Journal of Economics, Business & Organization Research

Year: 2023, Vol: 5, Issue: 2, pp. 161-174

Article Type: *Conceptual*

Citation: Sarp, S. (2023). Artificial Intelligence in advertisements: A conceptual framework based on the technology acceptance model. *Journal of Economics, Business and Organization Research, 5*(2), 161-174.

ARTIFICIAL INTELLIGENCE IN ADVERTISEMENTS: A CONCEPTUAL FRAMEWORK BASED ON THE TECHNOLOGY ACCEPTANCE MODEL

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Received: 16.10.2023 **Accepted:** 26.10.2023 **Published Online:** 29.10.2023

Abstract

Advertising plays a vital role in presenting a company's products or services to prospective customers with the aim of influencing their purchase intention. The impact of advertising is important for generating product recognition and sales. With the technological advancement in AI usage in businesses, the integration of Artificial Intelligence in contemporary advertising strategies is impactful. This study aims to explain how Artificial Intelligence (AI) can be used in advertising, underpinned by Technology Acceptance Model (TAM). Using the TAM model, the paper explains how people come to accept and use AI in ads. It is proposed that if people find AI in ads useful and easy to understand, they're more likely to respond positively. Besides, social impact is also considered when explaining consumer attitude and purchase intention. This research helps advertisers understand how to use AI better in their campaigns to engage consumers and get better results.

Keywords: *AI, Advertisement, TAM Model, Consumer Attitude*

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1. INTRODUCTION

Over the past few decades, the advertising industry has undergone radical transformation, as highlighted by Donthu et al. (2022). This evolution has been driven by modern technological advancements, particularly the integration of artificial intelligence (AI) and machine learning, which are fundamentally reshaping the traditional concept of advertising and its content (Campbell et al. 2022; Li 2019; Qin and Jiang 2019). AI, characterized as a set of disruptive technologies that enable solving problems, facilitating decision-making, and performing tasks akin to human intelligence (Qin and Jiang, 2019), has played a pivotal role in enhancing advertising's competence, personalization, targeting, and intelligence. This transformation has been achieved by automating and streamlining essential advertising functions, including consumer insight discovery, media planning, ad procurement, ad creation, and impact evaluation, as elucidated by Chen et al. (2019), Deng et al. (2019), and Li (2019). Simultaneously, spurred by new technologies and the proliferation of digital media, advertising has transitioned from its traditional forms to embrace a multitude of innovative media platforms. These advanced advertising mediums leverage artificial intelligence (AI) to bolster advertisement effectiveness.

AI plays a pivotal role in assisting advertisers across a spectrum of advertising functions. Its contemporary application in advertising has surged, primarily driven by its ability to facilitate the development of highly targeted promotions through automated ad scheduling, placement, and media planning and purchasing, as emphasized by Huh and Malthouse (2020). The domain of AI advertising is experiencing rapid growth, showcasing substantial industry potential and promising research opportunities.

This study delves beyond the realm of AI and advertising in isolation. It encompasses the convergence of technology, psychology, and business. Its focus lies in understanding how today's consumers think and help businesses figure out how to succeed in this changing landscape. As the exploration of this topic progresses, the goal is making things clear, and offer a map and a guide to advertiser to use AI in their advertisement campaigns. This will help them not only reach their audience but also connect with them, leading to successful and fruitful interactions.

However, with every technological leap, there are questions and concerns. How do everyday people – the consumers, the target audience of these advertisements – feel about this

AI-driven approach? Do they appreciate the personalized touch? Or does it feel too invasive? Is there trust in the algorithms that decide what ads they see, or is there skepticism? And perhaps most importantly, do they even understand the role AI plays in the ads they come across daily? Technology Acceptance Model, TAM, originally developed in the 1980s, TAM is a handy tool in understanding how users come to accept and use a particular technology. It looks at factors like how useful someone believes the technology is and how easy they think it is to use. For our study, it provides a lens to examine the acceptance of AI in advertising. After all, if people find AI-driven ads beneficial and straightforward, they're more likely to react positively. If not, the reception could be lukewarm or even negative.

There have been limited empirical studies employing the Technology Acceptance Model (TAM) to investigate consumers' acceptance to AI in ads. This research concentrates on understanding the role of perceived ease of use, perceived usefulness, and social influence on consumers' attitudes towards embracing AI in advertisements, and further examines the connection between these attitudes and their subsequent intention to engage.

The structure of this paper is organized as follows: first, in the subsequent sections on the conceptual framework and theoretical model, we will delve into the topic of AI in marketing and employ the Technology Acceptance Model to gain insights into how consumers perceive and accept new technology. This discussion will lead to the introduction of novel propositions that form the basis of our theoretical model. Towards the end, in the conclusion section, we will provide a summary of the paper, delineate its limitations, and suggest potential avenues for further research.

2. CONCEPTUAL FRAMEWORK AND THEORETICAL MODEL

2.1. AI in Marketing

In today's rapidly evolving advertising landscape, Artificial Intelligence (AI) has emerged as a central pillar. Defined by Panchiwala and Shah (2020) as the capability of algorithm-driven computers, or robots, to perform tasks that traditionally required human intelligence, AI aims to imbue systems with cognitive abilities mirroring those of humans. Such capacities encompass reasoning, understanding, extracting relevance, distinguishing, generalizing, and crucially, learning from past encounters.

A notable subset of AI that is gaining prominence in the realm of advertising is Machine Learning. Addressing the constraints posed by other advertising technologies, Machine

Learning capitalizes on the wealth of consumer data to make instantaneous, informed advertising decisions, as highlighted by Perlich et al. (2023). In the advertising context, Machine Learning is not just about data processing; it goes beyond to enhance specific operations, such as pinpointed media buying or astute audience segmentation. With every new data it processes, it hones its understanding and decision-making capacity, drawing parallels with the human ability to learn and improve, a perspective echoed by Shah et al. (2020).

Yet, for Machine Learning to function effectively, it requires a robust dataset. Big Data equips digital advertisers and marketers with invaluable insights into their target demographics. Utilizing state-of-the-art Big Data analytics tools, companies are empowered to sift through, manage, and derive insights from a vast array of structured and unstructured data. As pinpointed by Jin et al. (2015), this data becomes the backbone for both online and offline advertising strategies, with tailored analytics suggesting optimal advertising tactics rooted in nuanced mobile user behaviors, profiles, and even locomotive patterns.

As we delve deeper into the technological intricacies of modern advertising, the Internet of Things (IoT) emerges as a key player. By linking devices to the internet, IoT provides advertisers a golden opportunity to transcend traditional, broad-brush marketing strategies, pivoting towards more bespoke, personalized approaches, as outlined by Aksu et al. (2018).

Furthermore, Cloud computing, with its promise of on-demand access to a reservoir of shared computing assets, augments advertising mechanisms. It paves the way for instantaneous reactions and a collaborative digital framework, ensuring efficient dissemination of information. Notably, it also plays a pivotal role in assuaging privacy qualms, a perspective shared by Yin et al. (2015).

However, the path of integrating these technologies into advertising is not without its set of hurdles. Despite the advancements, there linger pertinent concerns, particularly centered around Big Data. Shah et al. (2020) highlighted several challenges, including rising privacy anxieties, the chaos of disorganized data, the lack of user-tailored results, hurdles in data accessibility, and the looming threat of data manipulation. As the industry forges ahead, addressing these concerns will be paramount to ensure a seamless and trust-driven relationship between advertisers and consumers.

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), established by Davis in 1989, specifically addresses user behavior in adopting new technologies, differing from its predecessor, the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), with a concentrated emphasis on information systems. TAM hinges on two primary constructs: 'perceived usefulness' and 'perceived ease of use' (Davis, 1989), serving as predictors for an individual's willingness to accept a specific technology (Tarhini et al., 2015). TAM model has been broadly applied in diverse areas such as internet usage (Porter and Donthu, 2006), social media (Rauniar et al., 2014), mobile marketing (Kim et al., 2008), online banking (Yiu et al., 2007), education (Tarhini et al., 2013), and e-government (Alenezi et al., 2015).

Davis (1989) posited that 'perceived usefulness' (PU) and 'perceived ease of use' (PEU) directly affect potential users' attitudes, subsequently shaping their intentions to adopt new technology. The core aim of TAM is forecasting a person's behavioural intention regarding technology use. TAM also posits that external factors can influence PU and PEU. Beyond the foundational elements of TAM, 'social influence' (SI) was introduced (Bagozzi et al., 2000) into the model to analyse the impact of external opinions on individual attitudes towards certain technology acceptance.

2.3. Research Propositions

In this research, 'perceived usefulness' refers to the user's belief level that utilizing an AI in ads can improve their performance, as per Davis (1989). Typically, 'perceived usefulness' is seen as a more immediate and potent influence on the decision to embrace technology compared to 'perceived ease of use' (Cha, 2010). Davis (1989) determined that 'perceived usefulness' primarily drives an individual's intention to adopt novel technology, with 'perceived ease of use' being a less influential factor. Numerous studies have identified positive relations between perceived usefulness, attitudes, and the behavioral intention to adopt technology (Cheung and Vogel, 2013; Farahat, 2012; Suki and Suki, 2011). Park (2009) found that users' perceived usefulness positively impacts their attitude and intention to accept e-learning systems. In a similar vein, Bhattacherjee and Hikmet (2008) demonstrated that the perceived usefulness of information technology had a positive effect on users' intentions to utilize such technology. Rauniar et al. (2014) also discovered a positive connection between individuals' perceived usefulness of social media platforms, like Facebook, and their intention to engage with them.

In the context of AI tools in marketing, professionals would assess whether the AI solutions at their disposal would lead to better marketing outcomes, be it in segmentation, targeting, ad delivery, or any other domain. Consequently, this current study proposes that individuals' perceived usefulness of an AI in ads will not only result in positive attitudes towards acceptance of AI ads but also positively influence behavioural intentions to adopt the technology.

P1: Perceived usefulness of AI-ads will be positively related to attitudes toward AI in ads.

P2: Perceived usefulness of AI-ads will be positively related to behavioural intention to purchase intention.

In the context of this research, 'perceived ease of use' is characterized as the extent to which a user believes that engaging with AI in ads would require minimal effort, following Davis's 1989 definition. Perceived ease of use refers to the extent to which an individual feels that using a specific system will require minimal effort (Davis, 1989). Users generally show a preference for technology that they perceive as less complicated to use relative to other options (Davis, 1989). The ease of novel technology's use can enhance performance, potentially increasing immediate perceived usefulness, while its absence can lead to frustration, hindering the adoption of new technologies (Taylor and Todd, 1995; Venkatesh and Davis, 2000). Fang et al. (2005) determined that an innovation's characteristics, or the specific tasks or services it entails, can shape its perceived ease of use. For instance, the impact of perceived ease of use on the intention to utilize an innovation is prominent only in cases where the innovation stimulates intrinsic motivation, as opposed to offering external rewards (Gefen and Straub, 2000). Many research efforts have highlighted the direct and indirect impacts of users' perceived ease on attitudes toward specific products or services (Ramayah and Ignatius, 2005). As global mobile phone usage rises, there's a growing propensity for online shopping (Tandon et al., 2016). This trend is attributed to the convenience people find in making purchases from the comfort of their homes, as opposed to the effort required to visit physical stores (Chao, 2019). Consequently, the subsequent propositions are presented.

P3: Perceived ease of use will be positively related to perceived usefulness of AI in ads.

P4: Perceived ease of use will be positively related to attitudes toward AI in ads.

Social influence pertains to the perceptions stemming from peers and acquaintances (Mathieson, 1991). When peers perceive the incorporation of AI in advertisements as beneficial and valuable, individuals tend to align with these peer opinions, fostering a favorable disposition towards AI in ads. Previous studies have indicated a positive correlation between social influence (SI) and the intention to utilize new technologies such as mobile services (Nysveen et al., 2005; Zhang and Mao, 2008). Within the theoretical framework, it is postulated that social influence has a positive correlation with attitudes towards AI in ads, as delineated in Proposition 5.

P5: Social Influence will be positively related to attitudes toward AI in ads.

In the domain of technology adoption and utilization, attitudes play a central role in shaping behavioural intentions. Rooted in the Technology Acceptance Model (TAM) postulated by Davis (1989), attitude emerges as a critical determinant that drives the intention to embrace technology, further influencing its actual adoption (Lunney et al., 2016). Indeed, the sentiment or perspective towards a specific technology can be perceived as a harbinger of behavioural intention (Ramos-de Luna et al., 2016). This sentiment has been empirically supported by a plethora of studies across diverse technological contexts. For instance, attitudes toward online learning platforms have been found to significantly steer the inclination to employ such technologies (Cheung and Vogel, 2013; Farahat, 2012). Similarly, attitudes have been underscored as pivotal in determining behavioural intentions related to the adoption of 3G mobile services (Suki and Suki, 2011) and even in the context of purchasing from online marketplaces (Ahn et al.,2004). In a similar vein, Park and Kim (2014) posited that the propensity to adopt mobile cloud services is positively influenced by the users' attitudes toward them.

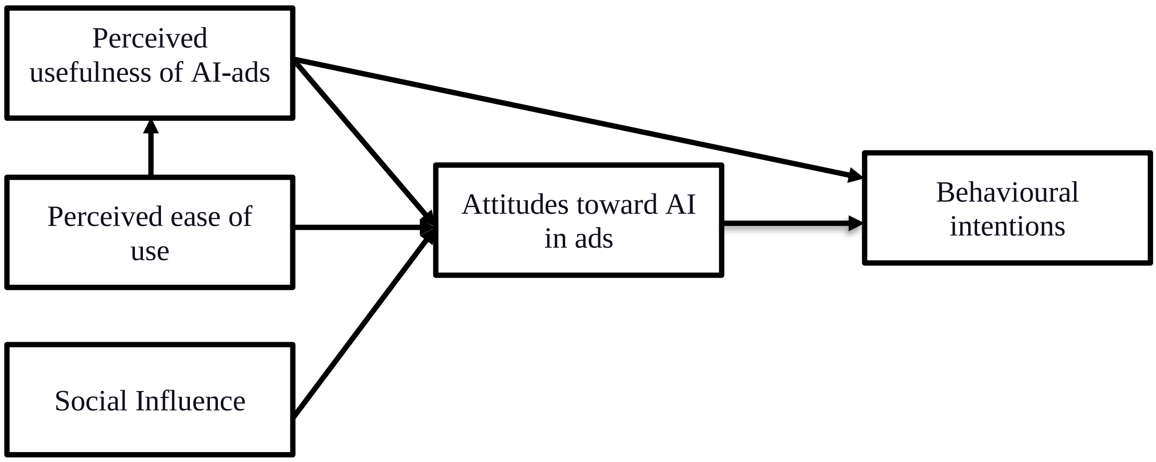
Delving deeper into the psychological interplay of attitudes and behaviours, a clear, intimate link emerges. Cao et al. (2021) elucidate that attitudes and behaviours are inherently intertwined. This is further complemented by Trip et al. (2019) who suggest that while attitudes delve into the intricate depths of human psychology, behaviours act as their tangible manifestations. As such, behaviours predominantly mirror the underlying attitudes.

Building on the evidence and insights, it is reasonable to propose that attitudes toward AI in ads will exhibit a positive relation with behavioural intentions. In essence, as individuals cultivate a favourable attitude towards AI in advertisements, they are likely to demonstrate heightened intentions to engage with or accept such AI-driven ads. This proposition is underpinned by the consistent findings across various technological contexts, emphasizing the pivotal role of attitudes in shaping behavioural outcomes. Consequently, the subsequent proposition is presented.

P6: Attitudes toward AI in ads will be positively related to behavioural intentions.

In summary, Figure 1 illustrates the conceptual framework for the adoption of AI in advertising, encapsulating the interplay of attitudes and behavioural intentions. Following this proposition, we will explore the managerial implications stemming from the constructs of this model in the following section.

Figure 1. Proposed Model for the Acceptance of AI in Advertising



3. CONCLUSION

This study is pioneering in its application of TAM to comprehend consumer reactions to AI in advertising. Historically, the TAM has been employed to understand the acceptance of many technologies; however, its application to AI in advertising remains limited. By integrating the TAM with the distinct context of AI advertising, this study illuminates two critical dimensions: It underscores how consumers' perceptions of AI advertising, driven by ongoing technological advancements, can directly shape their attitudes and consequent behavioural tendencies. Besides, the research emphasizes the profound role of external variables, especially social influences, in modulating consumer attitudes toward AI-powered advertisements. This study not only broadens the applicability of TAM but also provides a nuanced understanding of the factors influencing consumer responses to AI generated advertising campaigns.

AI's ever-evolving capabilities mean that its acceptance is an ongoing journey. The implications of AI adoption in advertising are vast and varied. Content creators, marketers, developers, policymakers, and researchers must consider these implications to measure the likely success and impact of incorporating AI into advertisement strategies and policies. Using TAM, it's vital to regularly assess and adapt to the perceived usefulness and ease of use of AI tools, guaranteeing they remain relevant and are used to their full potential. AI instruments, given their extensive features, can seem intricate to some. Through the TAM framework, we can assess how the perceptions of marketing experts regarding the usefulness and user-friendliness of AI can greatly influence its adoption. For example, if AI platforms can quickly evaluate customer data to predict patterns and offer an intuitive interface, their adoption rate is expected to rise. The conceptual model posits that both perceived usefulness and ease of use directly shape a user's attitude towards the technology, which then impacts their behavioural intention to adopt it. When behavioural intention is strong, it frequently leads to actual system utilization. Thus, if marketing experts perceive AI tools to be valuable and simple to navigate, they are more inclined to adopt them in their regular operations. Using TAM's insights, companies can plan ways to increase acceptance of AI in advertising. This could involve training sessions to highlight the ease of using AI in ad campaigns or by presenting actual ad success stories driven by AI to underscore its value.

The present paper acknowledges certain limitations. Specifically, the model has yet to be validated through data collection. For future research, empirical studies gathering data from consumers can be undertaken to assess the proposed relationships in the framework.

In conclusion, the Technology Acceptance Model (TAM) serves as a foundational framework to discern the factors influencing the adoption of AI tools in marketing. By highlighting the journey from perception to intention and actual use, TAM provides stakeholders the knowledge to effectively integrate AI into marketing.

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Declaration of Contribution Rate: The author has completed the article on his own.
Declaration of Support and Appreciation: The research did not receive any support from any institution or organisation.
Declaration of Conflict: The authors declare that there is no conflict of interest.
In this study, the rules stated in the **"Higher Education Institutions Scientific Research and Publication Ethics Directive"** were followed.
This article has been screened with **similarity** detection software.