital 2022: Global overview report [online] DataReportal. Available from: https://datareportal.com/reports/digital-2022-global-overview-report Accessed 15 July 2022.
19 Kietzmann, J., Mills, A. J., & Plangger, K. (2021). Deepfakes : Perspectives on the future “reality” of advertising and branding. International Journal of Advertising, 40(3), 473-485. https://doi.org/10.1080/02650487.2020.1834211
20 Kumar, T. A., Julie, E. G., Burugadda, V. R., Kumar, A., & Kumar, P. (Eds.). (2024). Computational Intelligence: Theory and Applications. Scrivener Publishing.
21 Lee, H., & Cho, C.-H. (2020). Digital advertising : Present and future prospects. International Journal of Advertising, 39(3), 332-341. https://doi.org/10.1080/02650487.2019.1642015
22 Lee, H., & Cho, C.-H. (2020). Digital advertising : Present and future prospects. International Journal of Advertising, 39(3), 332-341. https://doi.org/10.1080/02650487.2019.1642015
23 Leppaniemi, M., & Karjaluoto, H. (2005). Factors influencing consumers’ willingness to accept mobile advertising : A conceptual model. International Journal of Mobile Communications, 3(3), 197. https://doi.org/10.1504/IJMC.2005.006580
24 Lim, W. M., Kumar, S., & Ali, F. (2022). Advancing knowledge through literature reviews: ‘what’, ’why’, and ’how to contribute’. The Service Industries Journal, 42 (7–8), 481–513.
25 Linh, P. M., & Wu, T.-T. (2023). A conceptual framework on learner’s attitude toward using AI chatbot based on TAM Model in English classroom. The Proceedings of English Language Teaching, Literature, and Translation (ELTLT), 12, 146-154.
26 Marikyan, D.& Papagiannidis, S. (2024) Technology Acceptance Model: A review. In S. Papagiannidis (Ed), TheoryHub Book. Available at https://open.ncl.ac.uk / ISBN: 9781739604400
27 McLean, E. R., Sedera, D., & Tan, F. T. C. (2011). Reconceptualizing system use for contemporary information systems. Paper presented at the Pacific Asia Conference on Information Systems (PACIS), Brisbane, Australia. Association for Information Systems. ISBN: 978-1-86435-644-1.
28 Misischia, C. V., Poecze, F., & Strauss, C. (2022). Chatbots in customer service : Their relevance and impact on service quality. Procedia Computer Science, 201, 421-428. https://doi.org/10.1016/j.procs.2022.03.055

29 Naudé, W. (2019). The decline in entrepreneurship in the West : Is complexity ossifying the economy? IZA Discussion Papers. https://www.econstor.eu/handle/10419/207427
30 Neumann, N., Tucker, C. E., & Whitfield, T. (2019). Frontiers: How Effective Is Third- Party Consumer Profiling? Evidence from Field Studies., 38(6), 918–926.
31 Rondan-Cataluña, F. J., Arenas-Gaitán, J., & Ramírez-Correa, P. E. (2015). A comparison of the different versions of popular technology acceptance models. Kybernetes, 44(5), 788–805. https://doi.org/10.1108/K-09-2014-0184
32 Sestino, A., Prete, M. I., Piper, L., & Guido, G. (2020a). Internet of Things and Big Data as enablers for business digitalization strategies. Technovation, 98, 102173.
33 Shachak, A.; Kuziemsky, C.; Petersen, C. Beyond TAM and UTAUT: Future Directions for HIT Implementation Research; Academic Press: Cambridge, MA, USA, 2019.
34 Shankar, V., & Balasubramanian, S. (2009). Mobile Marketing : A Synthesis and Prognosis. Journal of Interactive Marketing, 23(2), 118-129. https://doi.org/10.1016/j.intmar.2009.02.002
35 Sharma, N., Arora, M., Tandon, U. and Mittal, A. (2024), "Chatbot integration for online shopping: a bibliometric review and future research agenda", Information Discovery and Delivery, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/IDD-11-2023-0132.
36 Smith, K. T. (2020). Marketing via smart speakers : What should Alexa say? Journal of Strategic Marketing, 28(4), 350-365. https://doi.org/10.1080/0965254X.2018.1541924
37 Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness : When does the message get through? Computers in Human Behavior, 98, 150-157.
38 Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology : Extending the unified theory of acceptance and use of technology. MIS quarterly, 157-178.
39 Watts, J., & Adriano, A. (2021). Uncovering the Sources of Machine-Learning Mistakes in Advertising : Contextual Bias in the Evaluation of Semantic Relatedness. Journal of Advertising, 50(1), 26-38. https://doi.org/10.1080/00913367.2020.1821411
40 Wu, L., Dodoo, N. A., Wen, T. J., & Ke, L. (2021). Understanding Twitter conversations about artificial intelligence in advertising based on natural language processing. International Journal of Advertising, 1– 18.