FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

UNVEILING THE ARTIFICIAL MINDSET: FACTORS INFLUENCING THE INTENTION TO INTEGRATE AI CONTENT CREATION TOOLS INTO DIGITAL MARKETING WORKFLOWS

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF BUSINESS ADMINISTRATION

by

Otis Kopp

2025

To: Dean William G. Hardin
College of Business

This dissertation, written by Otis Kopp, and entitled Unveiling the Artificial Mindset: Factors Influencing the Intention to Integrate AI Content Creation Tools into Digital Marketing Workflows, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Alfred Castillo, Committee Member

Mark Thibodeau, Committee Member

Mido Chang, Committee Member

Amin Shoja, Major Professor

Date of Defense: May 16, 2025

The dissertation of Otis Kopp is approved.

Dean William G. Hardin
College of Business

Andrés G. Gil
Senior Vice President for Research and Economic Development
and Dean of the University Graduate School

Florida International University, 2025

DEDICATION

To my mother, for her unwavering support.

ACKNOWLEDGMENTS

First and foremost, I would like to express my deepest gratitude to my advisor, Dr. Amin Shoja, for his constant support, insightful guidance, and invaluable feedback throughout the course of my dissertation. His expertise and encouragement have been instrumental in the completion of this work.

I extend my sincere thanks to my committee members, Dr. Alfred Castillo, Dr. Mark Thibodeau, and Dr. Mido Chang, for their thoughtful critiques and constructive suggestions. Their dedication and scholarly input have greatly enriched my research.

I would also like to extend my heartfelt appreciation to Dr. George Marakas and Dr. Miguel Aguirre-Urreta for their exceptional leadership and mentorship. Their commitment to academic excellence and their support has been invaluable. Additionally, I am thankful to the entire DBA faculty for their dedication and for providing a rigorous and enriching academic environment.

I am profoundly grateful to my cohort-mates and DBA colleagues. Your camaraderie, stimulating discussions, and mutual support have made this journey both intellectually rewarding and personally fulfilling.

Thank you to my father for his affirmation as I reached the completion of my research.

A special thank you goes to my wife, whose love, patience, and encouragement have been my anchor during the most challenging of times. Her steadfast belief in me has been a source of strength and motivation.

Lastly, I would like to acknowledge my non-academic family and friends for their understanding and support. Your encouragement and belief in my abilities have been invaluable, and I am deeply appreciative of your presence in my life.

ABSTRACT OF THE DISSERTATION

UNVEILING THE ARTIFICIAL MINDSET: FACTORS INFLUENCING THE INTENTION TO INTEGRATE AI CONTENT CREATION TOOLS INTO DIGITAL MARKETING WORKFLOWS

by

Otis Kopp

Florida International University, 2025

Miami, Florida

Professor Amin Shoja, Major Professor

The widespread proliferation of artificial intelligence (AI) is revolutionizing digital marketing by enabling hyper-personalization and improved efficiency through generative AI tools. Using the Unified Theory of Acceptance and Use of Technology (UTAUT) model, this study examines factors affecting digital marketers' intention to adopt AI content creation tools, including performance expectancy, effort expectancy, social influence, and organizational support, with a focus on attitude as a mediating factor and technological anxiety as a moderator. A novel INTAI measurement scale was developed based on validated scales from prior research, and data collected via a Qualtrics survey from 310 U.S.-based digital marketers was analyzed using exploratory and confirmatory factor analysis (EFA and CFA) and structural equation modeling (SEM). The results revealed significant positive impacts of performance expectancy, social influence, and organizational support on attitudes toward AI, which in turn strongly influenced behavioral intention. However, effort expectancy and technological anxiety were found to be insignificant. These findings indicate the need for customized social strategies and organizational support in shaping attitudes toward AI adoption, offering valuable insights for enhancing productivity and innovation in digital marketing.

TABLE OF CONTENTS

CHAPTER PAGE

I. INTRODUCTION 1

Research Question 5

II. BACKGROUND LITERATURE REVIEW AND THEORY 6

Artificial Intelligence in Digital Marketing 6
Unified Theory of Acceptance and Use of Technology 12
Performance Expectancy 16
Effort Expectancy 19
Social Influence 22
Organizational Support 23
Attitude 27
Technological Anxiety 30

III. RESEARCH DESIGN 37

Conceptual Framework 37
Theoretical Development and Hypotheses 37

IV. RESEARCH METHODOLOGY 53

Participants and Procedure 53
Research Design 54
Measurements 56
Informed Pilot 59
Blind Pilot – Data Collection 60
Blind Pilot - Results 60

V. FULL STUDY 77

Full Study Results 77

Descriptive Statistics 77
Exploratory Factor Analysis (EFA) 79
Reliability 82
Convergent Validity 82
Discriminant Validity 85
Confirmatory Factor Analysis (CFA) 87
Structural Model 90
Multi-Group Analysis 94
Findings 98

VI. SUMMARY, IMPLICATIONS AND OUTCOMES 103

Summary of Findings 103
Theoretical Implications 104
Practical Implications 107
Limitations and Future Research 110

LIST OF REFERENCE 113

APPENDICES 133

Appendix I: Informed Pilot Cover Letter 133
Appendix II: IRB Approval 136

VITA 137

LIST OF TABLES

TABLE PAGE

Table 1: Hypotheses 51

Table 2: Construct Definitions 52

Table 3: Blind Pilot Descriptive Statistics 62

Table 4: Blind Pilot Construct Reliability 65

Table 5: Blind Pilot Pattern Matrix (EFA) 67

Table 6: Blind Pilot Factor Loadings (CFA) 69

Table 7: Blind Pilot Heterotrait-Monotrait (HTMT) Values 70

Table 8: INTAI Measurement Scale 72

Table 9: Descriptive Statistics 78

Table 10: Full Study Pattern Matrix (EFA) 81

Table 11: Psychographic Analysis Table 84

Table 12: HTMT Matrix 86

Table 13: Fornell Larker 86

Table 14: Factor Loadings 88

Table 15: Model Fit 89

Table 16: Structural Model Estimation (Significance and Relevance) 92

Table 17: Common Method Bias (CMB) 93

Table 18: R-Square (Explanatory Power) 94

Table 19: MICOM Analysis 96

Table 20: Hypotheses Summary – Final Study 98

LIST OF FIGURES

FIGURE PAGE

Figure 1: UTAUT Diagram 16

Figure 2: The Conceptual Research Model 37

Figure 4: Measurement Model 85

Figure 5: Structural Model 90

I. INTRODUCTION

Artificial Intelligence (AI) is considered by many scholars to be the most significant technological advancement since the advent of the Internet (Dellermann, Calma, Lipusch, Weber, Weigel, & Ebel, 2021; Hirsch-Kreinsen, 2023). This is partly due to its effectiveness in enhancing human capabilities at a minimal cost (Benbya, Davenport, & Pachidi, 2020; Jia, Zhou, Xu & Jin, 2021; Shneiderman, 2020). The recent influx of AI tools has spearheaded a marked increase in its use within a range of business sectors (Nica, Stan, Luţan & Oaşa, 2021; Cubric, 2020). It is forecast that AI will permeate nearly every industry, contributing an estimated $15.7 trillion to the global economy by 2030 (Murphy, Di Ruggiero, Upshur, Willison, Malhotra, Cai, Lui, & Gibson, 2021; McKinsey & Company, 2023a). This technology has the potential to revolutionize key aspects of business particularly when combined with human expertise (Agarwal, Moehring, Rajpurkar & Salz, 2023). Companies investing in AI are discovering its ability to develop innovative solutions, with 86% of CEOs expecting AI to become mainstream by 2025 (PricewaterhouseCoopers, 2024). Generative AI, emerging from large-scale deep learning models trained on extensive datasets, is enabling rapid development of new applications, thus enhancing productivity (Dasborough, 2023; Davenport & Mittal, 2022).

The majority of research on AI has concerned itself with societal implications and the intricacies of how the technology operates (Collins, Dennehy, Conboy & Mikalef, 2021). In more recent studies, management scholars have turned their attention to the benefits of AI, demonstrating a positive correlation with both organizational and personal factors (Wang, 2023). These findings align with the general consensus held by the research community, who agree that AI use by practitioners should be encouraged (Wassan, 2021; Wang, 2023; Man Tang, Koopman, McClean, et al. 2022). Although scholars have alluded to the fact that the potential benefits of AI are only achievable if employees embrace it (Logg, Minson & Moore, 2019; Andronie, Lăzăroiu, Ștefănescu, Ionescu & Cocoșatu, 2021), AI remains a controversial topic (Duan, Edwards, & Dwivedi, 2019; Hou & Jung, 2021). Both researchers and practitioners have noted hesitance in its adoption (Burton, Stein & Jensen, 2019; Mahmud, Islam, Ahmed & Smolander, 2022). This reluctance may be due to insufficient training, uncertainty (Frey & Osborne, 2017), lack of understanding (Raisch & Krakowski, 2020), and mistrust (Glikson & Woolley, 2020).

In marketing, AI facilitates hyper-personalization, which drastically reduces content creation time while increasing engagement (Singh & Kaunert, 2024). This can result in a substantial financial impact, with marketing and sales capturing up to 75% of the estimated $4.4 trillion in annual productivity gains from generative AI (McKinsey & Company, 2023b). AI tools can help practitioners overcome creative blocks, allowing marketing teams to produce more engaging content efficiently (Zhang & Gosline, 2023). For employees, AI tools have been proven to be optimally utilized when combined with human input, although ongoing training is essential for successful integration (Agarwal et al., 2023; Frey et al., 2017). It has been demonstrated, time and again, that marketers gain immediate benefits when they automate content creation and use AI to personalize campaigns (Bloomberg, 2023). This success is dependent, however, on the implementation of measures designed to mitigate risks, such as those presented by potential violations of data privacy, as well as by human biases (Zhang et al., 2023). As

AI technology evolves, increased investment in strategic initiatives will serve to integrate AI even more intrinsically into marketing departments throughout the world (Davenport, Guha, Grewal & Bressgott, 2020; Huang & Rust, 2020).

The usage of AI in digital marketing has evolved significantly throughout the years, "(re)shaping strategy, activities, interactions, and relationships" (Hermann, 2022). Initially, AI was primarily used to analyze customer data (Faruk, Rahman & Hasan, 2021). Over time, it has grown to encompass more complex applications, such as personalized content creation and advanced analytics (Singh et al., 2024). The increased sophistication of machine learning algorithms with an ability to accurately predict consumer behavior is indicative of this advancement (Akter, Dwivedi, Sajib, Biswas, Bandara & Michael, 2022; Burton et al., 2019; Mahmud et al., 2022).

AI tools have become integral to the enhancement of content quality in digital marketing (Abdelkader, 2023). Prior research has revealed that these methods offer substantial benefits in the creation of SEO-optimized content and streamlined graphics, imbuing transformational power to marketing strategies (Somosi, 2022). Exciting as this evolution may be, there remain unresolved obstacles. The variables that affect digital marketers' intentions to adopt these AI tools have yet to be fully understood. This gap is problematic because understanding these factors is crucial in the development of strategies designed to encourage their effective use. Without this knowledge, it becomes unnecessarily challenging to design training programs, company policies, and tools that align with marketers' needs.

There have been studies on AI use among consumers in recent years, however there is still a lack of empirical data on usage intention among professionals and practitioners. A population gap also exists; digital marketers remain a population inadequately studied. Dwivedi et al. (2021) proposed that the increasing role of AI in digital and social media marketing warrants in-depth exploration of its adoption and impact. In addition, a systematic literature review on AI in business strategy emphasized the need for more studies regarding how AI tools align with organizational strategies, and what their impact on decision-making processes might be (Kitsios & Kamariotou, 2021). Another study that further validates the need for research in this area highlighted the importance of investigating AI's role in entrepreneurial decision-making, suggesting that understanding AI adoption in various sectors, including marketing, has become essential (Giuggioli & Pellegrini, 2023).

The objectives of this dissertation include:

1. To explore the psychological, organizational, and individual factors that impact the intention of digital marketers to adopt AI content creation tools.
2. To evaluate the relationship between attitude and intention.
3. To examine the moderating effect of technological anxiety on the relationship between attitude and intention.
4. To provide insights for both practitioners and scholars in the field of digital marketing.

Using a modified model of the unified theory of acceptance and use of technology (UTAUT), this study aimed to provide a comprehensive understanding of the dynamics that lead to user intention (Ajzen, 1991; Venkatesh, Morris, Davis & Davis, 2003). Such knowledge is important for businesses and marketers in their efforts to inform strategies for effectively integrating AI tools into their practices, thereby enhancing productivity and creativity (Dasborough, 2023; Davenport et al., 2022). Furthermore, evaluating the relationship between attitude and intention and assessing the moderating effect of anxiety can offer valuable insights into the complexities of technology adoption behavior (Chawla & Joshi, 2023; Huang, Jabor, Tang & Chang, 2022). The findings of such a study might be used to guide targeted interventions, to address existing barriers to adoption, and to foster a positive attitude toward AI tools. This research has the potential to make significant contributions to the fields of marketing, psychology, and technology management by providing a foundation for future studies and by initiating practical applications which can further innovation and competitiveness.

Research Question

What factors contribute to the intention to use AI content creation tools by digital marketers in the United States?

II. BACKGROUND LITERATURE REVIEW AND THEORY

Artificial Intelligence in Digital Marketing

- The integration of AI into digital marketing has been the subject of several scholarly articles in recent years. Collectively, they paint a comprehensive picture of AI's current impact on digital marketing, and its potential to influence future marketing endeavors. As AI continues to transform the industry, the readiness of employees to embrace these technologies is vital for successful implementation and ongoing innovation within organizations.

The term "artificial intelligence" was first used during a workshop known as the Dartmouth Conference in 1956 (Hildebrand, 2019). The idea was proposed that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy, Minsky, Rochester, & Shannon, 1955). In the years since, the term has taken on additional definitions. One scaled-down example is simply, "intelligence displayed by machines" (Siau, 2017). Others are more complex, describing such qualities as an intelligence that can perceive and interact with the environment (Russell & Norvig, 2003), a system capable of engineering intelligent computer programs (McCarthy, 2007), and a revolutionary advancement in the area of human-computer interaction (Van Esch, 2018). However it may be defined, AI is concerned with the challenge of enabling computers to understand human intelligence, extending beyond techniques capable of being observed biologically (Kellogg, Valentine, & Christin, 2020; Stanford, 2007).

This research concentrates on generative AI, a form of artificial intelligence that produces text and creative content resembling human output, while integrating data from various sources for analysis (Dasborough, 2023). It enables a collaboration between user and technology to complete “diverse knowledge-intensive tasks” (Seeber, Bittner, Briggs, et al., 2020). Generative AI augments human cognition and problem-solving capabilities, leading to greater efficiency within organizations (Malone, 2018; Wilson & Daugherty, 2018). The combination of man and machine has been shown to surpass individual efforts alone (Agarwal et al., 2023; Kamar, 2016; Wang, Pynadath, & Hill, 2016). This synergy can aid in forming unbiased judgments, heightening creativity, and improving rationality (Kahnemann, Rosenfield, Gandhi & Blaser 2016; Burton et al., 2019). For the purpose of this study, artificial intelligence (AI) is defined as generative computer programming capable of performing activities that usually require human intelligence, such as the ability to recognize patterns, make decisions, and interact with environmental systems.

Overgoor, Chica, Rand, and Weishampel (2019) explained AI’s role in marketing as "the development of artificial agents that, given the information they have about consumers, competitors, and the focal company, suggest and/or take marketing actions to achieve the best marketing outcome." The integration of AI into marketing is predicted to expand significantly, leading to more opportunities for marketing enterprises (Hermann, 2022; Singh et al., 2024; Wirth, 2018). Presently, AI impacts nearly every facet of marketing, though the extent of its influence varies. (Haleem, Javaid, Qadri, Singh, & Suman, 2022). These include the areas of product development (Haleem et al., 2022), market research (Pitt, Eriksson, Dabirian, & Vella, 2018), and business strategy (Hildebrand, 2019).

Vishnoi and Bagga (2019) provided insights into the interaction of AI with the physical environment, focusing on the development of technologies designed to support marketing processes to create a competitive edge. Such advantages include the enhancement of data processing capabilities, enabling more inclusive and representative decision-making processes and improving customer engagement through intelligent automation. The evolution of marketing, traced from a seller-centric approach to more customer-centric models, emphasized the role of AI technology in this transformation.

Additional studies have explored the impact of AI on more specific spheres of digital marketing. Chandra (2020) investigated modern applications of AI, with a focus on customer service and experience. Elhajjar, Karam, and Borna (2020) used interviews to facilitate an understanding of the factors that attract students to AI in marketing courses. Mogaji, Soetan, and Kieu (2020) studied low-income consumers, evaluating the effects of using AI in targeted marketing campaigns, revealing the role human interaction plays in achieving optimal customer experience. Murgai (2018) suggested that AI is positively transforming an array of marketing considerations, including lead generation, chatbots, content creation, and email marketing, all resulting in more efficient strategies.

Theodoridis and Gkikas (2019) explored how AI can potentially transform digital marketing campaigns, emphasizing its role in the enhancement of customer engagement, as well as the personalization of marketing strategies. Priyanga (2023) further investigated AI's effects on digital marketing, highlighting ways in which AI technologies, such as those found in machine learning and data analytics, have impacted marketing tactics and customer interactions. The literature-based study of applications in the marketing sector provided by Haleem et al. (2022) showcased the use of AI across a diverse range of marketing segments. These findings complement those of Capatina, Kachour, Lichy, Micu and Codignola (2020), who envisioned that AI applications in social media marketing would align with user expectations by trending towards more personalized experiences.

Frank (2021) demonstrated how AI can be leveraged in eco-friendly marketing strategies, citing the ways sustainable practices vary across different consumer demographics, locations, and product types. Devang, Chintan, Gunjan, and Krupa (2019) focused on general applications of AI in marketing, providing a comprehensive overview of the ways AI tools can be utilized to enhance the efficiency of marketing strategies and operations. Peyravi, Nekrošienė, and Lobanova (2020) offered a theoretical review in their discussion of "revolutionized" marketing technologies, with a specific focus on AI, emphasizing its transformative impact on the marketing sector as a whole.

AI has the ability to generate high-quality content that resonates well with target audiences (Singh et al., 2024). This quality makes it possible to streamline marketing strategies, and to enhance the effectiveness of digital campaigns (AIContentfy, 2023). Davenport and Mittal (2022), in an article published by the Harvard Business Review, examined ways that generative AI is capable of revolutionizing creative efforts. Their analysis emphasized the significant impact of AI on traditional content creation processes, noting the enhanced efficiency and innovation that it provides. Consequently, the generation of ideas, and the production of creative outputs, were deemed likely to improve other creative industries as well. Miller and Bhattacharyya (2023), in their examination of the role of AI in biomedical publishing, offered an additional perspective by providing insights into the broader implications of AI-assisted content creation. Their quantitative bibliometric analysis revealed an increasing reliance on AI for data analysis, content generation, and decision-making in diverse content creation domains, including digital marketing.

Innovative applications of AI content creation tools have paved the way for the future of marketing (Siau, 2017). One of the most utilized of these tools is ChatGPT, an artificial intelligence-generated content (AIGC) model (Du, Li, Niyato, Kang, Xiong, & Kim, 2023). It has earned its popularity by understanding and managing difficult tasks, as well as by generating language in conversational form (Wu, He, Liu, Sun, Liu, Han & Tang, 2023). GPT stands for Generative Pre-trained Transformer (Wu et al., 2023). The term "generative" describes its ability to generate text. "Pre-trained" means that the model undergoes training using a vast collection of text data before being optimized for specific tasks. "Transformer" is the name of the neural network architecture used in the model. The transformer architecture enables the model to efficiently manage long-range dependencies in text, enhancing its effectiveness for natural language processing tasks (Radford, Narasimhan, Salimans, & Sutskever, 2018). The core techniques also include in-context learning and reinforcement learning from human feedback (Wu et al., 2023). OpenAI has recently included Dall-E, an image generator (Ramesh, Dhariwal, Nichol, Chu & Chen, 2022), in its ChatGPT-4o application, providing additional capabilities, particularly to digital marketers in the development of advertising campaigns. ChatGPT has the potential to positively impact multiple business sectors and fields of study; however, it is essential to monitor its proper use in order to prevent potential risks, including challenges related to academic integrity and safety (Stokel-Walker & Van Noorden, 2023).

According to the Pew Research Center, 52% of Americans express more concern than excitement about the growing use of artificial intelligence (Tyson & Kikuchi, 2023). The acceptance of AI is a multifaceted consideration, often influenced by the preconceptions of the user (Kelly, Kaye, & Oviedo-Trespalacios, 2022). In 2020, a comprehensive investigation was conducted across 142 nations, involving over 154,000 participants, which revealed widespread concerns about the potential hazards of AI. The acknowledged need for such an extensive study indicates a level of global awareness regarding the risks associated with AI technologies (Neudert, Knuutila, & Howard, 2020). Gillespie, Lockey, & Curtis (2021) extended this understanding by demonstrating an apprehension toward AI acceptance. This hypothesis was explored using responses from participants from the US, Australia, Canada, Germany, and the UK, where overall confidence in AI was found to be low. Additional research focusing on the United States found that, while a considerable portion (41%) of Americans supported AI development, a significant minority (22%) are still opposed to it (Zhang, Baobao, & Dafoe 2019). Although 77% of the sample believed that AI will positively impact their work and life in the next decade, 82% advocated for careful governmental monitoring based on feared privacy risks.

These findings reinforce the conviction of AI's potential to enhance human life. However, the acceptance of AI remains context-dependent, especially with regard to its diverse applications and settings (Luan, Geczy, Lai, & Li, 2020).

Unified Theory of Acceptance and Use of Technology

Over the years, numerous theories on technology acceptance have emerged, many of which led to the creation of frameworks that further illuminate users' intentions to adopt new technologies (Momani & Jamous, 2017; Xu, Ge, Wang & Skare, 2021; Yadegari, Mohammadi & Masoumi, 2024). Researchers have spent countless hours exploring technology acceptance with the objective of improving methods for design, evaluation, and predicted user response to new technologies (Schwarz & Chin, 2007; Williams, Dwivedi, Lal, Schwarz, 2009; Xue, Rashid & Ouyang, 2024).

The Theory of Planned Behavior (TPB) (Ajzen, 1991), which evolved from the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1975), adding to TRA the component of perceived behavioral control, has become one of the most widely used models (Madden, Ellen & Ajzen, 1992). According to TPB, there are three key elements that influence a person's intention to undertake a behavior. These include their personal attitude toward the behavior, the subjective norms associated with the behavior, and their perceived behavioral control (Ajzen, 1991). A consideration of such factors has been proven to be instrumental in the prediction of actual behavior (Ajzen, 1991; Bosnjak, Ajzen, & Schmidt, 2020).

TPB influenced the creation of the Technology Acceptance Model (TAM) by imparting foundational concepts based on its use in researched studies of human behavior and decision making (Chen, Li, Gan, Fu & Yuan, 2020). Since its introduction by Fred Davis and his colleagues in 1989, TAM has been a leading model for predicting users' intentions to adopt or reject technology (Chauhan & Jaiswal; 2016; Cimperman & Trkman, 2016) by focusing on the key factors of perceived efficiency and ease of use (Marangunić & Granić, 2015). This focus has enabled TAM to offer a targeted method for predicting technology adoption, providing a strong model for understanding users' acceptance of technology (Yousafzai, Foxall & Pallister, 2007). Despite the strength of this method, some researchers have pointed out drawbacks of TAM, citing that it (1) fails to offer a comprehensive understanding of peoples' views of new systems (Sánchez-Prieto, Olmos-Migueláñez & García-Peñalvo, 2016), (2) overlooks its indicators by focusing directly on the external variables of perceived ease of use (PEOU) and perceived usefulness (PU) (Šumak ,Pušnik, Heričko & Šorgo, 2017), and (3) disregards the connection between usage attitude and the intention to use (Tsai, Chao, Lin & Cheng, 2018).

Subsequently, Davis teamed up with Viswanath Venkatesh to develop TAM2 (Venkatesh & Davis, 2000) in order to provide a deeper understanding of technology acceptance. This model incorporated additional constructs into its methodology, including social influence and cognitive instrumental processes (Lai, 2017; Wu, Chou, Weng & Huang, 2011). When TAM2 was empirically tested, it was found to account for 60% of the variance in perceived usefulness and usage intentions across multiple longitudinal field studies (Venkatesh & Davis, 2000).

Three years later, influenced by his work on TAM2, Venkatesh and his colleagues proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Alalwan, Dwivedi, & Rana, 2019; Almuraqab & Jasimuddin, 2017; Dwivedi, Rana, Jeyaraj, Clement & Williams, 2019). Since its introduction, UTAUT, examining user intention within multiple contexts (Williams et al., 2009; Xue et al., 2024) has been widely validated as a theoretical lens for adoption and diffusion research (Williams et al., 2009; Xue et al., 2024). Figure 1 illustrates the evolution, constructs, strengths and explanatory power of UTAUT.

Because of its straightforwardness, economy, and robustness (Tarhini, El-Masri, Ali & Serrano, 2016; Williams et al., 2009; Xue et al., 2024), the UTAUT model has been regarded as the most effective and widely utilized model for technological adoption. It is lauded as the "definitive model" for exploring how users' perceptions of relevant factors are influenced (Siripipatthanakul, Limna, Sriboonruang & Kaewpuang, 2022) and remains one of the “most cited” IS models appearing in technology adoption literature (Venkatesh, Sykes & Zhang, 2011). Lee, Kozar and Larsen (2003) have further categorized its efficacy in investigating user intention in general purpose systems (e.g. personal computers and the internet), office systems (e.g. desktop applications and database systems), specialized business systems (e.g. ERP systems), and communication systems (e.g. kiosks and instant messaging services).

Partial Least Squares Structural Equation Modeling (PLS/SEM), utilized in the validation and measurement of UTAUT’s reliability, contains the specific indices of minimum loading limits of .70 and internal consistency values above .70. Multiple PLS iterations were conducted over three separate time periods, controlling for voluntariness. These included various tests with moderators of gender, age, and experience (Venkatesh, et al., 2003). The UTAUT model accounted for approximately 56% of the variance in behavioral intention to use technology (Tandon, Kiran & Sah, 2016). Validation procedures for the combined scale by Venkatesh et al. (2003) resulted in an overall adjusted R2 of 69%, confirming the model's relevance and superiority over previous theories, as well as confirming its high explanatory power (Wang, Wu, Zhou & Lv, 2022).

The UTAUT model, with its mature technology adoption and diffusion research including different perspectives, theories, and methods, was created to harmonize these diverse viewpoints into one cohesive framework. It integrates elements from eight prominent theories, including the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1975), the Innovation Diffusion Theory (IDT) (Rogers & Williams, 1983), the Theory of Planned Behavior (TPB) (Ajzen, 1991), the Motivational Model (MM) (Deci & Ryan, 1985), the Technology Acceptance Model (TAM) (Davis, Bagozzi & Warshaw, 1989), Social Cognitive Theory (SCT) (Bandura, 1986), the Model of PC Utilization (MPCU) (Thompson, Higgins & Howell, 1991), and the combined C-TPB-TAM model (Taylor & Todd, 1995). In addition, it postulates four key constructs that influence user acceptance and usage: performance expectancy, effort expectancy, social influence, and facilitating conditions (Williams, Rana & Dwivedi, 2015; Venkatesh et al., 2003).

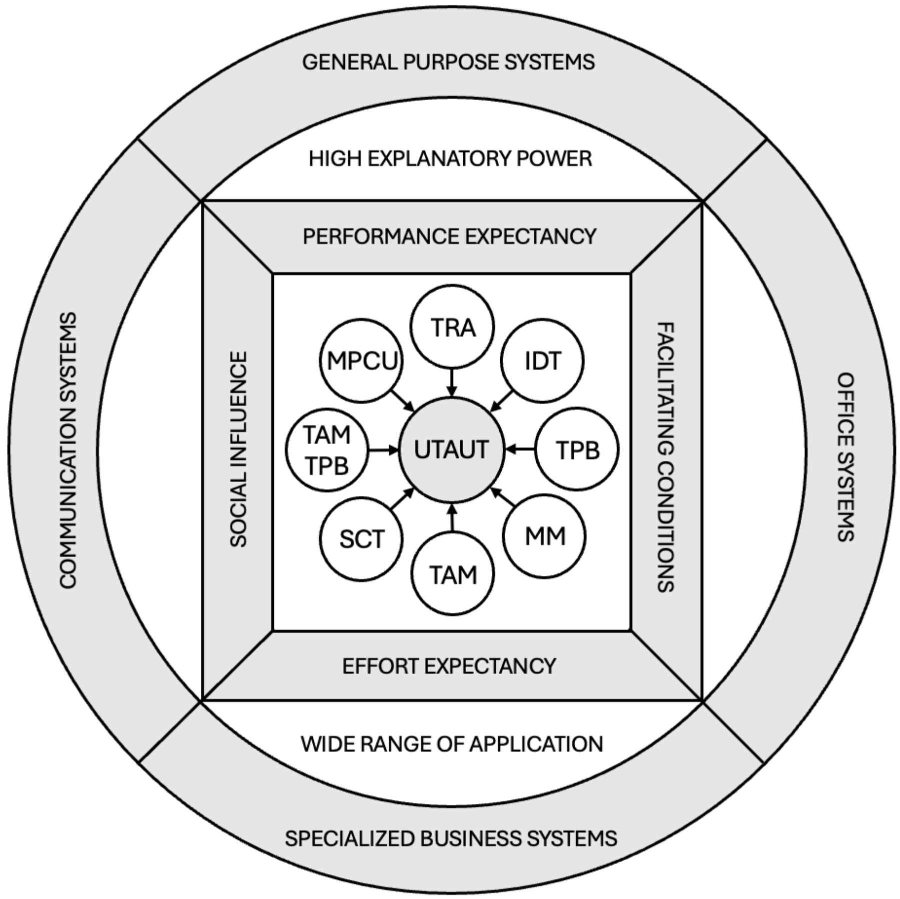


Figure 1: UTAUT Diagram
The evolution, constructs, strengths, and applications of the UTAUT model
(adapted from Teng et al., 2022)

Performance Expectancy

Performance Expectancy (PE) is defined as “the degree to which an individual believes that using a particular system will enhance their job performance” (Venkatesh et al., 2003). It is influenced by five key constructs from prior technology acceptance models, each contributing unique perspectives that augment our understanding of employee performance.

Perceived Usefulness (PU), originating from TAM, TAM2, and C-TAM-TPB, focuses on the benefits that users perceive as directly contributing to their work efficiency and effectiveness (Davis et al, 1989; Venkatesh & Davis, 2000; Taylor & Todd, 1995). Extrinsic Motivation, derived from MM, involves performing an activity in order to achieve distinct outcomes (Deci et al., 1985). In the context of technology acceptance, it demonstrates how external rewards or recognitions, such as bonuses or promotions, are instrumental in motivating workers to use a new system. Job-Fit, from MPCU, is concerned with how well a system aligns with an individual's job requirements. It suggests that the more a system is tailored to fit job tasks, the higher the perceived performance expectancy (Thompson, et al., 1991).

Relative Advantage, from IDT, measures the degree to which a system is perceived as being preferable to its precursor (Rogers & Williams, 1983). Users are more likely to adopt a system if they see that it offers significant improvements over existing options (Dibra, 2015). Outcome Expectations, originating from SCT, is a construct employing the belief that certain behaviors will lead to the desired outcomes (Bandura, 1986). In terms of technology usage, it describes the anticipated positive outcomes that will result from using a particular system. The work of Venkatesh et al. (2003) revealed PE to be the strongest predictor of an individual's intention to use any given system.

Jeon, Sung, and Kim (2020) examined customers' intentions to adopt self-service technology (SST) in restaurants by extending the UTAUT model to include perceived risk along with individual innovativeness. Their results aligned with research done by Venkatesh et al., (2003), confirming that PE is the strongest predictor of acceptance intention. These findings suggest that customers are more inclined to use SST if they believe it will improve their lives by being more time-effective and, overall, more efficient. In a similar vein, Sharma, Sharma, Singh and Bhatia (2023) explored blockchain adoption in agri-food supply chain management by surveying 200 stakeholders and analyzing the resulting data with structural equation modeling (SEM). Their study revealed that PE significantly influenced the stakeholders' behavioral intentions when it came to adopting blockchain technology, reflecting a positive relationship between performance expectancy and adoption intention.

In China, researchers investigating the factors affecting fitness software usage among college students (Wang, C. et al., 2022), confirmed that PE significantly and positively affected students' behavioral intention to use such software. The more that students perceived the software to be beneficial in performing tasks such as tracking exercise, managing weight, and enhancing social interactions, the more likely they were to employ that software. PE was identified as the second most influential factor to BI, reinforcing the importance of perceived usefulness in technology adoption.

Abdou and Jasimuddin (2020) explored the key factors that drive the adoption of e-learning technologies in French banks, demonstrating that PE is a pivotal factor in determining the intention to use this technology. Their findings revealed that individuals who expect higher performance gains from e-learning are more likely to plan to adopt these technologies. This conclusion was corroborated by prior empirical evidence showing a significant positive correlation between performance expectancy and the intention to use e-learning systems in the banking industry. Research on tourist behavior with technology usage, based on Information and Communication Technology (ICT), proposed that PE, as compared to perceived usefulness from the Technology Acceptance

Model (TAM), is a significant predictor of behavioral intention (Ali, Tuhin, Alim, Rokonuzzaman, Rahman & Nuruzzaman, 2024). PE, in this instance, was described using the dimensions of usefulness, convenience, time efficiency, and productivity. This supports the hypothesis (H1) that PE presents a significant positive influence on the behavioral intention of tourists in responding to ICT usage.

Since research in the area of generative AI is a fairly recent phenomenon, the number of studies on behavioral intention is limited, and not yet subject to the test of time. In 2021, UTAUT was used for a greater understanding of the intention to adopt AI technologies among librarians. Similar to the results of studies in prior technology acceptance literature, PE proved to have a significant effect on the intention to adopt AI (Andrews, Ward & Yoon, 2021). These results reinforced the hypothesis that librarians would do well to prioritize using technology in order to enhance their job performance. A study on the factors influencing students' intentions to use AI in education also demonstrated that PE had a significantly positive impact on the intention to use (Milicevic, Kalas, Djokic, Malcic, B. Djokic, 2024). These findings, added to the previously cited studies, confirm that higher PE leads to a stronger intention to use new technology.

Effort Expectancy

EE is defined as "the degree of ease associated with the use of a system" (Venkatesh et al., 2003). This concept encompasses several key constructs that contribute to its overall understanding, including ease of use, complexity, and perceived ease of use (Cimperman et al., 2016). Ease of use, originating from IDT, refers to how simple and straightforward a system is to operate (Rogers & Williams, 1983). This construct emphasizes the importance of user-friendly interfaces and intuitive design to encourage system adoption (Wang, Wu, Lin, Wang & He, 2012). Complexity, derived from the MPCU, is defined as the degree to which a system is perceived as difficult to understand and use (Thompson, et al., 1991). High complexity can be a barrier to acceptance; users might be deterred by systems that require extensive effort to learn and to operate (Morchid, 2020). Perceived Ease of Use (PEOU), taken from the TAM and its extension TAM2, measures the extent to which a person believes that using a system will be free of effort (Davis et al., 1989; Venkatesh & Davis, 2000). This construct posits that the less effort users expect to exert in using a system, the more likely they are to find it acceptable and to adopt it (Davis et al, 1989). Effort Expectancy has proven to be a significant predictor of technology acceptance in both voluntary and mandatory usage contexts (Venkatesh et al., 2003), with its influence most pronounced during the initial adoption phase. Over extended periods of sustained use, the significance of effort expectancy diminishes as users become more accustomed to the system and its ease of use (Venkatesh et al., 2003).

Data was collected from 412 university students in Jordan to investigate the use of cloud computing in higher education (Jaradat, Ababneh, Faqih & Nusairat, 2020). EE in this study measured the degree to which students believe that using cloud computing will be easy, requiring minimal effort. It was found that EE had a positive influence on students' intention to adopt cloud computing; the easier and more flexible the students perceived cloud computing to be, the more likely they were to adopt it. Research by Chen et al. (2020) utilized survey data from 913 citizens of Chongqing, China to analyze the impact of specific factors affecting the public acceptance of driverless buses. Their study hypothesized, and confirmed, that EE positively impacts acceptance intention (H1). The easier people find it to use driverless buses, the more likely they are to accept them.

An extended model of UTAUT was developed to investigate factors affecting users' behavior and willingness to pay for online knowledge platforms (Yu, Chen, Yao & Liu, 2021). The findings indicate that EE positively affects users' willingness-to-pay (H2a) and their paying behavior (H2b). When users perceive the platform to be easy to use, they are more likely to be willing to pay for the knowledge offered. The positive relationship between EE and intention highlights the importance of user-friendly interfaces to enhance the adoption and usage of these platforms. A study on the intention of consumers to make payments with mobile payment systems in India defined EE as the degree of ease associated with the use of technology. The study found that effort expectancy positively and significantly influences consumers' attitudes towards using mobile payment systems; as consumers perceive mobile payment systems to be easier to use, their intention to adopt them increases.

Kim and Kang (2023) worked to identify the determinants of consumer behavioral intentions to use dining apps in China, and the ways in which these factors contribute to the adoption and continued use of the technology. EE was shown as a significant predictor of behavioral intention; when users perceive a dining app to be easy to use, their intention to adopt and use it increases. This aligns with the UTAUT model's hypothesis stating that effort expectancy directly influences behavioral intention, which then affects the actual adoption and continued use of the technology.

Social Influence

Social influence (SI) stands for a person's perspective of how others, especially superiors, expect them to use a system (Venkatesh et al., 2003). It encompasses the constructs of subjective norms, social factors, and image to explain how external social pressures and perceptions impact an individual's technology acceptance and usage behavior (Venkatesh et al., 2003). It is significant in understanding the role that social dynamics play in user intention, initial adoption and ongoing use of new systems. Subjective norms, derived from the TPB, TAM2, and C-TAM-TPB, refer to the perceived social pressure inherent in the decision to perform or not to perform a particular behavior (Ajzen, 1991; Venkatesh & Davis, 2000; Taylor & Todd, 1995). These norms often focus on the impact of influential people, such as colleagues or supervisors, who act as influencers in decisions made about using a new system (Venkatesh & Davis, 2000). Social factors, originating from MPCU, include the perceived pressure of social groups and networks, as well as the influence of peers and group norms, emphasizing the role of social interaction in shaping technology adoption (Thompson, et al., 1991). Image, taken from IDT, refers to how using a new system can be seen to enhance a person's social status and reputation, thereby acting as a motivation to adopt such a system (Rogers, 1983).

A study on the teaching behavior of university instructors found that SI significantly affected their behavioral intention to adopt mobile teaching (Peng, 2022). The impact of SI on teachers' decisions to integrate mobile technologies into their instruction was demonstrated among colleagues, students, and relevant stakeholders. Kayali and Alaaraj (2020) also investigated remote learning, using UTUAT to investigate the factors influencing students' adoption of cloud-based e-learning (CBEL). Responses from Lebanese university students found that SI significantly affected students' behavioral intentions to use e-learning methods, in this case via cloud computing (CBEL). Social pressure, as well as recommendations from peers, family members, friends, and university management helped to shape their decisions.

Using the UTAUT model, factors influencing Bangladeshi farmers' willingness to adopt and pay for IoT technology, social influence (SI) was found to have a positive impact on its adoption (Shi et al., 2022). In this instance, SI referred to the degree to which farmers perceived that peers, experts, and other farmers believe they should use IoT technology. Acceptance of Electronic Document Management Systems (EDMS) was examined through survey data from 270 of the academic and administrative staff at Bartin University. This resulted in the finding that SI plays a crucial role in shaping users' intentions to adopt EDMS, further corroborating the importance of social support and peer influence in the successful implementation of new technologies in organizational settings.

Organizational Support

Organizational Support (OS) is derived from the Facilitating Conditions (FC) construct within the UTAUT. FC is defined as the degree to which an individual believes an organizational and technical infrastructure exists to support the use of a system (Venkatesh et al., 2003). This construct was renamed to better capture its essence from a practitioner's perspective; its usage has appeared in prior research, such as in the study by

Almagrashi, Almagrashi, Mujalli, Khan, and Attia (2023), where Organizational Influence (OI) was used as a variable in their modified UTAUT model.

In the context of UTAUT, FC is derived from three distinct constructs: perceived behavioral control from the TPB and C-TAM-TPB, facilitating conditions from the MPCU, and compatibility from IDT. Perceived behavioral control emphasizes users' perceptions of their ability to use a system, considering both internal and external constraints (Ajzen, 1991; Taylor & Todd, 1995). Facilitating conditions include the availability of resources and adequate support to assist in the use of the system (Thompson, et al., 1991). Compatibility refers to how well the system aligns with existing values, past experiences, and the needs of potential users (Rogers & Williams, 1983). Each of these constructs is designed to encapsulate aspects of the technological and organizational environment essential for mitigating barriers to system use.

OS has been evaluated using a variety of models and frameworks, including the PCMT Model of Organizational Support, the Social Exchange Theory, and the Delone and McLean Information Systems Success Model. The PCMT Model is the most recent of these frameworks, in which organizational support is composed of four distinct forms, based on their sources and targets. One of these forms is Perceived Organizational Support (POS), which was defined as the provision of a supportive and caring workplace environment (Matusik, Ferris & Johnson, 2022). In social exchange theory (SET), OS has its basis in a reciprocal relationship involving the organization's desire to fulfill the socio-emotional needs of its employees (Blau, 1964). The Delone and McLean Model considered OS in terms of the resources and infrastructure needed to ensure the success of information systems (DeLone & McLean, 1992).

Eisenberger, Huntington, Hutchinson, and Sowa (1986) were pioneers in introducing the concept of perceived organizational support, defining it as "the degree to which an employee believes their organization values their contributions and cares about their well-being." POS has been utilized to ensure that employees receive the necessary backing, and that they are not abandoned during stressful times (George, Reed, Ballard, Colin, & Fielding, 1993). Ballinger, Lehman, and Schoorman (2010) concurred, highlighting that organizations need to create a supportive and nurturing environment in order to become more appealing and to maintain competitiveness in a constantly evolving market, like IT.

Facilitating Conditions, one of the main constructs of UTAUT, has been used to measure organizational support in hundreds of studies to date. This research has focused primarily on students' perceptions of the institutions they attend, and employees' perceptions of their workplace organizations. One such study looked into the adoption of Eduverse, an educational metaverse platform among college students in China. FC referred to the learners' perceptions of the technical and organizational resources supporting their use of the Eduverse platform (Teng, Cai, Gao, Zhang, & Li, 2022). FC had a significantly positive effect on learners' satisfaction with using it and positively influenced their intention to continue. This indicates that the availability of adequate support and resources is necessary for sustained use. The continued use of a student portal by undergraduate students from UCSA (University College ShahPutra) also revealed that FC has a significant positive relationship with behavioral intention (Bakar et al., 2013), directly affecting the intention to use by providing the necessary support and infrastructure.

Antecedents of the adoption of Human Resource Information System (HRIS) in Jordanian public sector organizations were investigated by surveying 211 of its workers (Alkhwaldi, Alobidyeen, Abdulmuhsin & Al-Okaily, 2023). The study found that improvements in facilitating conditions enhanced users' BI to adopt and accept IT/IS. In this context, FC refers to users' perceptions regarding the availability of resources, such as training, technical support, and materials, necessary for supporting HRIS usage in the public sector. Their study concluded that a robust FC is a significant determinant of BI to use HRIS.

Almagrashi et al. (2022) investigated factors determining internal auditors' behavioral intention to use computer-assisted auditing techniques. In this study, FC was split into two components: organizational influence, representing the backing and motivation from top management, and a refined FC construct, encompassing the availability of the resources needed to support and utilize CAATs. Both of these variables were shown to positively influence the intention to use CAATs. It concluded that without adequate resources, training, and support, auditors are less likely to use these technologies.

Ahmad, Salim and Sham (2021) emphasized the significance of perceived organizational support in influencing employee behavior. OS was further explored by Cao et al.'s (2021) in a study on the impact of AI capabilities on organizational performance in the public sector, indicating the need for a comprehensive understanding of how different aspects of AI capabilities contribute to organizational outcomes. Randall, Cropanzano, Bormann and Birjulin (1999) confirmed the role of OS in shaping employee attitudes on citizenship behavior in his research on organizational politics. It was also found that OS positively affects employee job satisfaction (Pandey & Chairungruang, 2020). In 2020, a meta-analysis of over 70 studies was performed by Linda Rhoades and Robert Eisenberger, who found that OS was influenced by three major categories: fairness, supervisor support, and organizational rewards, which in turn often led to a positive attitude toward job functions.

Attitude

Influential attitude theorists have offered a variety of definitions of attitude, many of which have included cognitive processes that are explicitly linked to the concept of behavior. These include a description from Anderson (1981), who defined attitude as a disposition to reach with characteristic judgments and with characteristic goals across a variety of situations. Triandis (1971) proposed that an attitude is an idea charged with emotion which predisposes a class of actions to a particular class of social situations. Ajzen and Fishbein (1975), who developed TRA and TPB, described attitude as a learned predisposition to respond to an object in a consistently favorable or unfavorable way.

Consistency theory is one of the earliest frameworks in social psychology to suggest that attitude is a valid construct linked to behavior (Abelson, Aronson, McGuire, Newcomb, Rosenberg & Tannenbaum, 1968). Researchers, using one of several theories under the umbrella term, initially suggested that there was a bi-directional relationship between the two variables (Heider, 1946; Osgood & Tannenbaum, 1955; Rosenberg, 1956; Festinger, 1957). This connection was later theorized to be a causal link, with attitude being a precursor to behavior (Kahle & Berman, 1979). Martin Fishbein and Icek Ajzen were the main researchers responsible for proving this causal relationship. Their

Theory of Reasoned Action (TRA) has been credited with rescuing the attitude construct and "imposing some conceptual order" (Fishbein, 1979). Manstead and van der Pligt (1998) even claimed that attitude was "the single most indispensable construct in social psychology." TRA is among the earliest models to express the mediating effects of intention on behavior.

These assessments are rooted in beliefs regarding the consequences of that action, as well as evaluations of the potential outcomes (Eagly, Mladinic & Otto, 1991). This was later adapted into the TPB, which was the premise for the attitude construct used as a mediator for TAM. Tate, Evermann and Gable (2015) raised the issue that existing theories lacked the necessary constructs to more accurately explain students' intentions to use technology based on their attitudes. Since that time, attitude as a mediating variable has been borrowed and applied to a number of modified UTAUT models, which is the premise for its use in this research.

An examination of factors influencing consumer attitudes and intentions to use mobile wallets in India integrated both TAM and UTAUT to form a comprehensive model that includes the relationship between attitude and intention (Chawla & Joshi, 2019). Attitude toward using mobile wallets was shown to have a positive and significant effect on the intention to adopt them. Patil, Tamilmani, Rana and Raghavan's (2020) study on consumer adoption of mobile payments using an extended UTAUT model also showed a significant link between attitude and intention, emphasizing that performance expectancy and facilitating conditions can significantly boost consumer intention to adopt these services.

Using an extended TAM model that includes the construct of technological anxiety, which is also used in this study, the factors influencing students' intention to use tablet computers in K-12 educational settings was investigated (Zheng & Li, 2020). The statistically significant results indicated that fostering a positive attitude, by improving perceived usefulness and reducing technology anxiety, can significantly enhance students' intention to use tablet computers in educational settings. Dharun Lingam Kasilingam (2020) also used TAM to understand the attitudes and intention to use smartphone chatbots for shopping. Attitude here was defined as the degree to which consumers have a positive or negative evaluation of chatbot usage, and was shown to fully mediate the relationships between the independent variables and the intention to use.

Integrating the Diffusion of Innovations (DOI) theory, the Decomposed Theory of Planned Behavior (DTPB) and TAM to create a comprehensive model, the determinants influencing consumers' intentions to adopt mobile banking in Taiwan and Vietnam were explored (Ho, Wu, Lee & Pham, 2020). In this study, attitude referred to the degree to which people favorably or unfavorably evaluated the behavior of using mobile banking. It served as a mediator between perceived usefulness, compatibility, perceived risk, and the intention to adopt the service, and was shown to be significant direct precursors to the intention to adopt in both Taiwan and Vietnam. Similarly, TPB was used by Perri, Giglio and Covello (2020) to research the intention to adopt smart energy consumption behaviors. Attitude was conceptualized as a function of behavioral beliefs, representing the perceived consequences of the behavior and the evaluation of the consequences. In the context of their study, attitudes towards smart grid adoption were evaluated through perceived advantages and disadvantages derived from its adoption. Attitude towards behavior positively influenced the intention to adopt, further validating attitude as a pivotal predictor of behavioral intention.

There are several instances of attitude serving as a mediator in the UTAUT model. These relationships can be seen in Moya, Nabafu, Maiga and Mayoka's 2017 research on the role of attitude and behavioral intention in the adoption of e-tax services. Dwivedi reevaluated UTAUT in 2019, proposing an updated theoretical framework. In both studies, attitude was found to mediate the effects of performance expectancy, effort expectancy, and social influence on behavioral intention. Chawla (2023) and Roh et al. (2023) also investigated the role of attitude as a mediator; however, there was shown to be a partial mediation of facilitating conditions on attitude and behavioral intention in both studies.

Technological Anxiety

Technological anxiety is the cultural apprehension or fear that arises from the perception of technology as alien, confusing, and powerful, to the point of potentially becoming uncontrollable (Mokyr, Vickers & Ziebarth, 2015). It is characterized by extreme wariness of technology, criticism of technology, and efforts to decrease and avoid its usage (Doronina, 1995). In Mokyr's "History of Technological Anxiety and the Future of Economic Growth" (2015), the origins of technological anxiety were linked to the Industrial Revolution, a period marked by the fear of job displacement due to mechanization, the dehumanization of labor, and the predicted lasting effects of technological advancements. Although there were widespread fears about unemployment caused by technology, history reveals that this did not actually occur on a large scale. As a matter of fact, technological progress led to the creation of new industries and jobs, as well as to an increased demand for labor in complementary roles. Historical patterns suggest that while technological progress can create shifts and disruptions in the labor market, it is also capable of providing opportunities for growth and innovation (Domini, Grazzi, Moschella & Treibich, 2021). At the present time, concerns regarding technology persist, especially in the domain of automation, robotics, and artificial intelligence (Chiarini, Grando, Venturini & Borgonovo, 2023). The term "AI Anxiety" was introduced by Johnson and Verdicchio (2017) to describe the fear that AI might eventually spiral out of control.

Technological Anxiety can also be viewed through the lens of Technostress (TS). Initially, TS was defined as “a modern disease of adaptation caused by inability to cope with new computer technologies in a healthy manner” (Brod, 1984). Tarafdar, Tu & Ragu-Nathan (2007) elaborated on this by describing TS as “any negative impact on attitudes, thoughts, behaviors, or body physiology that is caused either directly or indirectly by technology” (Tarafdar et al., 2007). Subsequently, TS was defined as anxiety toward information and communication technology (ICT) exhibited by end users employed by companies (Ragu-Nathan, Tarafdar & Tu, 2008). Brod (1984), a pioneer in technostress research, explained that a more comprehensive understanding of the factors contributing to this type of anxiety is required. He broke it down into the following components: strain, which is the internal state of people; stressors, which are external events; and people’s interactions with their environment (Mason, 1975). This concept expands theories of general workplace stress, characterized by trauma due to demands placed on workers that are greater than what they are capable of achieving, what their available resources may be, and what they require to complete their jobs (Stranks, 2005).

Initially, research on technostress focused on its organizational impact (Ragu-Nathan et al., 2008), but it has since expanded into consumer and private contexts. Most research, however, has concentrated on technology users in business (Bondanini et al. 2020). One of the earliest and most widely adopted theoretical frameworks for studying technostress is the transactional model of stress (TMS) by Lazarus and Folkman (1984). This model has been used to examine technostress in both organizational and private usage contexts (Ragu-Nathan et al., 2008; Pirkkalainen, Salo, Tarafdar & Makkonen, 2019; Tarafdar, Cooper & Stich, 2019). TMS posits that the way people interact with their environments can be stressful when the environment is perceived to demand more than they can provide (Cooper, Dewe & O'Driscoll, 2001). When applied to human-technology interactions, TS has been described as "a process that includes (1) the presence of 'technology environmental conditions'; which are appraised as (2) demands or 'techno-stressors' taxing the individual and necessitating a change; leading to (3) 'coping responses'; and resulting in (4) psychological, physical, and behavioral 'outcomes' for the individual" (Tarafdar et al., 2019).

Tsai et al. (2020) investigated the technological anxiety (TA) among 31 elderly adults suffering from cardiovascular disease equipped with wearable cardiac monitoring systems. TA negatively affected the perceived ease of use (PEOU) and perceived ubiquity (PB) of such smart clothing among older adults in general, which in turn negatively affected their intention to use. In their article, TA referred to an emotional response that was elicited by the subjects through the actual use of the systems, as well as by the thought of using them. Arising from early studies of computer anxiety, this research also included factors such as apprehension about using technology, fear of making mistakes that cannot be corrected, concern that equipment may suddenly stop functioning, and reluctance to be seen wearing smart clothing. Using TAM, the impact of technostress on teachers' continuing intentions to use mobile technology in K-12 education in Palestine, was found to negatively affect both perceived usefulness and teachers' attitudes toward mobile technology. This, in turn, influenced their intentions to continue using the technology for educational purposes (Khlaif, Sanmugam & Ayyoub, 2023).

A study examining the effect of technology anxiety on the use of self-service technologies (SSTs) among 823 consumers found that individuals with higher anxiety levels were less likely to use SSTs. Technological anxiety was shown to negatively impact satisfaction, likelihood of future use, and positive word-of-mouth recommendations for those who had initially satisfying experiences (Meuter, Ostrom, Bitner & Roundtree, 2003). A study of the adoption and use of mobile payment systems among Indian consumers found that technological anxiety negatively influenced attitude, and that attitude positively influenced behavioral intention (Patil et al., 2020). These findings confirm that higher levels of anxiety result in a negative attitude towards mobile payments, thereby reducing the likelihood of adoption and use.

Brooks et al., (2023) defined technostress as the response experienced as a result of a person's incapacity to process new data and technologies without some form of anxiety. Reviewing survey responses from 512 IT professionals, they identified technostress as an influencing factor negatively affecting career outcomes. Technostress was shown to reduce IT professionals' commitment to their careers, to increase feelings of exhaustion, and to lead to higher turn-away intentions.

The moderating effect of TA was used in a study by Yang and Forney (2013), who examined the determinants of mobile shopping adoption, focusing on how consumer technology anxiety moderates the relationships within a modified UTAUT model. The influence of SI on BI was more pronounced among consumers with high technology anxiety, while FC was shown to be stronger for those with low technology anxiety. The moderating role of technostress in EFL Learners' mobile learning adoption used the TPB to show how technostress moderates the effect of subjective norms on the adoption intention of mobile English learning. The results showed that high levels of technostress can weaken the positive influence of subjective norms on adoption intention. This suggests that even if learners perceive themselves to be under social pressure to adopt mobile English learning, high technostress can deter them from doing so.

Four dimensions of AI Anxiety were proposed by Chang, Zhang, Cai and Guo (2024): lack of transparency, privacy violations, job displacement, and ethical concerns. The researchers proposed the question, "Does AI-driven technostress promote or hinder employees' artificial intelligence adoption intention?" According to H2b, AI anxiety was negatively related to AI adoption intention. This finding suggests that increased AI anxiety among employees can lead to a decrease in their willingness to adopt AI technologies. As AI anxiety rises, employees may feel more apprehensive and fearful about integrating AI into their work, which can result in resistance to adoption. Utilizing the Affective Events Theory (AET) and the Challenge–Hindrance Stressor Framework (CHSF) to explore how technostress influenced by AI affects employees' intentions to adopt AI in the workplace, two types of AI-related technostress were identified: challenge stressors, and hindrance stressors (Kaya et al, 2024). Challenge stressors are associated with personal growth and positive emotions, while hindrance stressors lead to negative emotions and anxiety. AI-driven challenge stressors positively impacted AI adoption intention by prompting positive responses; hindrance stressors had a negative influence by eliciting AI-related stress.

AI's impact on digital marketing is an immense one, emphasized by its potential to transform marketing strategies by means of improved data processing, customer engagement, and personalized consumer experiences. The role of employee readiness to embrace AI technologies is an important consideration when it comes to successful implementation. The perceptions and receptivity concerning AI have been reviewed in a number of different contexts through technology adoption models such as TPB, TAM and UTAUT. The existing literature tends to address marketing from a consumer perspective, failing to look into the behavior of the practitioners who help to create these digital marketing experiences. Using UTAUT as a theoretical foundation, the purpose of this dissertation is to answer the following questions: what components impact the attitudes of digital marketers when deciding whether or not to use generative AI tools, and how does technological anxiety moderate the relationship between attitude and behavioral intention to adopt this technology?

III. RESEARCH DESIGN

Conceptual Framework

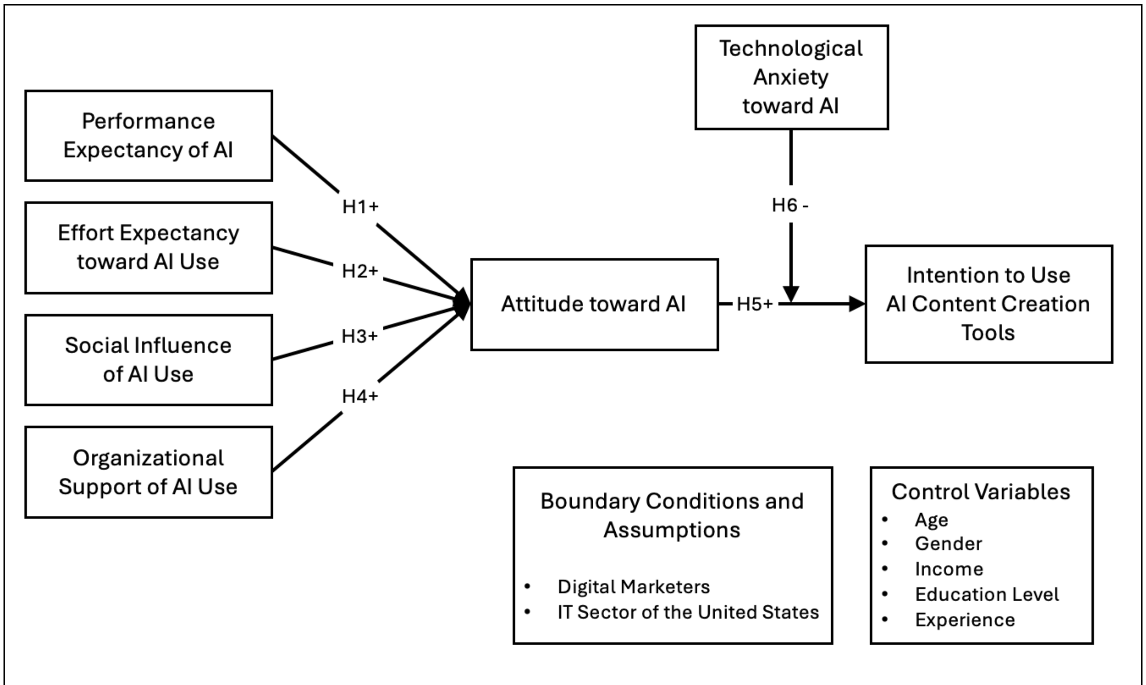


Figure 2: The Conceptual Research Model
Modified Version of the Theory of Planned Behavior (Ajzen, 1991) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003)

Theoretical Development and Hypotheses

In this chapter, the practical application of theoretical constructs will be applied to real-world phenomena, providing a solid foundation for empirical research. By integrating established constructs into the context of digital marketers within the IT industry, this study will undertake an investigation into the factors influencing the motives to use AI tools. The Unified Theory of Acceptance and Use of Technology (UTAUT) will serve as the theoretical backbone of this research, providing a comprehensive model that will consolidate elements found in a number of different theories in order to explain user intention.

Using the UTAUT model, it is expected that four constructs will be significant direct determinants of attitude toward AI use: performance expectancy, effort expectancy, social influence, and a modified facilitating conditions construct, entitled Organizational Support. These constructs have frequently confirmed an individual's acceptance of a given technology. In addition, the mediator of attitude toward AI is proposed to have a direct positive effect on user intention. Attitude has been historically used in technology studies, notably in models such as TPB and TAM. The mediating role of attitude on intention has also been used in modified versions of UTAUT (Dwivedi, 2019; Patil et al., 2020). The majority of previous studies employing UTAUT have overlooked the mediating role of attitude. Consequently, the empirical evidence supporting this effect has been dependent upon the link between the independent variables and their connection to behavioral intention. In this study, technological anxiety toward AI will be examined as a moderating factor in the relationship between attitude and intention; based on prior evidence this type of anxiety was shown to have a significant negative effect on attitudes and behavior. Through rigorous empirical testing, I will provide constructive insight into the factors that drive digital marketers' adoption of AI tools in the IT industry.

Intention has been the subject of investigation in behavioral and psychological theory for nearly a millennium. Developing hypotheses concerning this dependent variable will require an understanding of how intention is measured in different theoretical frameworks, specifically in the following eight theories that have influenced

UTAUT: TRA and TPB consider intention to be a readiness to perform a behavior; TAM focuses on perceived usefulness and ease of use; C-TAM-TPB integrates these two perspectives; MM views intention to be driven by intrinsic and extrinsic motivations; MPCU considers job relevance, as well as perceptions of complexity and support; and IDT states that intention to adopt an innovation is shaped by perceptions of relative advantage, compatibility, complexity, trialability, and observability. UTAUT combines these definitions, synthesizing intention into the perceived likelihood of engaging in a specific behavior related to technology use. Based on the above descriptions, for the purpose of this study, intention is defined as an individual's readiness and conscious plan to use AI content creation tools.

Performance expectancy refers to the degree to which an individual believes that using AI will enhance job performance (Davis, Bagozzi & Warshaw, 1992; Venkatesh et al., 2003). Based on this premise, digital marketers will be more likely to use AI content creation tools if they are assured that satisfactory results and benefits will be obtained. The results of the initial development of UTAUT showed that PE was the strongest predictor of intention, as compared to the other three main constructs (Venkatesh et al., 2003).

PE illuminates certain facets that explain the ways in which new technology can enhance job performance (Davis et al., 1992; Venkatesh et al., 2003). Improved efficiency and effectiveness play a significant role; as users perceive that AI tools are making their jobs easier and more efficient, their attitude regarding them will improve

(Jeon et al., 2020). Additionally, the expectation of receiving tangible rewards or recognition for using these tools has been shown to drive the intention to adopt them (Deci et al., 1985). When AI tools appear to be well-suited to job tasks, users are more inclined to use them, anticipating performance gains (Abdou et al., 2020). Furthermore, the perception that AI tools are superior to current methods significantly boosts the likelihood of their adoption (Milicevic et al., 2024).

Several studies have demonstrated that PE has a positive and significant influence on the intention to use technology. This causal route has been examined over a widespread array of technologies and contexts. When individuals believe PE will enhance their performance, they are more likely to adopt it. This relationship has been validated in studies on self-service technology in the restaurant industry ($\beta = 0.338$, $t = 3.381$, $p = 0.000$; Jeon et al., 2020); block chain adoption in the agri-food supply chain (T statistic (|0/STDEV|)) = 30.791, $p = 0.0000$; Sharma et al., 2023); the adoption of an educational metaverse platform ($\beta = 0.338$, $t = 3.381$, $p = 0.000$; Wang, C. et al., 2022); the intention to use e-learning technologies in France banks ($\beta = 0.485$, $p < 0.01$; Abdou et al., 2020); the acceptance and use of an ICT system among tourists ($\beta = 0.22$, $t = 2.98$; Ali et al., 2024); the adoption of AI-related technologies among librarians ($\beta = 0.463$, $p < 0.001$; Andrews, et al., 2021); and students' intention to use AI to assist in their education ($\beta = 0.463$, $p < 0.001$; Milicevic et al., 2024). These studies collectively affirm that performance expectancy is a significant determinant of attitude and behavioral intention. Thus, I hypothesize that:

H1: A digital marketer’s performance expectancy of AI will positively affect their attitude towards AI.

Effort expectancy (EE) refers to the degree of effort associated with the use of AI (Venkatesh et al., 2003), encompassing the key constructs of ease of use, complexity, and perceived ease of use (Cimperman et al., 2016). The relationship between EE and the intention to use AI tools has been explained through various theoretical frameworks and empirical studies. According to the Innovation Diffusion Theory (IDT), ease of use refers to how simple and straightforward a system is to operate (Rogers & Williams, 1983). User-friendly interfaces and intuitive designs have been shown to encourage system adoption (Wang, C. et al., 2012). When AI tools are perceived as easy to use, users anticipate reduced effort in learning and operating the system. According to the Model of PC Utilization (MPCU), complexity refers to the relative difficulty encountered in the understanding and operation of a system (Thompson et al., 1991). High complexity has been proven to be a barrier to acceptance (Morchid, 2020). AI tools that minimize complexity are more likely to be adopted by users because extensive effort to learn and operate are not required. Perceived Ease of Use (PEOU), from the Technology Acceptance Model (TAM) and its extension TAM2, measures the degree to which an individual expects that a system will require a minimum of effort to use (Davis et al., 1989; Venkatesh & Davis, 2000). The less effort users expect to exert using AI tools, the more likely they are to adopt them. This conclusion is supported by findings in which

PEOU significantly predicted technology acceptance in various contexts (Venkatesh et al., 2003).

Empirical evidence also supports the positive relationship between EE and intention to use AI tools. For example, a study among university students in Jordan found that the easier and more flexible the students perceived the technology to be, the more likely they were to adopt it ($\beta = 0.226$, $p < 0.001$; Jaradat et al., 2020). Easy-to-use systems were shown to reduce the cognitive effort required to learn and operate them, leading to higher adoption rates. In Chongqing, China, research demonstrated that EE increases public intention to accept driverless buses ($\beta = 0.43$, $p < 0.01$; Chen et al., 2020). An extended UTAUT model revealed that EE is an influential factor in users' willingness to pay for online knowledge platforms ($\beta = 0.164$, $t = 3.534$, $p < 0.001$; Yu et al., 2021). In India, EE was found to substantially shift consumers' attitudes towards mobile payment systems ($\beta = 0.32$, $p < 0.001$; Kim et al., 2023). Additionally, Williams et al. (2015) conducted a meta-analysis on the Unified Theory of Acceptance and Use of Technology (UTAUT), examining 102 quantitative studies. They found that relationships between EE and BI were significant 65 times, although 37 times they were not, indicating a general trend towards the importance of effort expectancy. Applying these findings to digital marketers, it is reasonable to expect a significant positive link between EE and ATT. Thus, I propose that:

> H2: A digital marketer’s effort expectancy of AI will positively affect their attitude towards AI.

Social influence refers to the degree an individual perceives the use of AI to be considered important by influential people (Diaz & Loraas, 2010; Venkatesh, 2003). SI encapsulates the multi-faceted ways social dynamics impact individual behavior (Ajzen, 1991; Venkatesh et al., 2000; Taylor et al., 1995). The UTAUT meta-analysis by Williams et al. (2015) found that relationships between SI and BI were significant 88 times, displaying a strong positive correlation between the two constructs. The proposed positive relationship between social influence and attitudes toward AI use is plausible through mechanisms of conformity (Thompson, et al., 1991), social pressure (Ajzen, 1991), and the pursuit of enhanced social status (Rogers et al., 1983). When individuals perceive that influential figures endorse AI tools, they are predicted to be more likely to adopt these technologies to align with social norms and expectations, thereby ensuring social cohesion and professional advancement (Venkatesh et al., 2003).

Peng (2022) investigated university teachers' mobile teaching behavior, studying 389 university teachers in Guangdong, China. It was found that SI was a determining factor in their intention to use mobile teaching techniques ($\beta = 0.229$, $t = 2.423$, $p = 0.015$). Similarly, Shi et al. (2022) explored the intention to adopt IoT in the industry of agriculture. Among 395 farmers residing in Bangladesh's rural areas, they found that SI influenced their willingness to adopt IoT ($\beta = 0.159$, $t = 3.206$, $p < 0.01$). Kayali et al. (2020) examined the feedback of 422 students from 4 universities in Lebanon, finding that SI played a role in shaping their adoption of cloud-based e-learning ($\beta = 0.151$, $t = 2.991$, $p = 0.003$).

These results suggest that when digital marketers perceive strong social support and endorsement for using AI tools, they are likely to develop a favorable attitude towards them, leading to increased acceptance and usage. Advancements in AI are enabling the creation of high-quality, engaging content through "intelligence-driven text" (Miller et al., 2023) and artificially generated visual content (Jeon et al., 2020), leading to a continuous evolution in the digital marketing field. This collective shift towards AI adoption is expected to exert a substantial social influence, directly shaping attitudes towards AI use (Haleem et al., 2020). As such, I formally hypothesize:

H3: A digital marketer's social influence of AI use will positively affect their attitude towards AI.

Organizational Support (OS) is used in this study to measure the degree to which an individual believes that organizational infrastructure exists to support AI use (Thompson et al., 1991; Venkatesh et al., 2003). OS is considered to be a modified version of the facilitating conditions (FC) construct, emphasizing the support and resources provided by the organization to enhance workers' potential. According to Social Exchange Theory (SET), when employees feel valued and supported, they are likely to develop positive attitudes towards new technologies (Blau, 1964). Innovation Diffusion Theory (IDT) suggests that organizational support ensures AI tools meet employees' needs and workflows, boosting perceived compatibility and usage intention (Rogers et al., 1983). The Delone and McLean Information Systems Success Model also highlights that sufficient resources and infrastructure lead to greater satisfaction and intention (DeLone & McLean, 1992). Together, these theories demonstrate that organizational support creates a favorable environment for adopting AI tools by removing barriers, increasing perceived value and compatibility, and addressing socio-emotional needs.

Consider the adoption of Eduverse, an educational metaverse platform used among college students in China, which showed that facilitating conditions positively affected learners' satisfaction with the Eduverse ($\beta = 0.321$, $p < 0.01$). Almagrashi et al. (2023) investigated 239 internal auditors in the public sector of Saudi Arabia. In a study on the use of computer assisted auditing tools, both FC ($\beta = 0.28$, $p = 0.001$), and organizational influence (OI) ($\beta = 0.19$, $p = 0.030$) were identified as significant predictors of user intention.

Alkhwaldi et al. (2023) looked into HRIS use among 211 workers in the Jordanian public sector, and found that FC was a major determinant of system adoption ($\beta = 0.25$, $p < 0.01$). Additionally, Bakar et al. (2013) analyzed the ongoing use of the student portal at UCSA (University College ShahPutra) with a sample of 279 students, demonstrating that facilitating conditions had a favorable and substantial effect on behavioral intention ($\beta = 0.40$, $t = 3.234$, $p < 0.01$).

These studies collectively demonstrate that facilitating conditions, which include organizational support elements, significantly influence users' intentions and their satisfaction with technologies presented to them. Thus, it is reasonable to hypothesize that:

H4: A digital marketer’s organizational support of AI will positively affect their attitude towards AI

Attitude toward AI is defined as an individual's overall evaluation of AI use (Ajzen, 1991). Theoretically, it has been shown to encompass cognitive evaluations and emotional responses that influence behavioral intentions. The positive link between attitude and intention can be explained through several mechanisms: consistency theory's attitude-behavior alignment (Abelson et al., 1968), TAM's attitude toward behavior (Davis et al., 1992), TPB's attitude toward use (Ajzen, 1991), and attitude-integrated constructs of UTAUT (Dwivedi etl al., 2019). Each theory supports the idea that fostering positive attitudes towards AI tools will enhance the intention to use them, making attitude a pivotal predictor in technology adoption models.

Priyanga et al. (2023) suggested that AI significantly enhances personalization in marketing efforts, while Theodoridis and Gkikas (2019) stated that the use of AI in digital marketing has been shown to increase customer engagement. This implies that digital marketers who recognize the benefits of utilizing AI in their marketing campaigns are likely to have a favorable attitude toward AI tools. Other considerations that may contribute to marketers’ positive attitudes are AI's ability to produce engaging, high-quality content that connects with target audiences (Miller et al., 2023), as well as its ability to revolutionize creative work (Davenport et al., 2022). These positive attitudes would likely influence the intention of digital marketers to use AI tools to create content.

Kim and Hunter's (1993) meta-analysis on the relationship between attitude and behavior offers decisive confirmation that attitudes deemed construct-valid directly impact behavior. By integrating findings from 138 attitude-behavior relationships, with a total sample size of 90,908, they found a strong overall A-B correlation ($r = .79$), affirming that "relevant attitudes strongly predict volitional behavior" (Kim & Hunter, 1993).

Attitude was also shown to have a significant positive affect on research investigating the usage of mobile wallets among consumers in India ($\beta = 0.364$, $T = 7.687$, $p = 0.000$; Chawla & Joshi, 2019); the adoption of mobile payments ($\beta = 0.613$, $p = 0.000$; Patil et al., 2020); the intention of middle schoolers to use tablet computers $\beta = 0.158$, $p = 0.0001$; Zheng et al., 2020); the use of smartphone chatbots among consumers on Facebook ($\beta = 0.388$, $t = 3.984$, $p = 0.000$; Kasilingam, 2020); a comparison of the intention to use mobile banking in Taiwan ($\beta = 0.737$, $t = 8.296$, $p = 0.000$) and Vietnam ($\beta = 0.584$, $t = 10.535$, $p = 0.000$; Ho et al., 2020); and the behavioral intention to adopt smart energy consumption tools among 173 citizens of Cosenza, Italy ($\beta = 0.47$, $p < 0.05$; Perri et al., 2020). Given the evidence provided across a broad range of theoretical and empirical research, I formally hypothesize the overall main effect to be:

H5: A digital marketer's attitude toward AI use will positively affect their intention to use AI content creation tools.

Technological Anxiety (TA) is the apprehension, characterized by feelings of unease, experienced by individuals who regard AI's advancements and implications to be potentially uncontrollable (Meuter, 2003; Johnson & Verdicchio, 2017). Technostress (TS), the subject of extensive theoretical research, is being used in conjunction with TA; they are similar constructs that overlap in many areas (Ragu-Nathan et al., 2008). Not only does TA align with theories of stress, but also with cognition and motivation. It includes the emotional responses (e.g., fear, apprehension), as well as the cognitive evaluations (e.g. perceptions of control) that influence individuals' interactions with technology (Mason, 1975; Tsai et al., 2020). The Transactional Model of Stress and Coping (TMSC) views technological anxiety (TA) as a phenomenon that individuals must assess and then manage, a response that impacts the overall levels and the resultant outcomes caused by stress (Lazarus & Folkman, 1984; Lei & Ngai, 2014). Social Cognitive Theory (SCT) has also been used to examine the ways in which individuals' self-efficacy beliefs influence their capacity to manage technology-related issues (Shu et al., 2011).

TA can stem from AI-generated misinformation, an insufficiently controlled development of AI, and negative biases towards its use (Akter et al., 2022). This "AI Anxiety," as Chang et al. (2024) describes it, can also result from worries about transparency, privacy, job displacement, and ethical concerns. Using Affective Events Theory (AET) and the Challenge–Hindrance Stressor Framework (CHSF), it was found that AI-related technostress affects employees' intentions to adopt AI, identifying two types: challenge stressors and hindrance stressors (Kaya et al, 2024). Challenge stressors, linked to positive emotions and personal growth, positively impact AI adoption intention, while hindrance stressors, associated with negative emotions and anxiety, negatively affect adoption intention.

Research suggests that reducing the perception of anxiety can be achieved by making changes in how potential users view the adoption of AI technology (Johnson, 2017). If a digital marketer harbors high levels of anxiety towards a perceived unpredictability bringing with it potential negative consequences, these fears might overshadow any positive attitudes, leading to a decrease in the marketer's intention to adopt AI content creation tools. Low levels of TA correlate with an increased positive attitude and subsequent intention. With reduced anxiety, digital marketers would be better able to focus on the benefits and effective use of AI content creation tools.

Tsai et al. (2020) investigated the technological anxiety of a wearable cardiac monitoring system among elderly adults. They found that perceived ease of use (PEOU) positively affected attitude ($\beta = 0.276$, $t = 3.867$, $p < 0.001$), and that anxiety negatively affected perceived ease of use ($\beta = -0.317$, $p < 0.001$). Khlaif et al. (2023) examined the impact of technostress on continued intentions to use mobile technology among 367 K-12 teachers in Palestine. Their results demonstrated that technostress negatively impacted intention ($\beta = -0.17$, $p < 0.001$), highlighting the detrimental effect of stress.

Patil et al. (2020) studied consumer adoption of mobile payments with 491 mobile users in India, and found that anxiety negatively affects attitude ($\beta = -0.099$, $p = 0.000$). Similarly, Nasirpouri and Biros (2022) explored technostress, and its influence on employee information security policy compliance among 356 employees in technology-based professions, revealing that technostress negatively affects intention ($\beta = 0.34$, $p < 0.001$). Brooks et al. (2023) focused on IT professionals' turnaway intention and found that it was positively influenced by technostress ($\beta = 0.583$, $p < 0.001$). Yang et al. (2013) examined technological anxiety in mobile shopping adoption, and found that anxiety moderated the relationship between social influence and behavioral intention, with high anxiety showing a stronger negative effect ($\beta = -0.275$, $p < 0.01$).

Chang et al. (2024) investigated AI-driven technostress among 301 employees from Guangdong Province, China, and found that AI anxiety is negatively related to AI adoption intention ($\beta = -0.48$, $p < 0.001$). Kaya et al. (2024) explored the role of AI anxiety in the attitudes toward artificial intelligence among 350 individuals, and found that AI configuration anxiety ($\beta = -0.379$, $p < 0.001$) and AI learning anxiety ($\beta = -0.211$, $p < 0.001$) significantly predicted negative attitudes toward AI.

In addition to the aforementioned studies, several meta-analyses on technostress have revealed its significant impact on user behavior and technology adoption. For example, studies by Nastjuk, Trang, Grummeck-Braamt, Adam and Tarafdar (2024), Gerdiken, Reinwald and Kunze (2021), and La Torre, Esposito, Sciarra and Chiappetta (2019) provide comprehensive insights into how anxiety affects various aspects of technology use. Thus, I propose that:

> H6: As a digital marketer's level of technological anxiety toward AI use increases, it will negatively affect the relationship between attitude toward AI use and intention to use AI content creation tools.

Table 1

Hypotheses

	Hypothesis	Reference
H1+	A digital marketer's **performance expectancy of AI** will positively affect their **attitude towards AI**.	(Venkatesh et al., 2003)
H2+	A digital marketer's **effort expectancy of AI** will positively affect their **attitude towards AI**.	(Venkatesh et al., 2003)
H3+	A digital marketer's **social influence of AI use** will positively affect their **attitude towards AI**.	(Venkatesh et al., 2003)
H4+	A digital marketer's **organizational support of AI** will positively affect their **attitude towards AI**.	(Venkatesh et al., 2003)
H5+	A digital marketer's **attitude toward AI use** will positively affect their **intention to use AI content creation tools**.	(Davis et al., 1989; Ajzen 1991)
H6-	As a digital marketer's level of **technological anxiety toward AI use** increases, it will negatively affect the relationship between **attitude toward AI use** and **intention to use AI content creation tools**.	(Mokyr et al., 2015)

Table 2

Construct Definitions

Construct	Definition	Reference
Performance Expectancy of AI (PE)	The degree to which an individual believes that using AI will enhance job performance.	(Davis et al., 1992; Venkatesh et al., 2003)
Effort Expectancy towards AI Use (EE)	The degree of effort associated with the use of AI.	(Venkatesh et al., 2003)
Social Influence of AI Use (SI)	The degree to which an individual perceives the use of AI to be considered important by influential people	(Diaz & Loraas, 2010; Venkatesh et al., 2003)
Organizational Support of AI Use (OS)	The degree to which an individual believes that organizational infrastructure exists to support AI use.	(Thompson et al., 1991; Venkatesh et al., 2003)
Attitude Toward AI Use (ATT)	An individual's overall evaluation of AI use.	(Ajzen, 1991)
Technological Anxiety Toward AI (ANX)	The apprehension and feelings of unease experienced by individuals who regard AI's advancements and implications to be potentially uncontrollable.	(Meuter et al., 2003; Johnson et al., 2017)
Intention to Use AI Content creation Tools (INT)	An individual's readiness and conscious plan to use AI content creation tools.	(Ajzen, 1991; Venkatesh et al., 2003)

IV. RESEARCH METHODOLOGY

Participants and Procedure

The population of interest for this research is digital marketing professionals who work in major business sectors of the United States. These individuals possess a unique blend of skills and insights relevant to the use of AI tools, making them ideal participants for this study.

The recruitment strategy involved utilizing CloudResearch, an online platform known for its robust participant recruitment capabilities. CloudResearch offers advanced tools and services to identify and vet potential participants, ensuring that they meet the specific criteria required for the study. The platform's Sentry® participant vetting system was used to screen participants to ensure that they would be attentive and engaged, as well as meeting the study's qualifications, thus maintaining the quality and reliability of the data collected.

Once the participants were recruited and verified, they were invited to complete an online survey that was designed in Qualtrics. The data collected was then securely stored and analyzed using appropriate statistical methods to draw meaningful conclusions. This streamlined approach ensured that high-quality data was efficiently gathered while adhering to ethical standards and protecting participants' privacy.

Research Design

In order to explore the factors that influence digital marketers' decisions to use AI content creation tools, this study adopted a quantitative research methodology. Empirical evidence was used to validate each construct. A descriptive approach was followed, using deductive reasoning and a cross-sectional survey design was utilized. A simple random sampling method was used to ensure representation across different levels of expertise in digital marketing. A structured questionnaire was developed, consisting of Likert-scale items to measure the factors that affect the intention to use AI content creation tools. Additional questions assessed demographic information as control variables. Prior to the dissemination of the pilot, each of the hypotheses were pre-registered with AsPredicted.com to ensure a further level of transparency, as well as validation of the hypotheses by documenting the research plan before data collection began.

Once approval from the FIU Institutional Review Board (IRB) was obtained *(see Appendix III)*, the survey was distributed online through CloudResearch. Participants were informed of the study's purpose, assured of their anonymity, and given instructions on how to complete the survey. The collected data was then analyzed using statistical software. Descriptive statistics provided an overview of the sample characteristics. Inferential statistics, such as multiple regression analysis and PLS-SEM, examined the relationship between each construct. The analysis also explored several control variables such as a participant’s age, gender, income, and educational level in order to determine whether or not these factors affected the relationships.

A systematic approach to data analysis was adopted, covering several steps designed to ensure a comprehensive and robust examination of the data. The first step involved descriptive statistics, in which a summary of the data was provided, using the measure of mean, median, standard deviation, and range. This facilitated an understanding of the distribution and variability of each construct.

The next step was an Exploratory Factor Analysis (EFA), which was carried out to explore the underlying factor structure of the variables. The pattern matrix showing the partial regression coefficients was evaluated for cross-loadings. The correlation matrix was analyzed to measure the strength and direction of relationships between the variables. Additional analyses were performed on the mediating and moderating effects of the variables in each relationship.

Partial Least Squares Structural Equation Modeling (PLS-SEM) was also used to model the relationships between latent constructs, as well as to estimate the path coefficients in the structural model. Indicator reliability was assessed by examining the outer loadings, with values above 0.7 considered satisfactory. Additionally, the internal consistency reliability of the constructs was evaluated using Cronbach's alpha, reliability coefficient ρA, and composite reliability ρC. Convergent validity was assessed by examining the Average Variance Extracted (AVE) for each construct, with values above 0.5 indicating adequate convergent validity. Discriminant Validity was evaluated using the Heterotrait-Monotrait ratio (HTMT), with values below 0.85 suggesting discriminant validity.

Collinearity in the outer model was assessed using the Variance Inflation Factor (VIF), with values below 5 indicating no collinearity concerns. The significance and relevance of the model were assessed using the evaluation of confidence intervals, beta-values, and p-values. VIF values of the inner model were tested for common method bias among the constructs. The explanatory power of the model was evaluated using adjusted R-square and f-square values. By following these steps, the proposed methodology provided insights into the relationships among the variables and the validity and reliability of the constructs to ensure a comprehensive analysis of the data.

Measurements

The *Intention to Use AI (INTAI) Measurement Scale* was designed with questions covering 7 factors: 4 independent variables, 1 mediator, 1 moderator, and 1 dependent variable *(see Figure 2)*. It includes the following constructs: Social Influence of AI Use (SI), Performance Expectancy of AI (PE), Effort Expectancy towards AI Use (EE), Organizational Support of AI Use (OS), Technological Anxiety Toward AI (ANX), and Intention to Use AI Content Creation Tools (INT). Closed-ended questions were phrased as statements using a 7-point Likert scale with respondents asked to specify their level of agreement using the following points: (1) Strongly Disagree, (2) Disagree, (3) Somewhat Disagree, (4) Neither Agree nor Disagree, (5) Somewhat Agree, (6) Agree, (7) Strongly Agree.

SI, consisting of 5 items, was used to evaluate the impact of social norms and the influence of other people on an individual's decision to use AI. SI1 and SI2 were derived from items used to measure the subjective norm construct of the Theory of Planned

Behavior (TPB) (Ajzen 1991; Davis, et al., 1989; Ajzen & Fishbein, 1975; Mathieson, 1991; Taylor & Todd 1995). SI3 was based on the social factors construct from the Model of PC Utilization (MPCU), emphasizing the influence of social context on technology adoption (Thompson et al., 1991). SI4 and SI6 were borrowed from Moore and Benbasat's (1991) image construct of the Innovation Diffusion Theory (IDT).

PE, consisting of 6 items, measures the degree to which individuals believe that using AI will help them perform better in their jobs. PE1, PE2, and PE3 were drawn from the perceived usefulness construct of the Technology Acceptance Model (TAM), reflecting the belief that AI can enhance job performance (Davis et al., 1992). PE5, PE6, and PE6 originate from the job-fit construct of the Personal Computer Utilization (MPCU), which explores how individuals perceive the utility of PCs in enhancing job performance (Moore & Benbasat, 1991).

EE, consisting of 6 items, evaluates how easy or how difficult the use of AI is perceived to be. EE1, EE2, EE3, and EE4 were taken from the perceived ease of use construct of TAM, indicating the simplicity of AI adoption (Davis et al., 1992). EE5 and EE6 were derived from the ease of use construct of IDT, assessing the user-friendliness of AI technology (Moore & Benbasat, 1991).

OS, consisting of 5 items, measures the extent to which an organization provides the necessary resources and support for AI adoption. OS1, OS2, and OS3 were based on the facilitating conditions construct from MPCU, highlighting the role of organizational infrastructure and support in enabling AI use (Thompson et al., 1991). OS4 was taken from the perceived behavior control factor of TPB (Ajzen, 1991). The compatibility factor of IDT was used for OS5.

The mediating variable of ATT, which consists of 7 items, was designed to measure an individual's overall evaluation of using AI. ATT1 and ATT2 was derived from the attitude toward behavior construct of TPB, reflecting cognitive beliefs and perceptions about the behavior of using AI (Davis et al. 1992; Ajzen, 1975; Taylor & Todd 1995). ATT3 was taken from the intrinsic motivation construct of the Self-Determination Theory (SDT), capturing the degree of internal satisfaction and enjoyment achieved from using AI (Davis et al. 1992). ATT4 originates from the affect toward use construct of MPCU, measuring the emotional responses associated with using AI (Thompson et al. 1991). Lastly, ATT5, ATT6, and ATT7 were taken from the affect construct, further emphasizing the emotional and affective reactions towards AI use (Compeau & Higgins, 1995; Compeau, Higgins & Huff, 1999).

INT, consisting of 5 items, is the dependent variable in this study. The items INT1, INT2, and INT3 were adapted from the questionnaires used for both UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh, Thong & Xu, 2012). Items used to measure the behavioral intention construct from Yen et al. (2010) influenced INT4 and INT5.

The 7 ANX items were taken from the AI Anxiety Scale (Wang & Wang, 2022). This scale quantifies the level of discomfort, fear, or nervousness individuals experience when they interact with AI, or when they consider the implications of AI technologies. It was developed by evaluating motivated learning behaviors to understand how such anxiety impacts a person's willingness to engage with AI.

Informed Pilot

An informed pilot was carried out to verify the reliability and validity of the measurement instrument *(see Figure 2)*. The participants were given a cover letter that provided an overview of the study *(see Appendix II)*, including the measurement model and explanations of the different groups included in the survey. These groups consisted of qualifier items, constructs, and control questions. The reviewers were presented with potential issues and asked to consider each one while assessing the items in the measurement instrument. A link to the informed pilot was sent to 5 marketing professionals and 5 colleagues from the DBA program at FIU, of which 9 responded. Each respondent was asked to evaluate the clarity and relevance of the questions, specifically considering whether or not each question was understandable, was targeted at marketing professionals, and was an accurate measurement of the intended variable. They were also asked to be on the lookout for potential double-barreled questions that addressed more than one topic; leading questions that could sway the respondent's answer; and loaded questions that rely on emotional responses. A text field was provided under each group of items for comments and suggestions. Based on the feedback, I removed 2 redundant items and rephrased 11 items to improve clarity and to focus on AI tools used on the job. I also revised 3 items in the organizational support (OS) construct to ensure consistency in tense.

Blind Pilot – Data Collection

A blind pilot study was conducted using the Cloud Research platform. An advertisement was created entitled "Opinions on AI Use by Digital Marketers in the IT Sector of the United States." The survey aimed to collect 100 viable responses, with data collection taking place on September 1, 2024. A total of 125 participants engaged with the survey. The survey data was exported from Qualtrics into the Jamovi software suite and SmartPLS for further analysis.

A series of data-cleaning steps were completed to ensure the validity of the responses. Specifically, 20 participants were excluded: 10 did not complete the survey; 7 indicated that they did not work as marketers; and 3 outliers were identified based on Z-scores that were calculated for each response. After these exclusions, a final sample of 105 participants was retained for analysis. The survey was constructed to include indicators from each factor, ensuring that the participants stayed engaged. The resulting dataset was complete with no missing data.

Blind Pilot - Results

Descriptive statistics for the control variables are displayed in Table 1 below. The sample (n) consisted of 43 men (41.0%) and 62 women (59.0%). The age distribution among participants was mainly between the ranges of 19-59 years old, with 36 between the ages of 19-29 (34.3%), 35 between the ages of 30-39 (33.3%), 19 between the ages of 40-49 (18.1%), 12 between the ages of 50-59 (11.4%), with 1 respondent between the ages of 60-69 (1.0%) and 2 people over 70 years old (1.9%).

In terms of income level, 11 people reported to make less than $24,999 a year (10.5%), 27 within the range of $25,000-$49.999 (25.7%), 18 people between $50,000-$74,999 (17.1%), 24 respondents making $75,000-$99,999 (22.9%), 24 making over $100,000 (22.9%), while 1 person preferred not to answer (1.0%)

The educational level of the sample ranged from High School graduates and those earning a GED, all the way up to those with doctorate degrees. 20 people reported their highest level of education to be high school or a GED (19.0%); 12 people earned an Associate Degree (11.4%); 53 people reported a Bachelor's Degree (50.5%); 18 of the respondents earned a Master's Degree (17.1%); while 2 people reported a doctorate as their highest completed level of education (1.9%).

Experience with AI and Digital Marketing was also measured. 1 person reported never having used AI (1.0%); 1 person had only used AI for less than a month (1.0%); 27 of the marketers indicated using AI between 1 month and a day and 1 year (25.7%); 44 people had between 1 and 2 years of experience (41.9%); while 32 people had been using AI for more than 2 years (30.5%). There were 20 people with less than a year of marketing experience (19.0%); 21 people had worked as marketers between 1 year and a day and 2 years (20.0%); 18 people had between 2 years and a day and 3 years of marketing experience (6.7%); 7 people reported between 3 years and a day and 4 years of experience (6.7%); and 20 people said they had been marketing professionals for longer than.4 years (19.0%).

Marketers working in the top 10 industries listed in Cloud Research were targeted as follows: 2 in construction (1.9%); 5 in consumer goods (4.8%); 8 in education (7.6%);

10 in finance (9.5%); 6 in healthcare (5.7%); 9 in hospitality (8.6%); 37 in information technology (35.2%); 14 in media and entertainment (13.3%); 3 in real estate (2.9%); and 11 in retail (10.5%).

Table 3

Blind Pilot Descriptive Statistics

Characteristics	Frequency	% of Sample
Gender		
Male	43	41.0%
Female	62	59.0%
Age		
19-29 years old	36	34.3%
30-39 years old	35	33.3%
40-49 years old	19	18.1%
50-59 years old	12	11.4%
60-69 years old	1	1.0%
70+ years old	2	1.9%
Income		
$0 - $24,999	11	10.5%
$25,000 - $49,999	27	25.7%
$50,000 - $74,999	18	17.1%
$75,000 - $99,999	24	22.9%
$100,000+	24	22.9%
Prefer not to answer	1	1.0%
Education Level		
High School / GED	20	19.0%
Associate Degree	12	11.4%
Bachelor's Degree	53	50.5%
Master's Degree	18	17.1%
Doctorate Degree	2	1.9%
AI Experience		
Never	1	1.0%
1 day – 1 month	1	1.0%

1 month and 1 day – 1 year	27	25.7%
1 year and 1 day – 2 years	44	41.9%
More than 2 years	32	30.5%
Marketing Experience		
Less than 1 year	20	19.0%
1 year and 1 day – 2 years	21	20.0%
2 years and 1 day – 3 years	18	6.7%
3 years and 1 day – 4 years	7	6.7%
More than 4 years	20	19.0%
Industry		
Construction	2	1.9%
Consumer Goods	5	4.8%
Education	8	7.6%
Finance	10	9.5%
Healthcare	6	5.7%
Hospitality	9	8.6%
Information Technology	37	35.2%
Media and Entertainment	14	13.3%
Real Estate	3	2.9%
Retail	11	10.5%

The descriptive statistics and reliability scores for all items used in the blind pilot study are presented in Table 2 below, including the item codes, means, standard deviations, number of responses, and Cronbach's alpha scores for each construct. The results indicated that the measurement tool utilized in the pilot study is reliable and demonstrates satisfactory construct validity for all constructs except Performance Expectancy (PE). The blind pilot study identified a factor structure that accurately measures the other six primary constructs: Intention (INT), Effort Expectancy (EE), Social Influence (SI), Organizational Support (OS), Attitude (ATT), and Technological Anxiety (ANX).

For the INT construct, four items (INT1, INT3, INT4, and INT5) were measured, with means ranging from 5.79 to 6.08 and standard deviations between 1.03 and 1.17. The Cronbach's Alpha for this construct is 0.933, showing high internal consistency. The PE construct included only one item (PE4), which has a mean of 5.02 and a very low standard deviation of 0.20. Since there is only one item, a Cronbach's Alpha was not applicable for this construct. The EE construct consists of five items (EE1, EE2, EE3, EE4, and EE6), with means between 5.29 and 5.93, and standard deviations ranging from 1.03 to 1.21. The Cronbach's Alpha for this construct is 0.890, indicating strong reliability.

The SI construct measured four items (SI1, SI2, SI3, and SI4), with means between 3.69 and 4.55, and relatively higher variability in responses, as the standard deviations range from 1.53 to 1.77. The Cronbach's Alpha for this construct is 0.888, indicating high internal consistency. The OS construct has three items (OS1, OS2, and OS3), with means from 4.09 to 4.71 and standard deviations between 1.70 and 1.91. The Cronbach's Alpha is 0.870, indicating good reliability. For the ATT construct, three items (ATT3, ATT4, and ATT5) were measured, with means ranging from 5.07 to 5.32, and standard deviations between 1.44 and 1.55. The Cronbach's Alpha for this construct is 0.895, demonstrating strong internal consistency.

Finally, the ANX construct, with seven items (ANX1 to ANX7), has means ranging from 2.12 to 4.10, showing more variability in responses. The standard deviations range from 1.33 to 1.97, with a Cronbach's Alpha of 0.888, indicating strong reliability. Overall, the table demonstrates strong internal consistency for all constructs except PE, as reflected in the Cronbach's Alpha values above 0.870, suggesting that the measures were reliable.

Table 4

Blind Pilot Construct Reliability

Construct Name	Item Code	Mean ($\bar{x}$)	Standard Deviation (s)	Sample Size (n)	Cronbach Alpha
Intention	INT1	6.08	1.03	105	0.933
	INT3	5.79	1.15	105	
	INT4	5.92	1.14	105	
	INT5	5.99	1.17	105	
Performance Expectancy	PE4	5.02	0.20	105	N/A
Effort Expectancy	EE1	5.93	1.03	105	0.890
	EE2	5.88	1.06	105	
	EE3	5.90	1.09	105	
	EE4	5.83	1.11	105	
	EE6	5.29	1.21	105	
Social Influence	SI1	4.55	1.53	105	0.888
	SI2	4.32	1.77	105	
	SI3	4.28	1.61	105	
	SI4	3.69	1.60	105	
Organizational Support	OS1	4.71	1.70	105	0.870
	OS2	4.36	1.73	105	
	OS3	4.09	1.91	105	
Attitude	ATT3	5.32	1.44	105	0.895
	ATT4	5.27	1.50	105	
	ATT5	5.07	1.55	105	
Technological Anxiety	ANX1	2.74	1.61	105	0.888
	ANX2	4.10	1.97	105	
	ANX3	3.19	1.72	105	
	ANX4	2.41	1.36	105	
	ANX5	3.39	1.81	105	
	ANX6	3.08	1.70	105	
	ANX7	2.12	1.33	105	

An Exploratory Factor Analysis (EFA) was performed using principal axis factoring with oblimin rotation in order to identify which factors correlate with each other. Ten items were eliminated from the pattern matrix that cross-loaded in the following order: ATT6 loaded under factor 1 (0.653) and factor 5 (-0.388); PE1 loaded under factor 2 (0.521) and factor 3 (0.337); PE2 loaded under factor 2 (0.463) and factor 5 (0.319); OS4 loaded under factor 2 (0.479) and factor 6 (0.310); EE5 loaded under factor 1 (0.362) and factor 6 (0.310); ATT1 loaded under factor 2 (0.354) and factor 4 (0.314); INT2 loaded under factor 2 (0.433) and factor 5 (0.525); PE6 loaded under factor 4 (0.319) and factor 5 (0.488); ATT7 loaded under factor 1 (0.356) and factor 5 (-0.444); SI5 loaded under factor 3 (-0.311), factor 4 (0.634) and factor 5 (0.322). Three additional items were eliminated due to low loadings: OS5, PE7, and PE5. Finally, ATT2 was eliminated since it loaded in factor 2, while all other items in the construct loaded under factor 5.

Table 5

Blind Pilot Pattern Matrix (EFA)

	Factor							
	1	2	3	4	5	6	7	Uniqueness
ANX6	0.927							0.1227
ANX1	0.745							0.2887
ANX4	0.731							0.2812
ANX3	0.728							0.4645
ANX5	0.717							0.4558
ANX7	0.643							0.3061
ANX2	0.608							0.6602
EE3		0.845						0.2047
EE4		0.837						0.2841
EE2		0.717						0.2489
EE6		0.682						0.4240
EE1		0.656						0.3750
INT1			0.924					0.1549
INT5			0.812					0.1504
INT3			0.795					0.2283
INT4			0.774					0.2018
SI1				0.815				0.1971
SI2				0.814				0.1879
SI3				0.734				0.2965
SI4				0.606				0.4970
ATT5					0.893			0.1601
ATT4					0.839			0.2551
ATT3					0.704			0.2927
OS2						0.928		0.1280
OS1						0.779		0.3171
OS3						0.662		0.3141
PE4							0.947	0.0957

NOTE: 'Principal axis factoring' extraction method was used in combination with an 'oblimin' rotation.

After running a Confirmatory Factor Analysis (CFA), the standardized estimates for each factor are as follows: INT ranges from 0.902 to 0.917; PE has a value of 1.000, EE ranges from 0.678 to 0.890; SI ranges from 0.674 to 0.906; OS ranges from 0.817 to 0.822; ATT ranges from 0.826 to 0.902; and ANX ranges from 0.474 to 0.868. The factor covariances show that the strongest covariance is between SI and ATT, with an estimate of 0.5658, a confidence interval of 0.41539 to 0.7163, and a p-value of less than 0.001, indicating significance. The weakest covariance is between EE and ANX, with an estimate of -0.5243, a confidence interval of -0.68135 to -0.3673, and a p-value of less than 0.001, also indicating significance. Significant relationships exist between SI-ATT, EE-ANX, SI-OS, SI-EE, and ATT-OS, while INT-PE, PE-EE, and INT-ANX are not significant.

Table 6

Blind Pilot Factor Loadings (CFA)

FACTOR LOADINGS

				95% Confidence Interval				
Factor	Indicator	Estimate	SE	Lower	Upper	Z	P	Stand. Est.
INT	INT1	0.921	0.0780	0.768	1.074	11.80	< .001	0.902
	INT3	0.980	0.0907	0.802	1.158	10.81	< .001	0.857
	INT4	0.972	0.0902	0.795	1.148	10.77	< .001	0.856
	INT5	1.070	0.0884	0.897	1.243	12.11	< .001	0.917
PE	PE4	0.194	0.0134	0.168	0.221	14.49	< .001	1.000
EE	EE1	0.750	0.0890	0.575	0.924	8.43	< .001	0.731
	EE2	0.904	0.0851	0.738	1.071	10.53	< .001	0.855
	EE3	0.964	0.0850	0.797	1.130	11.34	< .001	0.890
	EE4	0.888	0.0922	0.707	1.069	9.63	< .001	0.801
	EE6	0.814	0.1068	0.605	1.023	7.62	< .001	0.678
SI	SI1	1.323	0.1211	1.085	1.560	10.92	< .001	0.868
	SI2	1.599	0.1368	1.330	1.867	11.69	< .001	0.906
	SI3	1.308	0.1321	1.050	1.567	9.91	< .001	0.817
	SI4	1.073	0.1423	0.794	1.352	7.54	< .001	0.674
OS	OS1	1.393	0.1429	1.113	1.673	9.75	< .001	0.822
	OS3	1.551	0.1624	1.232	1.869	9.55	< .001	0.817
	OS2	1.489	0.1428	1.210	1.769	10.43	< .001	0.864
ATT	ATT3	1.181	0.1182	0.949	1.413	9.99	< .001	0.826
	ATT4	1.282	0.1202	1.046	1.517	10.66	< .001	0.857
	ATT5	1.394	0.1212	1.157	1.632	11.59	< .001	0.902
ANX	ANX1	1.366	0.1275	1.116	1.616	10.72	< .001	0.855
	ANX2	0.929	0.1886	0.560	1.299	4.93	< .001	0.474
	ANX3	1.142	0.1522	0.844	1.440	7.50	< .001	0.667
	ANX4	1.122	0.1110	0.904	1.340	10.10	< .001	0.827
	ANX5	1.261	0.1584	0.951	1.572	7.96	< .001	0.700
	ANX6	1.470	0.1349	1.205	1.734	10.90	< .001	0.868
	ANX7	1.078	0.1087	0.865	1.291	9.92	< .001	0.816

The HTMT (Heterotrait-Monotrait) ratio table generated using SmartPLS provides insight into the discriminant validity of constructs in the model. Discriminant validity ensures that the constructs being measured are distinct from one another. Starting with EE ↔ ATT, the HTMT value is 0.313, indicating a fairly low correlation between these two constructs, meaning they are distinct but somewhat related. The next value, INT ↔ ATT, is 0.612, which shows a moderate relationship between these constructs, suggesting that intention to use AI is moderately influenced by the user's attitude toward AI. The correlation between INT ↔ EE is 0.446, also a moderate relationship, signifying that effort expectancy positively impacts intention to adopt technology.

The OS ↔ ATT value of 0.444 shows that organizational support has a moderate influence on attitude, while OS ↔ EE at 0.364 highlights a somewhat weaker relationship. The weak correlation between OS ↔ INT (0.211) suggests that organizational support has a limited impact on individuals' intentions. The PE ↔ ATT value is 0.072, indicating a very low correlation, which shows that these constructs are highly distinct. Similarly, PE ↔ EE at 0.147 and PE ↔ INT at 0.115 further highlight weak relationships between performance expectancy and both effort expectancy and intention.

The data also shows a moderate relationship between SI ↔ ATT at 0.585. However, SI ↔ EE at 0.244 indicates a weaker relationship, implying that SI does not significantly affect EE. The moderate relationship between SI ↔ INT (0.473) suggests that SI is somewhat impactful on INT, while the correlation between SI ↔ OS at 0.565 shows that social influence is related to the level of organizational support. The weakest correlation is between SI ↔ PE at 0.117.

Table 7

Blind Pilot Heterotrait-Monotrait (HTMT) Values

	HTMT Ratio
EE ←→ ATT	0.313
INT ←→ ATT	0.612
INT ←→ EE	0.446
OS ←→ ATT	0.444
OS ←→ EE	0.364
OS ←→ INT	0.211
PE ←→ ATT	0.072
PE ←→ EE	0.147
PE ←→ INT	0.115
PE ←→ OS	0.101
SI ←→ ATT	0.585
SI ←→ EE	0.244
SI ←→ INT	0.473
SI ←→ OS	0.565
SI ←→ PE	0.117
ANX ←→ ATT	0.185
ANX ←→ EE	0.488
ANX ←→ INT	0.298
ANX ←→ OS	0.167
ANX ←→ PE	0.207
ANX ←→ SI	0.136

Based on the results of the blind pilot study, the data revealed strong internal consistency for most constructs, with Cronbach's Alpha values exceeding 0.870, indicating high reliability of the instrument. The only exception was the Performance Expectancy (PE) construct, where the exploratory factor analysis (EFA) resulted in the retention of only one item (PE4) after removing cross-loading items. This indicated a weakness in the PE construct's ability to measure the intended variable comprehensively.

Given this limitation, an additional scale was introduced for the full study to address the shortcomings of the PE items that were used for the pilot. The added items were adapted from the Outcome Expectations scale developed by Compeau and Higgins (1995), which was originally applied in their study on computer self-efficacy and used by Venkatesh (2003) in the development of PE within the UTAUT framework. This addition was made to ensure that the PE construct would be adequately represented in the full study, thus enhancing the robustness of the measurement instrument.

Additionally, the confirmatory factor analysis (CFA) demonstrated strong factor loadings and significant relationships between key constructs, with moderate covariances found between factors such as SI and ATT, EE and ANX. Adequate discriminant validity was also demonstrated, since the HTMT showed that each construct was distinct and measured different concepts. This detailed analysis confirms the overall reliability and validity of the measurement instrument, aside from the noted issue with the PE construct.

Table 8

INTAI Measurement Scale

<table>
<tr><th>Construct</th><th>INTAI Measurement Scale</th><th>References</th></tr>
<tr><td colspan="3">Qualifier (QAL)
Used to determine if the respondent is eligible to participate in the survey and to ensure the data collected is based on the intended population of interest.</td></tr>
<tr><td>QAL1</td><td colspan="2">How long have you worked as a digital marketer?
(a) Never
(b) Less than 1 year
(c) 1-2 years
(d) 3-4 years
(e) 5+ years</td></tr>
<tr><td>QAL2</td><td colspan="2">How long have you worked with companies in the IT industry?
(a) Never
(b) Less than 1 year
(c) 1-2 years
(d) 3-4 years
(e) 5+ years</td></tr>
<tr><td>QAL3</td><td colspan="2">Do you work in the United States?
(a) Yes
(b) No</td></tr>
</table>

Control (CTL) Used to remove respondents who may affect the overall quality of the data that is collected.	
CTL1	What is your age range? (a) 18 or younger (b) 29-29 (c) 30-39 (d) 40-40 (e) 50-50 (f) 60-69 (g) 70+
CTL2	What is your gender? (a) Male (b) Female
CTL3	What is your income level? (a) $0 – $24,999 (b) $25,000 – $49,999 (c) $50,000 – $74,999 (d) $75,000 – $99,999 (e) More than $100,000 (f) Prefer not to answer
CTL4	What is your highest completed level of education? (a) No formal education (b) High School / GED (c) Associate Degree (d) Bachelor's Degree (e) Master's Degree (f) Doctorate Degree
CTL5	How long have you been using AI? (a) Never (b) 1 day – 1 month (c) 1 month and 1 day – 1 year (d) 1 year and 1 day – 2 years (e) More than 2 years
CTL6	How long have you worked as a Digital Marketer? (a) Less than 1 year (b) 1 year and 1 day – 2 years (c) 2 years and 1 day – 3 years (d) 3 years and 1 day – 4 years (e) More than 4 years
Red Herring (RED) Used to identify those who are fully engaged in the survey and those who are not.	
RED1	Please select "Somewhat Agree." (a) Strongly Disagree (b) Disagree (c) Somewhat Disagree (d) Neither Agree nor Disagree (e) Somewhat Agree (f) Agree (g) Strongly Agree
For the purpose of this survey, **AI tools** are defined as a form of generative artificial intelligence capable of producing text, images, and other creative content that resembles human output, while also integrating data from various sources for analysis (i.e. ChatGPT and DALL-E).	

Performance Expectancy of AI (PE) The degree to which an individual believes that using AI will enhance job performance. On a scale from 1- 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree **Answer the following statements.**		
PE1	Using AI tools would enable me to accomplish tasks more quickly.	Perceived Usefulness *(Davis 1989; Davis et al. 1989)*
PE2	Using AI tools would improve my job performance.	
PE4	Using AI tools would decrease the time needed for important job responsibilities.	
PE5	Use of AI tools would significantly increase the quality of output on my job.	Job-fit *(Thompson et al. 1991)*
PE6	Use of AI tools would significantly increase the quantity of output on my job.	
PE7	I would find using AI tools useful on my job.	
PE8R	Use of AI tools would have no effect on my job performance.	
PE9	Use of AI tools could increase the effectiveness of performing job tasks.	
PE10	Use of AI tools would enable me to accomplish tasks more quickly.	Relative Advantage (Moore and Benbasat, 1991)
PE11	Use of AI tools would improve the quality of work I do.	
PE12	Use of AI tools would make it easier to do my job.	
PE13	Use of AI tools will allow me to spend less time on routine job tasks.	Outcome Expectations (Compeau & Higgins, 1995b)
Effort Expectancy towards AI Use (EE) The degree of ease associated with the use of AI. On a scale from 1- 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree **Answer the following statements.**		
EE1	I expect learning to operate AI tools to be easy for me.	Perceived Ease of Use *(Davis 1989; Davis et al. 1989)*
EE2	I expect my interaction with AI tools to be clear and understandable.	
EE3	I expect it would be easy for me to become skillful at using AI tools.	
EE4	I expect AI tools to be easy to use.	
EE5	The benefits of AI tools do not outweigh the time needed to learn them.	Complexity *(Thompson et al. 1991)*
EE6	I believe that it is easy to get AI tools to do what I want them to do.	*Ease of Use (Moore & Benbasat 1991)*
Social Influence of AI Use (SI) The degree to which an individual perceives that significant persons believe AI use to be important. On a scale from 1- 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree **Answer the following statements.**		
SI1	People who influence my behavior think that I should use AI tools.	

SI2	People who are important to me think that I should use AI tools.	Subjective Norms *(Ajzen 1991; Davis et al. 1989; Fishbein & Ajzen 1975; Mathieson 1991; Taylor & Todd 1995a, 1995b)*
SI3	I use AI tools due to the significant number of coworkers who also utilize them.	Social Factors *(Thompson et al. 1991)*
SI4	People in my organization who use AI tools have more prestige than those who do not.	Image *(Moore & Benbasat 1991)*
SI5	Using AI tools is a status symbol in my organization.	
Organizational Support of AI Use (OS) The degree to which an individual believes that organizational infrastructure exists to support AI use. On a scale from 1- 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree **Answer the following statements.**		
OS1	Guidance is available to me in the selection of AI tools.	Facilitating Conditions *(Thompson et al. 1991)*
OS2	Specialized instruction concerning AI tools is available to me.	
OS3	A specific person (or group) is available for assistance should I experience difficulty with AI tools.	
OS4	I have the resources necessary to use AI tools.	Perceived Behavioral Control *(Ajzen 1991; Taylor & Todd 1995a, 1995b)*
OS5	Using AI tools is compatible with all aspects of my job.	Compatibility *(Moore & Benbasat 1991)*
Attitude Toward AI Use (ATT) An individual's overall evaluation of using AI. On a scale from 1- 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree **Answer the following statements.**		
ATT1	Using AI tools at work is a good idea.	Attitude Toward Behavior *(Davis et al. 1989; Ajzen, 1975; Taylor & Todd 1995a, 1995b)*
ATT2	Using AI tools at work is pleasant.	
ATT3	I have fun using AI tools at work.	Intrinsic Motivation *(Davis et al. 1992)*
ATT4	AI makes work more interesting.	Affect Toward Use *(Thompson et al. 1991)*
ATT5	I look forward to aspects of my job that require me to use AI tools.	Affect

ATT6R	Using AI tools at work is frustrating to me.	*(Compeau & Higgins, 1995b; Compeau, 1999)*
ATT7R	I get bored quickly when using AI tools at work.	
Technological Anxiety Toward AI (ANX) The apprehension and unease experienced by individuals regarding potentially uncontrollable advancements and implications of AI. On a scale from 1- 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree **Answer the following statements.**		
ANX1	Learning to use AI tools makes me anxious.	AI Anxiety Scale *(Wang and Wang, 2022)*
ANX2	I am afraid that AI tools will replace someone's job.	
ANX3	I fear that it is necessary to use an AI tool on my job.	
ANX4	Interpreting an AI tool output makes me anxious.	
ANX5	I am afraid of various problems potentially associated with AI content creation tools.	
ANX6	As a whole, I am anxious about the development of AI tools.	
ANX7	As a whole, I am afraid to use AI tools.	
Intention to Use AI Content Creation Tools (INT) An individual's readiness and conscious plan to use AI content creation tools. On a scale from 1- 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree **Answer the following statements.**		
INT1	I intend to use AI tools on my job in the future.	Intention *(Venkatesh 2003; 2012)*
INT2	I will try to use AI tools in my daily life.	
INT3	I plan to use AI tools more frequently on my job.	
INT4	Assuming AI tools would be available on my job, I predict that I will use them on a regular basis in the future.	Behavioral Intention (Yen et al 2010)
INT5	Overall, I intend to use AI tools on my job.	

V. FULL STUDY

Full Study Results

The final data set consisted of 310 responses collected for the study. After applying data cleaning procedures, 4 participants were removed due to incorrect responses to red-herring questions, while 6 responses were excluded for being incomplete and not providing the necessary completion code. The data set showed no notable outliers, indicating a relatively normal distribution across the variables with reliable results.

Descriptive Statistics

Of the respondents, 52% were male and 48% were female, indicating a near-equal gender distribution. The majority of participants fell within the 30-39 age group (37.7%), followed by those aged 40-49 (35.7%). The mean income level of the respondents was in the $50,000-$74,999 range (29%). The participants demonstrated relatively high education levels, with 51.7% of participants reporting a bachelor's degree as their highest level of education and 17.6% earning post-graduate degrees.

Regarding experience, 41.7% of participants had 1-2 years of AI experience, while 30% reported having more than 4 years of experience in marketing. The sample was drawn from various industries, with responses fairly distributed across the top ten business sectors listed in the CloudResearch platform. Information technology was the most represented industry (18.3%), while construction had the least representation at 4%.

Additional information regarding the respondents' demographics and control variables is provided in Table 9 below.

Table 9

Descriptive Statistics

Characteristics	Frequency	% of Sample
Gender		
Male	156	52.0%
Female	144	48.0%
Age		
19-29 years old	4	1.3%
30-39 years old	113	37.7%
40-49 years old	107	35.7%
50-59 years old	45	15.0%
60-69 years old	24	8.0%
70+ years old	7	2.3%
Income		
$0 - $24,999	27	9.0%
$25,000 - $49,999	73	24.3%
$50,000 - $74,999	87	29.0%
$75,000 - $99,999	52	17.3%
$100,000+	59	19.7%
Prefer not to answer	2	0.7%
Education Level		
High School / GED	52	17.3%
Associate Degree	43	14.3%
Bachelor's Degree	155	51.7%
Master's Degree	42	14.9%
Doctorate Degree	8	2.7%
AI Experience		
Never	7	2.3%
1 day – 1 month	14	4.7%
1 month and 1 day – 1 year	66	22.0%

1 year and 1 day – 2 years	125	41.7%
More than 2 years	88	29.3%
Marketing Experience		
Less than 1 year	67	22.3%
1 year and 1 day – 2 years	69	23.0%
2 years and 1 day – 3 years	39	13.0%
3 years and 1 day – 4 years	35	11.7%
More than 4 years	90	30.0%
Industry		
Construction	12	4.0%
Consumer Goods	15	5.0%
Education	27	9.0%
Finance	24	8.0%
Healthcare	32	10.7%
Hospitality	16	5.3%
Information Technology	55	18.3%
Media and Entertainment	44	14.7%
Real Estate	36	12.0%
Retail	14	4.7%
Other	25	8.3%

Exploratory Factor Analysis (EFA)

An EFA was performed using principal axis factoring with oblimin rotation in order to identify which factors correlate with each other. Eleven items were eliminated from the pattern matrix that cross-loaded in the following order: PE11 loaded under factor 1 (0.590) and factor 6 (0.327); ATT1 loaded under factor 2 (0.380) and factor 6 (0.303); PE7 loaded under factor 1 (0.438) and factor 3 (0.423); ANX7 loaded under factor 2 (0.544) and factor 7 (0.321); ANX1 loaded under factor 4 (0.469) and factor 6 (-0.498); PE5 loaded under factor 1 (0.528) and factor 7 (0.314); SI3 loaded under factor 5

(0.311) and factor 6 (0.502); EE5 loaded under factor 2 (-0.304) and factor 6 (0.309); PE8R was eliminated due to a low loading; and ATT6 loaded under factor 5 (0.317) while all other items from this construct loaded under factor 6.

Table 10

Full Study Pattern Matrix (EFA)

	Factor							
	1	2	3	4	5	6	7	Uniqueness
PE10	0.842							0.266
PE12	0.816							0.206
PE6	0.794							0.371
PE9	0.793							0.276
PE13	0.743							0.362
PE4	0.707							0.516
PE1	0.634							0.292
PE2	0.451							0.321
INT3		0.916						0.115
INT5		0.914						0.103
INT1		0.862						0.162
INT4		0.719						0.285
INT2		0.473						0.439
EE3			0.822					0.245
EE1			0.812					0.349
EE2			0.801					0.281
EE4			0.739					0.385
EE6			0.399					0.473
OS2				0.942				0.140
OS1				0.890				0.216
OS3				0.766				0.321
OS4				0.497				0.535
OS5				0.330				0.558
ANX6					0.832			0.286
ANX5					0.759			0.365
ANX2					0.727			0.455
ANX4					0.636			0.406
ANX3					0.617			0.520
ATT5						0.840		0.240
ATT4						0.820		0.187
ATT3						0.781		0.199
ATT2						0.582		0.284
SI2							0.825	0.223
SI1							0.781	0.292
SI5							0.530	0.385
SI4							0.455	0.517

NOTE: ‘Principal axis factoring’ extraction method was used in combination with an ‘oblimin’ rotation.

Reliability

Indicator reliability, measured by factor loadings (see Table 11), shows that most items exceeded the recommended threshold of 0.7, indicating strong relationships between the individual items and their corresponding constructs. One item, ANX3, had a loading of 0.627, falling below the preferred threshold, indicating that it may be less effective in representing its construct compared to the other items.

In terms of internal consistency reliability, Cronbach's alpha (CA) values for all constructs were strong, ranging from 0.845 to 0.939. This indicates that the items within each construct consistently measured the same underlying factor. Technological anxiety (ANX), while still acceptable, had a Cronbach's alpha of 0.852, slightly lower than the others but still within a reliable range.

Composite reliability (CR) was similarly robust across all constructs, with values exceeding the recommended 0.7 threshold. The CR values ranged from 0.874 (SI) to 0.943 (PE), reinforcing the internal consistency of the measures.

Convergent Validity

The average variance extracted (AVE), which assesses convergent validity, also showed strong results. All constructs had AVE values greater than 0.5, signifying that the constructs explained a satisfactory amount of variance in their items. AVE values ranged from 0.620 (ANX) to 0.821 (ATT), indicating adequate convergent validity across the board.

Table 11

Psychographic Analysis Table

Variable	Items	Mean ($\bar{x}$)	Standard Deviation (s)	Loading	CA	CR (rho_a)	AVE
Intention	INT1	5.65	1.41	0.920	0.939	0.941	0.808
	INT2	5.23	1.44	0.803			
	INT3	5.45	1.43	0.938			
	INT4	5.72	1.25	0.880			
	INT5	5.62	1.41	0.945			
Performance Expectancy	PE1	5.96	1.04	0.860	0.938	0.943	0.700
	PE2	5.54	1.29	0.876			
	PE4	5.39	1.36	0.898			
	PE6	5.56	1.13	0.819			
	PE9	5.58	1.15	0.822			
	PE10	5.75	1.17	0.737			
	PE12	5.64	1.30	0.799			
	PE13	5.81	1.14	0.872			
Effort Expectancy	EE1	5.78	1.04	0.814	0.891	0.901	0.696
	EE2	5.74	1.09	0.865			
	EE3	5.72	1.09	0.875			
	EE4	5.76	1.08	0.833			
	EE6	5.28	1.11	0.781			
Social Influence	SI1	4.19	1.61	0.879	0.845	0.874	0.680
	SI2	4.14	1.58	0.889			
	SI4	3.54	1.62	0.759			
	SI5	3.14	1.65	0.761			
Organizational Support	OS1	4.30	1.84	0.821	0.861	0.875	0.637
	OS2	4.15	1.90	0.862			
	OS3	3.83	1.94	0.789			
	OS4	5.03	1.50	0.762			
	OS5	4.46	1.71	0.752			
Attitude	ATT2	5.37	1.25	0.884	0.927	0.929	0.821
	ATT3	5.26	1.42	0.924			
	ATT4	5.18	1.50	0.919			
	ATT5	5.07	1.46	0.896			
Technological Anxiety	ANX2	4.14	1.96	0.789	0.852	0.889	0.620
	ANX3	3.16	1.67	0.627			
	ANX4	2.86	1.57	0.745			
	ANX5	3.80	1.83	0.851			
	ANX6	3.55	1.79	0.897			

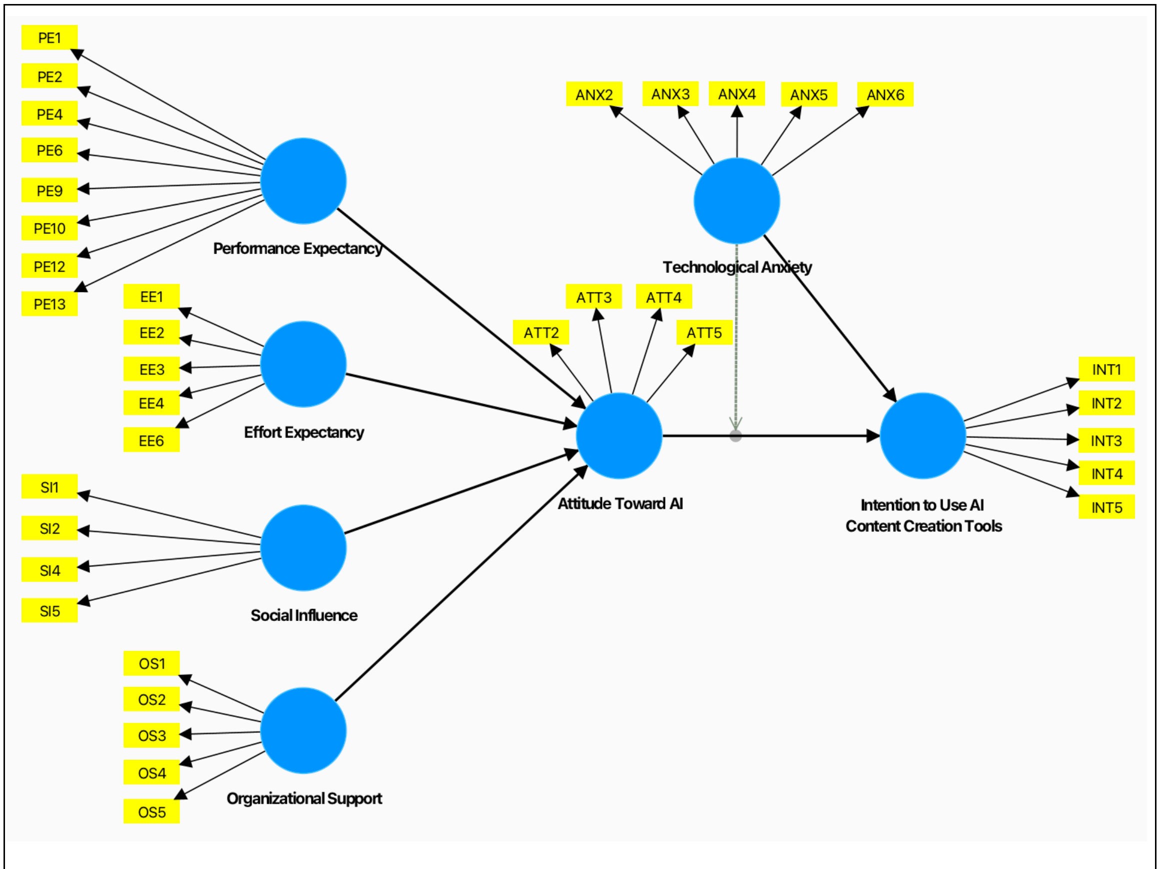


Figure 3: Measurement Model
Taken from SmartPLS (Ringle et al, 2015)

Discriminant Validity

Discriminant validity is the extent to which a construct is distinct from other constructs. Table 12 presents the heterotrait-monotrait (HTMT) ratios, which were used as an estimate of what the true correlation between two constructs would be if they were perfectly measured. Typically, HTMT values below 0.90 indicate adequate discriminant validity. All values fell below this threshold, suggesting acceptable discriminant validity between each construct. The highest HTMT values were found between PE and INT at 0.803, and INT and ATT at 0.742.

The Fornell-Larcker criterion, displayed in Table 13, is an additional method for evaluating discriminant validity. It compares the square root of the average variance extracted (AVE) on the diagonal with the correlations between constructs. For discriminant validity to be established, the diagonal values should be higher than the off-diagonal correlations. The results indicate that each construct shared more variance with its own indicators than with other constructs, which supports the claim that the model has good discriminant validity. The lowest correlation is between ANX and SI at -0.055, indicating minimal overlap. Although the HTMT ratio has been suggested to be a more reliable measure compared to Fornell-Larcker, it has been evaluated to further illustrate the discriminant validity of the model.

Table 12

HTMT Matrix

	ATT	EE	INT	OS	PE	SI	ANX
ATT							
EE	0.669						
INT	0.768	0.561					
OS	0.563	0.444	0.429				
PE	0.769	0.644	0.803	0.393			
SI	0.586	0.399	0.460	0.647	0.350		
ANX	0.234	0.066	0.224	0.129	0.134	0.075	

Table 13

Fornell Larker

	ATT	EE	INT	OS	PE	SI	ANX
ATT	0.906						
EE	0.536	0.834					
INT	0.694	0.524	0.899				
OS	0.518	0.422	0.426	0.798			
PE	0.694	0.600	0.760	0.388	0.837		
SI	0.465	0.288	0.434	0.541	0.339	0.825	
ANX	-0.406	-0.407	-0.323	-0.244	-0.324	-0.055	0.787

Confirmatory Factor Analysis (CFA)

The confirmatory factor analysis (CFA) illustrates the factor loadings for different indicators linked to various constructs. Each row details the loading of an indicator onto its respective latent factor, along with its estimate, standard error, confidence intervals, z-score, p-value, and standardized estimate. The statistical significance of all loadings is confirmed by p-values less than 0.001.

Most factor loadings exceeded the recommended threshold of 0.70, which suggests strong convergent validity. Although a few indicators, such as SI3 (0.559) and ANX3 (0.600), fell slightly below this threshold, they remain within an acceptable range. The confidence intervals for each estimate further confirms the statistical significance of the loadings, since they do not cross zero. Standardized estimates provide additional support for the strength of these loadings, highlighting their reliability in measuring the latent variables. Overall, the CFA results validate the structure of the measurement model, confirming that the indicators appropriately loaded onto their intended constructs.

Table 14

Factor Loadings

Factor	Indicator	Estimate	SE	95% Confidence Interval Lower	Upper	z score	p value	Stand. Est.
INT	INT1	1.302	0.0628	1.179	1.425	20.72	< .001	0.917
	INT2	1.028	0.0729	0.885	1.171	14.10	< .001	0.713
	INT3	1.335	0.0624	1.212	1.457	21.40	< .001	0.934
	INT4	1.038	0.0587	0.923	1.153	17.67	< .001	0.833
	INT5	1.339	0.0602	1.221	1.457	22.24	< .001	0.954
PE	PE1	0.868	0.0490	0772	0.964	17.72	< .001	0.837
	PE2	1.027	0.0627	0.904	1.150	16.37	< .001	0.796
	PE4	0.935	0.0700	0.798	1.072	13.36	< .001	0.687
	PE6	0.854	0.0558	0.745	0.963	15.31	< .001	0.759
	PE9	0.978	0.0536	0.872	1.083	18.22	< .001	0.852
	PE10	1.007	0.0541	0.901	1.113	18.61	< .001	0.863
	PE12	1.152	0.0588	1.037	1.267	19.58	< .001	0.890
	PE13	0.903	0.0553	0.795	1.011	16.33	< .001	0.793
EE	EE1	0.825	0.0517	0.724	0.927	15.98	< .001	0.792
	EE2	0.921	0.0523	0.819	1.024	1762	< .001	0.846
	EE3	0.937	0.0518	0.835	1.038	18.09	< .001	0.860
	EE4	0.846	0.0534	0.741	0.951	15.83	< .001	0.787
	EE6	0.746	0.0585	0.631	0.861	12.76	< .001	0.675
SI	SI1	1.451	00736	1.306	1.595	19.70	< .001	0.905
	SI2	1.447	0.0723	1.305	1.588	20.01	< .001	0.915
	SI3	0.902	0.0900	0.725	1.078	10.02	< .001	0.559
	SI4	0.953	0.0915	0.773	1.132	10.41	< .001	0.578
OS	OS1	1.646	0.0837	1.482	1.811	19.67	< .001	0.897
	OS2	1.784	0.0839	1.619	1.948	21.26	< .001	0.940
	OS3	1.547	0.0943	1.362	1.732	16.40	< .001	0.800
	OS4	0.863	0.0815	0.703	1.022	10.59	< .001	0.576
	OS5	0.860	0.0952	0.673	1.046	9.03	< .001	0.504
ATT	ATT2	1.043	0.0590	0.927	1.159	17.68	< .001	0.839
	ATT3	1.282	0.0643	1.156	1.409	19.94	< .001	0.903
	ATT4	1.337	0.0680	1.203	1.470	19.65	< .001	0.895
	ATT5	1.250	0.0684	1.116	1.384	18.27	< .001	0.856
ANX	ANX2	1.381	0.1038	1.177	1.584	13.30	< .001	0.706
	ANX3	1.001	0.0941	0.817	1.185	10.64	< .001	0.600
	ANX4	1.080	0.0843	0.915	1.245	12.81	< .001	0.690
	ANX5	1.473	0.0919	1.292	1.653	16.02	< .001	0.805
	ANX6	1.516	0.0877	1.344	1.688	17.29	< .001	0.850

Table 15 presents the results of the model fit assessment using goodness-of-fit indices. The chi-square test for exact fit (x^2) yielded a value of 1433 with 573 degrees of freedom (df) and a p-value less than 0.001. This indicates that the model does not fit the data perfectly. A low p-value typically suggests a significant difference between the model and the data. In the fit measures section, the Comparative Fit Index (CFI) is 0.902, and the Tucker-Lewis Index (TLI) is 0.892. These values approach the commonly recommended threshold of 0.90, suggesting an acceptable model fit, though the TLI is slightly below the threshold. The root mean square error of approximation (RMSEA) is 0.0707, which falls within an acceptable range, while the 90% confidence interval for RMSEA is 0.0661 to 0.0753. These values are close to the upper end of the commonly accepted range of 0.06 to 0.08, indicating that the model has a reasonable fit. While the chi-square test does not point towards a perfect fit, the incremental fit indices of CFI, TLI, and RMSEA imply that the model provided an acceptable fit to the data.

Table 15

Model Fit

Text for Exact Fit

x^2	df	p
1433	573	< .001

Fit Measures

			RMSEA 90% CI	
CFI	TLI	RMSEA	Lower	Upper
0.902	0.892	0.0707	0.0661	0.0753

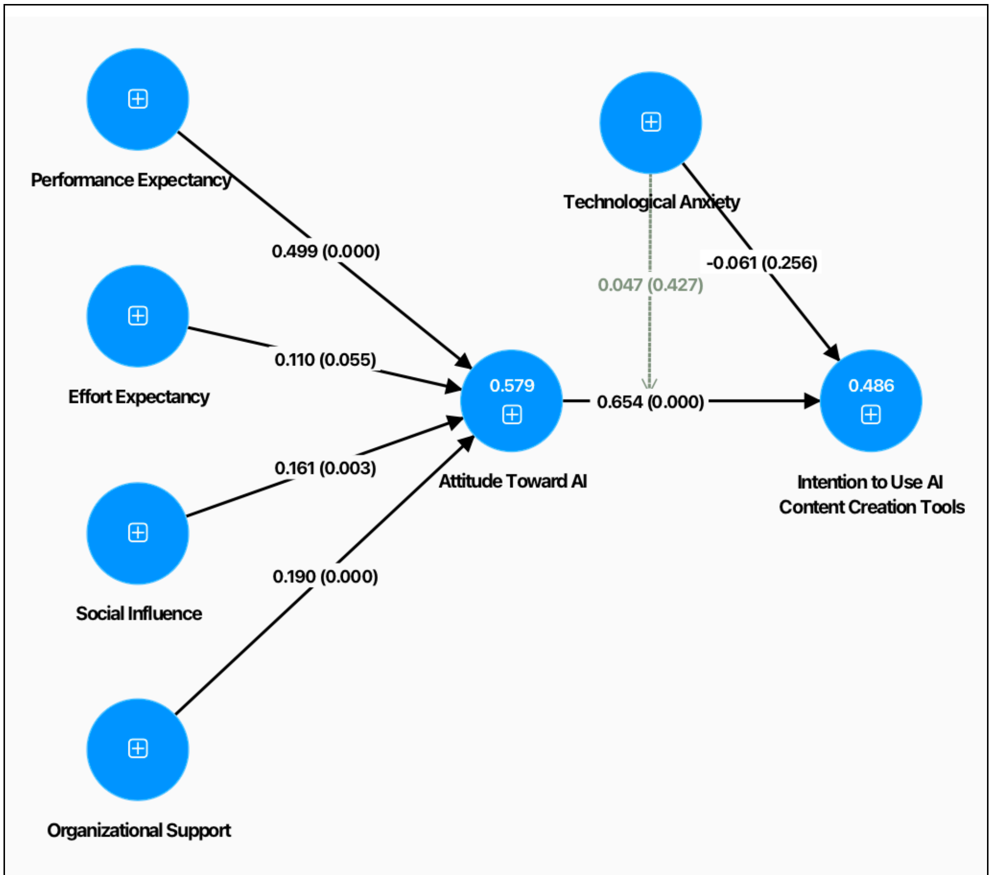


Figure 4: Structural Model
Taken from SmartPLS (Ringle et al, 2015)

Structural Model

The structural model analysis (see Table 16) displays the hypothesized relationships using several key metrics, including path coefficients, t-values, p-values, sample means, confidence intervals, and beta values. For the relationship H1: PE → ATT, the path coefficient was 0.499, with a t-value of 8.541 and a p-value of 0.000, indicating a significant and strong positive relationship. The sample mean was 0.498, with a 95% confidence interval ranging from 0.378 to 0.610, and a beta value of 0.499, reflecting the strong influence of PE on ATT. In contrast, H2: EE → ATT had a lower path coefficient of 0.110, a t-value of 1.923, and a p-value of 0.055, indicating that the relationship was not statistically significant. H3: SI → ATT and H4: OS → ATT had moderate to strong positive effects. The strongest influence observed was H5: ATT → INT (path coefficient 0.654, p-value 0.000). On the other hand, H6: ANX x ATT → INT showed a weak, non-significant negative relationship, with a path coefficient of -0.047 and a p-value of 0.256, indicating that ANX had little to no effect on the relationship between ATT and INT.

Table 16

Structural Model Estimation (Significance and Relevance)

Hypothesized Path	Path Coefficient	t value	p value	Sig.	Sample Mean (M)	Confidence Interval 2.5%	Confidence Interval 97.5%	β	Relation-ship
H1+: PE → ATT	0.499	8.541	0.000	Yes	0.498	0.378	0.610	0.499	Strong Positive
PE → INT	*0.326*	*6.024*	*0.000*	*Yes*					
H2+: EE → ATT	0.110	1.923	0.055	No	0.113	0.005	0.228	0.110	Moderate Positive
EE → INT	*0.072*	*1.952*	*0.051*	*No*					
H3+: SI → ATT	0.161	2.941	0.003	Yes	0.161	0.054	0.268	0.161	Moderate Positive
SI → INT	*0.105*	*3.079*	*0.002*	*Yes*					
H4+: OS → ATT	0.190	3.853	0.000	Yes	0.193	0.095	0.287	0.190	Moderate Positive
OS → INT	*0.125*	*3.584*	*0.000*	*Yes*					
H5+: ATT → INT	0.654	12.145	0.000	Yes	0.650	0.539	0.749	0.654	Strong Positive
H6-: ANX x ATT→ INT	0.047	1.135	0.256	No	0.051	-0.071	0.159	0.047	Weak Positive
ANX → INT	*-0.061*	*0.794*	*0.427*	*No*	*-0.067*	*-0.170*	*0.039*	*-0.061*	*Weak Negative*

Common method bias (CMB) occurs when a measurement error arises that can potentially inflate relationships between variables. One of the ways to test for CMB is through collinearity diagnostics, such as the variance inflation factor (VIF). Table 17 presents the VIF values to assess the potential for collinearity in the inner model. Collinearity can cause problems by inflating the variance of the coefficient estimates, making them unstable. A general rule is that VIF values above 5 indicate problematic levels of collinearity. In the model, all the VIF values are well below 5, with the highest being 1.672 for the relationship between EE and ATT. This suggests that multicollinearity is not a concern. The VIF values for PE, SI, and OS with ATT are 1.654, 1.454, and 1.601, respectively, indicating that these constructs are not overly correlated. ATT to INT has a VIF of 1.355, while ANX moderating ATT and INT, and directly influencing INT, both have low VIF values (1.135 and 1.247). Overall, these results suggest that the model does not suffer from significant collinearity issues, which supports the robustness of the results in evaluating the relationships between these constructs. Therefore, CMB is not likely to distort the results in this model.

Table 17

Common Method Bias (CMB)

Collinearity Statistics (VIF) – Inner Model – List

	VIF
PE → ATT	1.654
EE → ATT	1.672
SI → ATT	1.454
OS → ATT	1.601
ATT → INT	1.355
ANX x ATT → INT	1.135
ANX → INT	1.247

Table 18 displays the R-Square values, which indicate the explanatory power of the model for the mediating and dependent variables ATT and INT. These values provide insight into how much variance is explained by each variable. The R-Square for ATT is 0.579, meaning that the model explains approximately 57.9% of the variance in ATT. The adjusted R-Square, which accounts for the number of predictors in the model and adjusts for potential overfitting, is 0.573. Both values suggest a strong explanatory power.

For INT, the R-Square is 0.486, meaning that the model accounts for 48.6% of the variance in INT. The adjusted R-Square is 0.481, also indicating strong explanatory power. Overall, these values suggest that the model does a good job of explaining the variation in both ATT and INT with a higher explanatory power for ATT compared to INT. This implies that the model is effective in capturing the relationships between the predictors and these key outcome variables.

Table 18

R-Square (Explanatory Power)

	R-Square	R-Square Adjusted	Power
ATT	0.579	0.573	Strong
INT	0.486	0.481	Strong

Multi-Group Analysis

The industry control variable was divided into two groups: service-oriented and product-oriented sectors. Service-oriented sectors included education, finance, healthcare, hospitality, and real estate; while product-oriented sectors encompassed information technology, media and entertainment, construction, retail, and consumer goods. A MICOM analysis was conducted to compare these two categories, with the results presented in Table 19 below.

For digital marketers in service-oriented sectors, performance expectancy (PE) and social influence (SI) were pivotal in shaping their attitudes toward their intention to adopt AI tools. Organizational support (OS) was more influential in product-oriented sectors, while effort expectancy (EE) did not appear to be a major barrier in either sector, suggesting that marketers across all industries were confident in the usability of these technologies.

. The role of PE was indicated by its higher impact on attitudes in service-oriented sectors (PE → ATT = 0.628) compared to product-oriented sectors (PE → ATT = 0.354). In service-oriented sectors, the data showed a negative path coefficient (SI → ATT = -0.019) compared to a positive impact in product-oriented sectors (SI → ATT = 0.248). This highlights a potential barrier where performance expectations might hinder AI adoption among service-oriented marketers.

OS was perceived as less impactful in service-oriented sectors (OS → ATT = 0.149) compared to product-oriented sectors (OS → ATT = 0.218). This perception aligns with Step 3a results, where service-oriented marketers reported significantly lower levels of organizational support (OS mean = -0.269). Without strong organizational backing, service marketers may hesitate to adopt AI tools, emphasizing the importance of fostering supportive environments.

All constructs, except technological anxiety (ANX), exhibited high compositional invariance with non-significant permutation p-values (> 0.05), as seen in Step 2. The significant p-value (0.032) of ANX indicates a potential variability in how anxiety is measured across groups, appearing to play a more pronounced role in marketers of service-oriented sectors (ANX mean = 0.256, p = 0.016). This could stem from uncertainties about AI integration by marketers who work in intangible and relationship-based service environments.

Despite these differences, the variance tests in Step 3b indicate that variability in ATT is consistent across both sectors. This means that while the specific factors driving attitudes may differ, the overall range of attitudes within each sector is comparable, reflecting similar levels of diversity in how digital marketers perceive AI tools.

Table 19

MICOM Analysis

Step 1 (Configural Invariance)

	Original (Service-Oriented)	Original (Product-Oriented)	Original Difference	Permutation Mean Difference	5.0%	95.0%	Permutation p value
ATT→INT	0.633	0.582	0.051	-0.002	-0.213	0.218	0.345
EE→ATT	0.188	0.107	0.080	-0.004	-0.229	0.230	0.265
OS→ATT	0.149	0.218	-0.069	-0.002	-0.175	0.159	0.265
PE→ATT	0.628	0.354	0.274	0.002	-0.208	0.215	0.017
SI→ATT	-0.019	0.248	-0.266	0.004	-0.225	0.229	0.023
ANXxATT →ATT	0.139	0.014	0.125	0.000	-0.228	0.225	0.183

Step 2 (Compositional Invariance)

	Original Coefficient	Correlation Permutation Mean	5.0%	Permutation p value
ATT	0.999	0.997	0.991	0.751
EE	0.999	0.998	0.995	0.818
INT	1.000	1.000	0.999	0.726
OS	1.000	0.994	0.982	0.961
PE	1.000	1.000	0.999	0.446
SI	0.993	0.995	0.984	0.219
ANX	0.960	0.987	0.964	0.032

Step 3a (Mean)

	Original Coefficient	Permutation Mean Difference	5.0%	95.0%	Permutation p value
ATT	-0.098	0.003	-0.200	0.212	0.220
EE	0.016	0.003	-0.191	0.203	0.444
INT	-0.117	-0.000	-0.198	0.198	0.170
OS	-0.269	-0.000	-0.209	0.190	0.016
PE	0.032	-0.000	-0.196	0.198	0.389
SI	0.055	0.001	-0.205	0.193	0.340

Step 3a (Mean)

	Original Coefficient	Permutation Mean Difference	5.0%	95.0%	Permutation p value
ANX	0.256	-0.003	-0.219	0.198	0.016

Step 3b (Variance)

	Original Coefficient	Permutation Mean Difference	5.0%	95.0%	Permutation p value
ATT	0.080	0.001	-0.328	0.320	0.350
EE	-0.287	-0.007	-0.495	0.484	0.182
INT	0.241	-0.003	-0.406	0.402	0.155
OS	0.244	-0.004	-0.258	0.246	0.051
PE	-0.256	-0.005	-0.432	0.406	0.174
SI	0.110	0.001	-0.242	0.253	0.238
ANX	0.121	-0.000	-0.236	0.229	0.199

Table 20

Hypotheses Summary – Final Study

Hypotheses Summary – Final Study			
	Hypothesis	**Result**	**p value**
H1+	A digital marketer's performance expectancy of AI will positively affect their attitude towards AI.	Supported	0.000
H2+	A digital marketer's effort expectancy of AI will positively affect their attitude towards AI.	Not Supported	0.055
H3+	A digital marketer's social influence of AI use will positively affect their attitude towards AI.	Supported	0.003
H4+	A digital marketer's organizational support of AI will positively affect their attitude towards AI.	Supported	0.000
H5+	A digital marketer's attitude toward AI use will positively affect their intention to use AI content creation tools.	Supported	0.000
H6-	As a digital marketer's level of technological anxiety toward AI use increases, it will negatively affect the relationship between attitude toward AI use and intention to use AI content creation tools.	Not Supported	0.256

The analysis revealed that the performance expectancy (PE) of AI content creation tools significantly influences digital marketers' attitudes (ATT), with a standardized coefficient of $\beta = 0.499$ and a p-value of 0.000, indicating a strong positive relationship. This finding aligns with Cao et al.'s (2021) research on managers' attitudes toward using AI for organizational decision-making ($\beta = 0.410$; $p < 0.001$), demonstrating a significant positive effect. Similarly, Patil et al.'s (2020) study on consumer adoption of mobile payments found a significant positive relationship between

PE and ATT ($\beta = 0.273$; $p = 0.000$). These consistent results across different domains confirm the role of PE in shaping positive attitudes toward AI technologies.

The second hypothesis proposed that effort expectancy (EE) would positively influence the attitudes of digital marketers (ATT) and yielded a standardized coefficient of $\beta = 0.110$ with a p-value of 0.055. This result indicates a non-significant relationship, leading to the rejection of H2. The findings align with Garcia et al.’s (2024) study on electric vehicle adoption ($\beta = 0.005$; $p = 0.977$), also indicating a non-significant effect of EE on ATT. Conversely, while Puriwat et al.'s (2021) research on social media adoption found a significant positive relationship between EE and ATT ($\beta = 0.194$; $p < 0.01$), they observed a non-significant effect of EE on INT ($\beta = 0.051$). Despite these outcomes, the majority of studies using UTAUT to measure technology adoption have demonstrated significant positive associations between EE and both ATT and INT, which served as the foundation for formulating H2. Though the results were not as expected, they offer insight into how digital marketers view the amount of effort needed to engage with AI tools, and how this perception does not affect their overall attitude. Perhaps additional, more nuanced investigation can further validate and uncover the reasoning behind this phenomenon.

Social influence (SI) was shown to have a significant positive impact on attitude ($\beta = 0.161$; $p = 0.003$), supporting the hypothesis that SI helps shape marketers’ attitudes toward the adoption of AI tools. This finding aligns with the work of Dwivedi et al. (2019), who found a significant relationship between SI and ATT in the context of individuals’ intention to use information systems and technologies ($\beta = 0.15$; $p < 0.001$).

Moreover, the findings are further corroborated by Kayali et al. (2020), who examined the adoption of cloud-based e-learning in developing countries and reported a similar relationship between SI and INT ($\beta = 0.151$, $p = 0.003$). These findings reinforce the results of SI in shaping the attitude of marketers which affect their intention to use generative AI in their content creation.

The analysis of hypothesis 4 reveals that organizational support (OS) significantly influences ATT, with a standardized coefficient of $\beta = 0.190$ and a p-value of 0.000, indicating positive statistical significance. Within the UTAUT framework, OS is often conceptualized as facilitating conditions (FC), which encompass the resources and support available to users for effective system utilization. The findings of this relationship align with prior research from Dwivedi et al. (2019) who reported that FC positively affects user attitudes toward IS/IT innovations ($\beta = 0.20$; $p < 0.001$). Similarly, Chatterjee et al. (2023) found that FC significantly enhances attitudes toward AI-integrated CRM systems ($\beta = 0.33$; $p < 0.01$). Further support can be validated from Almagrashi et al. (2023), who demonstrated that organizational influence (OI) directly impacts internal auditors' behavioral intentions to adopt computer-assisted auditing techniques ($\beta = 0.26$; $p < 0.01$). These studies are examples which corroborate the pivotal role of OS in shaping the attitude toward AI among digital marketers.

The mediating effect of attitude on its relationship with intention was shown as significant ($\beta = 0.354$; $p = 0.000$). This is supported by Zhuang et al. (2021), who reported that individual attitudes significantly influence their intention to use augmented reality technology in tourism experiences ($\beta = 0.52$, $p = 0.00$). Similarly, Bano et al.

(2024) found a significant relationship between consumers' attitudes and their intentions to adopt smart technologies in the tourism and hospitality industry ($\beta = 0.354$, $p < 0.001$). This can be further demonstrated by Kasilingam et al. (2020) who showed that attitudes significantly predict intentions to use smartphone chatbots for shopping purposes ($\beta = 0.388$, $p = 0.000$). In addition to these studies, there is overwhelming empirical evidence of the positive and significant relationship between ATT and INT using a variety of technology acceptance models including UTAUT, TAM and TPB; all of which support the findings of this study in the context of AI tool usage intention.

Surprisingly, the moderating effect of technological anxiety (ANX) on the relationship between ATT and INT was not statistically significant ($\beta = -0.029$, $p > 0.05$). Wang, Q. et al. (2022) reported a similar lack of significance in their study on the moderating role of technostress on the effect of subjective norms on mobile English learning adoption intention ($\beta = -0.029$, $p > 0.05$). Similarly, Tsai et al. (2020) found no significant moderating effect of technological anxiety in their study on the wearable cardiac monitoring system among those with cardiovascular disease ($\beta = -0.214$; $t = 0.940$), where the interaction between technological anxiety (TA), perceived ease of use (PEOU), and attitude (AT) yielded a non-significant result; however. significant results were garnered from those who did not have cardiovascular issues ($\beta = -0.317$; $t = 3.867$). Yang et al (2013) also reported significant results when investigating the moderating effect of ANX on SI and BI (High Anxiety: $\beta = -.275$ / Low Anxiety: $\beta = -.094$; $p < 0.01$). Interestingly, when technological anxiety and technostress were evaluated as independent variables, these factors showed overwhelmingly significant results, indicating their direct influence on both ATT and INT (Chang et al., 2024; Hwang et al., 2022; Nasirpouri et al., 2022). Since the moderating effect of ANX was not significant for the sample used in this study, we can conclude that hypothesis H6 is unsupported.

VI. SUMMARY, IMPLICATIONS AND OUTCOMES

Summary of Findings

Performance expectancy (PE) emerged as a significant predictor of positive attitudes toward AI tools. This strong relationship ($\beta = 0.499$, $p = 0.000$) indicates that marketers who perceive AI as beneficial are more likely to develop favorable attitudes. In contrast, effort expectancy (EE) did not significantly influence attitudes ($\beta = 0.110$, $p = 0.055$), a result that diverges from most UTAUT-based studies. This suggests that digital marketers' attitudes may not be strongly impacted by perceived effort, perhaps due to their existing familiarity with technology.

Social influence (SI) significantly affected attitudes ($\beta = 0.161$, $p = 0.003$), emphasizing the role of peer support and social norms when it comes to encouraging AI adoption. Organizational support (OS) also demonstrated a significant positive effect on attitudes ($\beta = 0.190$, $p = 0.000$). By providing resources and fostering a supportive environment, organizations can enhance marketers' receptiveness to AI tools.

Attitudes (ATT) were found to significantly predict intention to use AI tools ($\beta = 0.354$, $p = 0.000$), confirming findings from technology acceptance models such as TAM and TPB. This result demonstrates the importance of cultivating positive attitudes toward adoption. Interestingly, technological anxiety (ANX) did not significantly moderate the relationship between attitudes and intentions ($\beta = -0.029$, $p > 0.05$). These findings can offer useful insights to organizations adopting AI tools for their digital marketers. Emphasizing performance benefits, and creating a supportive organizational culture are essential strategies to ensure a successful integration. Social influence mechanisms, including peer advocacy and testimonials, could enhance positive attitudes. The non-significance of effort expectancy is notable; this might indicate that ease of use is not perceived to be a primary concern, perhaps due to digital marketers' already accustomed proficiency with technology.

Theoretical Implications

The results of the study reinforced the applicability of UTAUT as an effective instrument in the explanation of behavioral intention within AI adoption. UTAUT contributes meaningful insights into a theoretical understanding of the adoption undertaking, clarifying the attitude-to-intention relationship. PE's confirmation as the strongest predictor of intention was consistent with UTAUT's foundational proposition, which hypothesizes that perceived utility significantly drives adoption (Venkatesh, 2003). The study also provided further evidence that social dynamics, including peer and superior endorsements, remain influential in shaping behavioral intention. This is particularly relevant in collaborative and creative fields such as in digital marketing, where collective acceptance often drives individual adoption decisions. Organizational support (OS), framed as a modification of the facilitating conditions construct, offered a novel contribution by demonstrating how organizational infrastructure and resources positively impact adoption, extending the UTAUT model to better capture workplace dynamics. By integrating these constructs into the context of digital marketing, the study built on existing literature while addressing several notable gaps.

First, it addressed the lack of research on technology adoption among digital marketers. This professional group plays a pivotal role in shaping consumer experiences yet remains under researched in adoption literature. By focusing on practitioners rather than on consumers, the study provided a unique perspective, one that is capable of enriching the understanding of technology adoption within creative industries.

Second, the research examined the moderating effect of technological anxiety, a construct that has been underexplored in UTAUT and attitude-to-intention studies. Although technological anxiety did not moderate attitudes and intentions in the study, based on empirical evidence it is expected that measuring its direct effects might further improve intention and adoption rates.

Lastly, the study expanded the theoretical framework of UTAUT by incorporating a modified facilitating conditions construct of organizational support. This approach more effectively reflects the realities of workplace dynamics in AI adoption by providing additional understanding for practitioners, paving the way for future research to continue similar explorations in other professional and technological contexts.

The non-significance of effort expectancy (EE) and technological anxiety (ANX) was unexpected, highlighting the complexity and context-dependence of technology adoption. Several potential factors could explain these findings. First, the measurement scales used for EE and ANX may not have fully captured the nuances inherent in digital marketers' experiences with AI tools. For example, the EE scale may have overlooked the cognitive and operational effort associated with advanced or creative usage, while the ANX scale may not have adequately addressed AI-specific concerns, such as ethical considerations or data security. Second, the characteristics of the sample population likely played a role. Digital marketers, as a technologically proficient group, might experience lower levels of perceived effort and anxiety as compared to general populations, particularly if they have prior experience with AI or similar tools. Such familiarity might reduce variability in responses, making it difficult to detect appreciable effects. Additionally, since the results were based on a self-reporting instrument, responses about anxiety could have been under-reported since there exists a stigma attached to such perceived appellations.

The specific context of digital marketing offers its own explanation. In a fast-paced and results-driven industry, perceived performance gains may overshadow concerns about ease of use or anxiety. Marketers might prioritize AI's ability to enhance outcomes over the effort required to learn or to implement these tools. Moreover, constant exposure to technological advancements could desensitize marketers to feelings of anxiety, reducing its impact as a moderating factor. From a theoretical perspective, the findings might indicate that EE is less critical in environments where performance expectancy dominates decision-making. Similarly, the non-significance of ANX could suggest that its moderating role is dependent on the presence of other influential factors, such as organizational support or social influence, which may overshadow its effect in the study.

Methodological factors might also have contributed to the unanticipated results. Although the surveys were validated from prior studies, ambiguities in item wording may have limited a respondent's ability to detect significant relationships for EE and ANX. To address these challenges, future research might consider refining measurement scales in order to capture context-specific dimensions of EE and ANX, incorporating questions concerning advanced functionality, as well as more AI-specific anxiety concerns. Complementing quantitative data with qualitative research might uncover deeper insights into unmeasured factors influencing effort and anxiety in AI adoption.

The implication of the research extends beyond validating existing theories. It also offers nuanced insights into the ways in which digital marketers perceive and adopt AI tools. The study contributes both to theoretical advancement and to practical applications through the confirmation of key constructs of UTAUT, emphasizing the mediating role of attitude, and addressing perceived gaps in practitioner-focused adoption literature. Findings such as these can be instrumental in opening new avenues for research. It is hoped that this contribution might provide a robust foundation for strategies aimed at enhancing AI adoption in professional settings.

Practical Implications

Both marketers and managers could benefit by putting into use many of the practical implications presented in the study. Marketers might use the research findings to extol the performance advantages of AI tools to their workers. Potential users would be more likely to adopt them if they were sufficiently convinced of tangible benefits, including improved efficiency, enhanced creativity, and superior content quality. Demonstrating real-world applications and recounting success stories might be an advantageous method of reinforcement. Since digital marketers are often called upon to juggle multiple platforms and technologies, tools with streamlined interfaces, minimal setup requirements, and seamless integration into existing workflows might be regarded as a welcome remedy. Clear navigation, straightforward features, and thoughtful design could go far in alleviating potential frustrations.

Marketers themselves are positioned well when it comes to using AI tools to directly benefit their personal and professional growth. One example might be the adoption of AI tools to liberate time previously spent on repetitive tasks, thus allowing more focus on strategy, innovation, and creative problem-solving. Additionally, marketers could benefit by setting measurable goals to improve their output. In the areas of faster turnaround times and enhanced content engagement metrics, progress could be effectively tracked.

Marketers also have the ability to leverage social influence by actively engaging with industry communities, as well as by networking with peers who have successfully integrated AI tools into their companies. Following thought leaders, attending webinars, and participating in forums where professionals share their AI success stories could be instrumental when it comes to inspiring confidence and providing practical tips for implementation. Building connections with colleagues who are early adopters is another useful way to make the adoption process less daunting. By staying informed and connected, marketers are more likely to view AI as an opportunity rather than as a threat. When marketers observe their colleague's achieving success, they might even feel an obligation to follow their lead. An actual culture of AI advocacy might develop within an organization, in which marketers can be provided a forum to share their experiences and insights.

For managers, organizational support is a key factor in driving AI adoption. Investing in robust technical infrastructure, ongoing training programs, and access to the appropriate resources could create a supportive environment that encourages innovation and reduces resistance to change. Team leaders and influential employees might be engaged to act as advocates, sharing positive experiences and inspiring broader acceptance. Recognizing and rewarding employees who effectively use AI tools could further strengthen positive perceptions. Carefully tailored strategies are essential to accommodate the technological proficiency, as well as the comfort level of each worker. Advanced users might benefit from workshops designed to maximize AI capabilities, while less experienced users might need step-by-step guidance. Managers would do well to remain vigilant in order to detect potential risks, such as algorithmic biases, data privacy concerns, and over-reliance on automation. Establishing ethical guidelines and conducting periodic evaluations of AI tools are essential practices in the mitigation of these risks, thereby remaining aligned with societal and organizational values.

It is important for managers to focus on long-term integration, considering AI tools as strategic assets contributing to sustained success. This might include setting measurable goals, evaluating ROI, and adapting strategies based on performance data and evolving market trends. Overall, the study highlights the increasing positive potential of AI in digital marketing, while emphasizing the importance of coordinating tools and strategies with user needs. By fostering a supportive and collaborative environment, marketers and managers can optimize the use of AI tools to enhance productivity, creativity, and decision-making, ultimately gaining a competitive edge in a competitive and evolving market.

Limitations and Future Research

The sample, consisting of digital marketers in major business sectors of the United States, may have limited the range of the findings to global contexts, as well as to subgroups, including those in niche industries and startups within the marketing profession. Such organizations potentially face unique challenges and opportunities. Furthermore, digital marketing practices and AI adoption trends can vary significantly across different cultural, economic, and regulatory environments, thus limiting the applicability of the findings in international settings. The inclusion of participants from more varied industries and global regions might offer a more comprehensive understanding of AI adoption dynamics. Future studies might also explore the ways in which smaller firms and startups, often with limited resources and different strategic priorities, compare to larger, more established companies in the area of AI integration. By broadening the scope of research, it would likely be possible to gain a clearer picture of AI's role in the marketing profession as a whole.

Investigating AI adoption in different organizational settings would also have its benefits, since workplace dynamics often differ significantly. Due to the parameters of the research, it was conducted specifically within the domain of digital marketing workflows, possibly restricting the applicability of the findings in other areas of business where AI tools are also being adopted. Factors such as organizational culture, regulatory environments, and socio-economic conditions might very well influence adoption behaviors. Comparative studies across industries and regions might provide a richer understanding of AI’s variability dynamics. Examining how organizations with varying resource levels adapt to the introduction of AI would lend further insight into adoption strategies and challenges. Future research might also focus on how leadership styles and management practices influence AI adoption, particularly in industries with complex regulatory and/or ethical considerations.

In addition, the study focused exclusively on AI content creation tools. While providing depth, this focal point excluded a number of other potential applications of AI, including data analytics and customer relationship management (CRM), that could offer a broader understanding for digital marketers who utilize these tools. Examining a broader range of AI applications would enable future researchers to reveal additional material, such as how predictive analytics might be used by marketers to identify trends, enhance targeting, and optimize campaign performance. AI-powered CRM systems, and similar tools designed to streamline customer interactions while personalizing experiences, are integral to modern digital marketing strategies and warrant further exploration. Additional exploration of these areas could provide a more comprehensive view of AI's influence on marketing workflows and decision-making processes. Research could also investigate the interaction among such tools, exploring the ways integrating multiple AI solutions might impact productivity, creativity, and overall campaign effectiveness. Such studies could be helpful in identifying challenges faced by marketers who choose to adopt a multi-tool AI approach. Moreover, examining the role of AI in emerging fields, including voice search optimization and virtual reality marketing, might further clarify its potential to reshape the future of digital marketing. By broadening the scope in the above-mentioned ways, future studies have the potential to provide an in-depth picture of AI's transformative impact across the entire marketing ecosystem.

The fast-paced advancement and popularity of AI technology itself could be said to pose a contextual limitation; insights that are pertinent in today's world will undoubtedly become less relevant over time. Future research might do well to adopt a longitudinal approach, observing how attitudes, perceptions, and adoption behaviors evolve as AI technologies mature and become more integrated into everyday life. A longitudinal perspective would enable researchers to capture trends over extended periods, offering constructive insights into the ways in which businesses, as well as individuals, adapt to the rapid pace of AI innovation. Studying shifts in societal attitudes toward AI over time could result in the identification of factors either encouraging or hindering its widespread adoption. For example, tracking the development of AI tools when it comes to privacy and ethical concerns could provide crucial information for policymakers and industry leaders. Moreover, longitudinal research would have the capacity to evaluate the long-term effectiveness of AI tools to enhance business outcomes and productivity across a range of industries. The possibilities continue to advance; understanding AI's impact on workplace dynamics over time will continue to highlight new challenges and opportunities.

LIST OF REFERENCE

Abdelkader, O. A. (2023). ChatGPT's Influence on Customer Experience in Digital Marketing: Investigating the Moderating Roles. *Heliyon*, *9(8)*. https://doi.org/10.1016/j.heliyon.2023.e18770

Abdou, D., & Jasimuddin, S. M. (2020). The Use of the UTAUT Model in the Adoption of E-Learning Technologies: An Empirical Study in France Based Banks. *Journal of Global Information Management (JGIM)*, *28(4)*, 38-51. https://doi.org/10.4018/JGIM.2020100103

Abelson, R. P., Aronson, E., McGuire, W. J., Newcomb, T. M., Rosenberg, M. J., & Tannenbaum, P. H. (Eds.). (Theories of Cognitive Consistency: A Sourcebook). *1968*. Rand-McNally.

Agarwal, N., Moehring, A., Rajpurkar, P., & Salz, T. (2023). Combining Human Expertise with Artificial Intelligence: Experimental Evidence from Radiology. *National Bureau of Economic Research*.

Ahmad, N. A., Salim, S. S., & Sham, F. M. (2021). Is Perceived Organizational Support an Antecedent of Employee Behaviour? *International Journal of Human Resource Studies*, *11(1)*, 351265-351265.

AIContentfy. (2023). *The Future of Content Creation: How AI Tools are Changing the Game*. https://aicontentfy.com/en/blog/future-of-contentcreation-how-ai-tools-are-changing-game

Ajzen, I., & Fishbein, M. (1975). A Bayesian Analysis of Attribution Processes. *82(2)*, 261.

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, *50(2)*, 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Akter, S., Dwivedi, Y. K., Sajib, S., Biswas, K., Bandara, R. J., & Michael, K. (2022). Algorithmic Bias in Machine Learning-Based Marketing Models. *Journal of Business Research*, *144*, 201-216. https://doi.org/10.1016/j.jbusres.2022.01.083

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2019). Factors Influencing Adoption of Mobile Banking by Jordanian Bank Customers: Extending UTAUT2 with Trust. *International Journal of Information Management*, *37(3)*, 99–110. https://doi.org/10.1016/j.ijinfomgt.2017.01.002

Ali, M. B., Tuhin, R., Alim, M. A., Rokonuzzaman, M., Rahman, S. M., & Nuruzzaman, M. (2024). Acceptance and Use of ICT in Tourism: The Modified UTAUT Model. *Journal of Tourism Futures*, *10(2)*, 334-349. https://doi.org/10.1108/JTF-06-2021-0137

Alkhwaldi, A. F., Alobidyeen, B., Abdulmuhsin, A. A., & Al-Okaily, M. (2023). Investigating the Antecedents of HRIS Adoption in Public Sector Organizations: Integration of UTAUT and TTF. *International Journal of Organizational Analysis*, *31(7)*, 3251-3274. https://doi.org/10.1108/IJOA-04-2022-3228

Almagrashi, A., Mujalli, A., Khan, T., & Attia, O. (2023). Factors Determining Internal Auditors' Behavioral Intention to Use Computer-assisted Auditing Techniques: An Extension of the UTAUT Model and an Empirical Study. *Future Business Journal*, *9(1)*, 74. https://doi.org/10.1186/s43093-023-00231-2

Almuraqab, N., & Jasimuddin, S. M. (2017). Exploring Factors that Influence End-Users' Adoption of Smart Government Services: A Conceptual Framework in the UAE. *The Electronic Journal of Information Systems Evaluation*, *20(1)*, 11–23.

Anderson, N. H. (1981). Integration theory applied to cognitive responses and attitudes. In RE Petty, TM Ostrom, & TC Brock (Eds.). In *Cognitive Responses in Persuasion* (pp. 361-397). Lawrence Erlbaum.

Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a Model for Understanding Intention to Adopt AI and Related Technologies Among Librarians. *The Journal of Academic Librarianship*, *47(6)*, 102437.

Andronie, M., Lăzăroiu, G., Ștefănescu, R., Ionescu, L., & Cocoșatu, M. (2021). Neuromanagement Decision-Making and Cognitive Algorithmic Processes in the Technological Adoption of Mobile Commerce Apps. *Oeconomia Copernicana*, *12(4)*, 1033-1062.

Bakar, A. A., Razak, F. Z. A., & Abdullah, W. S. W. (2013). Assessing the Effects of UTAUT and Self-Determination Predictor on Students Continuance Intention to Use Student Portal. *World Applied Sciences Journal 21.10*, 1484-1489. https://doi.org/10.5829/idosi.wasj.2013.21.10.2920

Ballinger, G. A., Lehman, D. W., & Schoorman, F. D. (2010). Leader–Member Exchange and Turnover Before and After Succession Events. *Organizational Behavior and Human Decision Processes*, *113(1)*, 25-36.

Bandura, A. (1986). In *Social Foundations of Thought and Action* (pp. 23-28).

Bano, M., Siddiqui, S. (2022). Consumers' intention towards the use of smart technologies in tourism and hospitality (T&H) industry: A deeper insight into the integration of TAM, TPB, and trust. Journal of Hospitality and Tourism Insights, 7(2). https://doi.org/10.1108/JHTI-06-2022-0267

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial Intelligence in Organizations: Current State and Future Opportunities. *MIS Quarterly Executive*, *19(4)*.

Blau, P. (2017). *Exchange and Power in Social Life*. Routledge.

Bloomberg. (2023). *Marketers Overwhelmed by Data Look to AI for Help*. https://sponsored.bloomberg.com/quicksight/contentful/marketers-overwhelmed-by-data-look-to-ai-for-help

Bondanini, G., Giorgi, G., Ariza-Montes, A., Vega-Muñoz, A., & Andreucci-Annunziata, P. (2020). Technostress, the Dark Side of Technology in the Workplace: A Scientometric Analysis. *International Journal of Environmental Research and Public Health, 17(21)*, 8013.

Bosnjak, M., Ajzen, I., & Schmidt, P. (2020). The Theory of Planned Behavior: Selected Recent Advances and Applications. *Europe's Journal of Psychology*, *16(3)*, 352.

Brod, C. (1984). *Technostress: The Human Cost of the Computer Revolution*.

Brooks, S., Zaza, S., Erskine, M., & Greer, T. (2023). IT Professionals' Turnaway Intention and the Role of Technostress. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *54(2)*, 97-110.

Burton, J., Stein, M., and Jensen, T. (2019). A Systematic Review of Algorithm Aversion in Augmented Decision Making. *Journal of Behavioral Decision Making*, *33*, 220–239. https://doi.org/10.1002/bdm.2155

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation, 106, 102312.

Capatina, A., Kachour, M., Lichy, J., Micu, A., Micu, A. E., & Codignola, F. (2020). Matching the Future Capabilities of an Artificial Intelligence-based Software for Social Media Marketing with Potential Users' Expectations. *Technological Forecasting and Social Change*, *151*, 119794.

Chandra, A. (2020). Customer Experience is Catalyst to New Marketing Strategy in the Era of Artificial Intelligence and Machine Learning. *Economic Challenger*, *87*, 53–60.

Chang, P. C., Zhang, W., Cai, Q., & Guo, H. (2024). Does AI-Driven Technostress Promote or Hinder Employees' Artificial Intelligence Adoption Intention? A Moderated Mediation Model of Affective Reactions and Technical Self-Efficacy. *Psychology Research and Behavior Management,* 413-427. https://doi.org/10.2147/PRBM.S441444

Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2023). Assessing organizational users' intentions and behavior to AI integrated CRM systems: A meta-UTAUT approach. Information Systems Frontiers, 25(4), 1299-1313.

Chauhan S., J. M. (2016). Determinants of Acceptance of ERP Software Training in Business Schools: Empirical Investigation Using UTAUT Model. *International Journal of Management Education*, *14(3)*, 248–262.

Chawla, D., & Joshi, H. (2019). Consumer Attitude and Intention to Adopt Mobile Wallet in India–An Empirical Study. *International Journal of Bank Marketing*, *37(7)*, 1590-1618. https://doi.org/10.1108/IJBM-09-2018-0256

Chawla, D., & Joshi, H. (2023). Role of Mediator in Examining the Influence of Antecedents of Mobile Wallet Adoption on Attitude and Intention. *Global Business Review*, *24(4)*, 609-625. https://doi.org/10.1177/0972150920924506

Chen, J., Li, R., Gan, M., Fu, Z., & Yuan, F. (2020). Public Acceptance of Driverless Buses in China: An Empirical Analysis Based on an Extended UTAUT Model. *Discrete Dynamics in Nature and Society*, *4318182*. https://doi.org/10.1155/2020/4318182

Chiarini, A., Grando, A., Venturini, S., & Borgonovo, E. (2023). Do Automation and AI Impact Job Reduction? A Study on Perceived Risk of Losing Jobs Among White-Collars in Italian Manufacturing Companies. *Production Planning & Control*, 1-14.

Cimperman, M., Brenčič, M.M., Trkman, P. (2016). Analyzing Older Users' Home Telehealth Services Acceptance Behavior—Applying an Extended UTAUT Model. *International Journal of Medical Informatics*, *90*, 22–31.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial Intelligence in Information Systems Research: A Systematic Literature Review and Research Agenda. *International Journal of Information Management*, *60*. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study. *MIS Quarterly*(145-158).

Compeau, D. R., & Higgins, C. A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS quarterly,*, 189-211.

Cooper, C., Dewe, P., & O'Driscoll, M. (2001). Organizational Stress: A Review and Critique of Theory, Research, and Applications.

Cubric, M. (2020). Drivers, Barriers and Social Considerations for AI Adoption in Business and Management: A Tertiary Study. *Technology in Society*, *62, 101257*. https://doi.org/10.1016/j.techsoc.2020.101257

Dasborough, M. T. (2023). Awe-Inspiring Advancements in AI: The Impact of ChatGPT on the Field of Organizational Behavior. *Journal of Organizational Behavior (John Wiley & Sons, Inc.)*, *44(2)*. https://doi.org/10.1002/job.2695

Davenport, T., Guha, A., Grewal, D., and Bressgott, T. (2020). How Artificial Intelligence Will Change the Future of Marketing. *Journal of the Academy of Marketing Science 48*, 24-42. https://doi.org/10.1007/s11747-019-00696-0

Davenport, T. H., & Mittal, N. (2022). How Companies Can Prepare for the Coming "AI-First" World. *Strategy & Leadership*, *51(1)*, 26-30.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). Technology Acceptance Model. *Journal of Management Science*, *35(8)*, 982-1003.

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.

Deci, E. L., & Ryan, R. M. (1985). The General Causality Orientations Scale: Self-Determination in Personality. *Journal of Research in Personality*, *19(2)*(109-134).

Dellermann, D., Calma, A., Lipusch, N., Weber, T., Weigel, S., & Ebel, P. . (2021). The Future of Human-AI Collaboration: A Taxonomy of Design Knowledge for Hybrid Intelligence Systems. (arXiv preprint arXiv:2105.03354)

DeLone, W. H., & McLean, E. R. (1992). Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research*, *3(1)*, 60-95.

Devang, V., Chintan, S., Gunjan, T., & Krupa, R. (2019). Applications of Artificial Intelligence in Marketing. *Annals of Dunarea de Jos University of Galati. Fascicle I. Economics and Applied Informatics*, *25(1)*, 28-36.

Diaz, M. C., & Loraas, T. (2010). Learning New Uses of Technology While on an Audit Engagement: Contextualizing General Models to Advance Pragmatic

Understanding. *International Journal of Accounting Information Systems*, *11(1)*, 61-77.

Dibra, M. (2015). Rogers Theory on Diffusion of Innovation-The Most Appropriate Theoretical Model in the Study of Factors Influencing the Integration of Sustainability in Tourism Business. *Procedia-Social and Behavioral Sciences*, *195*, 1453-1462.

Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2021). Threats and Opportunities in the Digital Era: Automation Spikes and Employment Dynamics. *Research Policy*, *50(7)*, 104137.

Doronina, O. V. (1995). Fear of Computers: Its Nature, Prevention, and Cure. *Russian Social Science Review*, *36(4)*, 79-95.

Du, H., Li, Z., Niyato, D., Kang, J., Xiong, Z., & Kim, D. I. (2023). arXiv preprint arXiv. (2023). Enabling AI-Generated Content (AIGC) Services in Wireless Edge Networks. *2301.03220*.

Duan, Y., Edwards, J., and Dwivedi, Y. (2019). Artificial Intelligence for Decision Making in the Era of Big Data – Evolution, Challenges and Research Agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. *Information Systems Frontiers*, *21(3)*, 719–734. https://doi.org/10.1007/s10796-017-9774-y

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy. *International Journal of Information Management*, *57, 101994*. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Eagly, A. H., Mladinic, A., & Otto, S. (1991). Are Women Evaluated More Favorably than Men? An Analysis of Attitudes, Beliefs, and Emotions. *Psychology of Women Quarterly*, *15(2)*, 203-216.

Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived Organizational Support. *Journal of Applied Psychology*, *71(3)*, 500.

Eisenberger, R., Rhoades Shanock, L., & Wen, X. (2020). Perceived Organizational Support: Why Caring About Employees Counts. *Annual Review of Organizational Psychology and Organizational Behavior*, *7(1)*, 101-124.

Elhajjar, S., Karam, S., & Borna, S. (2020). Artificial Intelligence in Marketing Education Programs. *Marketing Education Review*, *31*(2-13). https://doi.org/10.1080/10528008.2020.1835492

Faruk, M., Rahman, M., & Hasan, S. (2021). How Digital Marketing Evolved Over Time: A Bibliometric Analysis on Scopus Database. *Heliyon*, *7(12)*. https://doi.org/10.1016/j.heliyon.2021.e08603

Festinger, L. (1957). *A Theory of Cognitive Dissonance*. Stanford University Press.

Fishbein, M. (1979). A Theory of Reasoned Action: Some Applications and Implications.

Frank, B. (2021). Artificial Intelligence-Enabled Environmental Sustainability of Products: Marketing Benefits and Their Variation by Consumer, Location, and Product Types. *Journal of Cleaner Production*, *285*, 125242.

Frey, C., and Osborne, M. (2017). The Future of Employment: How Susceptible Are Jobs to Computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

García de Blanes Sebastián, M., Sarmiento Guede, J. R., Azuara Grande, A., & Juárez-Varón, D. (2024). Analysis of factors influencing attitude and intention to use electric vehicles for a sustainable future. The Journal of Technology Transfer, 49(4), 1347-1368.

George, J. M., Reed, T. F., Ballard, K. A., Colin, J., & Fielding, J. (1993). Contact with AIDS Patients as a Source of Work-related Distress: Effects of Organizational and Social Support. *Academy of Management Journal*, *36(1)*, 157-171.

Gerdiken, E., Reinwald, M., & Kunze, F. (2021). Outcomes of Technostress at Work: A Meta-analysis. In Academy of Management Proceedings. *Academy of Management Annals*, *2021*(1), 11907.

Gillespie, N., Lockey, S., & Curtis, C. (2021). Trust in Artificial Intelligence: A Five Country Study.

Giuggioli, G., & Pellegrini, M. M. (2023). Artificial Intelligence as an Enabler for Entrepreneurs: A Systematic Literature Review and an Agenda for Future Research. *International Journal of Entrepreneurial Behavior & Research*, *29(4)*, 816-837. https://doi.org/10.1108/IJEBR-05-2021-0426

Glikson, E., and Woolley, A. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, *14*, 627–660. https://doi.org/10.5465/annals.2018.0057

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2020). Artificial Intelligence (AI) Applications for Marketing: A Literature-based Study. *International Journal of Intelligent Networks*.

Heider, F. (1946). Attitudes and Cognitive Organizations. *Journal of Psychology*, *21*, 107–112.

Hermann, E. (2022). Leveraging Artificial Intelligence in Marketing for Social Good—An Ethical Perspective. *Journal of Business Ethics*, *179(1)*, 43-61. https://doi.org/10.1007/s10551-021-04843-y

Hildebrand, C. (2019). The Machine Age of Marketing: How Artificial Intelligence Changes the Way People Think, Act, and Decide. *NIM Marketing Intelligence Review, 11*, 10–17.

Hirsch-Kreinsen, H. (2023). Artificial Intelligence: A "Promising Technology". *AI & SOCIETY*, 1-12. https://doi.org/10.1007/s00146-023-01629-w

Ho, J. C., Wu, C. G., Lee, C. S., & Pham, T. T. T. (2020). Factors Affecting the Behavioral Intention to Adopt Mobile Banking: An International Comparison. *Technology in Society*, *63*, 101360. https://doi.org/10.1016/j.techsoc.2020.101360

Huang, M., and Rust, R. (2020). A Strategic Framework for Artificial Intelligence in Marketing. *Journal of the Academy of Marketing Science*, *49*, 30-50. https://doi.org/10.1007/s11747-020-00749-9

Huang, R. T., Jabor, M. K., Tang, T. W., & Chang, S. C. (2022). Examine the Moderating Role of Mobile Technology Anxiety in Mobile Learning: A Modified Model of Goal-Directed Behavior. *Asia Pacific Education Review*, *23(1)*, 101-113.

Hwang, I., Kim, S., & Rebman, C. (2022). Impact of Regulatory Focus on Security Technostress and Organizational Outcomes: The Moderating Effect of Security Technostress Inhibitors. *Information Technology & People*, *35(7)*, 2043-2074. https://doi.org/10.1108/ITP-05-2019-0239

Jaradat, M. I. R. M., Ababneh, H. T., Faqih, K. M., & Nusairat, N. M. (2020). Exploring Cloud Computing Adoption in Higher Educational Environment: An Extension of the UTAUT Model with Trust. *International Journal of Advanced Science and Technology*, *29(5)*, 8282-8306.

Jeon, H. M., Sung, H. J., & Kim, H. Y. (2020). Customers' Acceptance Intention of Self-Service Technology of Restaurant Industry: Expanding UTAUT with Perceived

Risk and Innovativeness. *Service Business*, *14*, 533-551. https://doi.org/10.1007/s11628-020-00425-6

Jia, L., Zhou, Z., Xu, F., & Jin, H. (2021). Cost-Efficient Continuous Edge Learning for Artificial Intelligence of Things. *IEEE Internet of Things Journal*, *9(10)*, 7325-7337. https://doi.org/10.1109/JIOT.2021.3104089

Johnson, D. G., & Verdicchio, M. (2017). AI Anxiety. *Journal of the Association for Information Science and Technology*, *68(9)*, 2267-2270.

Kahle, L. R., & Berman, J. J. (1979). Attitudes Cause Behaviors: A Cross-Lagged Panel Analysis. *Journal of Personality and Social Psychology*, *37(3)*, 315.

Kahneman, D., Rosenfield, A. M., Gandhi, L., & Blaser, T. (2016). Noise: How to Overcome the High, Hidden Cost of Inconsistent Decision Making. *Harvard Business Review*, *94(10)*, 38-46.

Kamar, E. (2016). Directions in Hybrid Intelligence: Complementing AI Systems with Human Intelligence. *In IJCAI* 4070-4073.

Kasilingam, D. L. (2020). Understanding the Attitude and Intention to Use Smartphone Chatbots for Shopping. *Technology in Society*, *62*, 101280. https://doi.org/10.1016/j.techsoc.2020.101280

Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetişensoy, O., & Demir Kaya, M. (2024). The Roles of Personality Traits, AI Anxiety, and Demographic Factors in Attitudes Toward Artificial Intelligence. *40(2)*, 497-514. https://doi.org/10.1080/10447318.2022.2151730

Kayali, M., & Alaaraj, S. (2020). Adoption of Cloud Based E-Learning in Developing Countries: A Combination of DOI, TAM and UTAUT. *The International Journal of Contemporary Management and Information Technology (IJCMIT) 1(1)*, 1-7.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). lgorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, *14(1)*, 366-410.

Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2022). What Factors Contribute to Acceptance of Artificial Intelligence? A Systematic Review. *Telematics and Informatics*, 101925.

Khlaif, Z. N., Sanmugam, M., & Ayyoub, A. (2023). Impact of Technostress on Continuance Intentions to Use Mobile Technology. *The Asia-Pacific Education Researcher*, *32(2)*, 151-162. https://doi.org/10.1007/s40299-021-00638-x

Kim, J. H., & Kang, E. (2023). An Empirical Research: Incorporation of User Innovativeness into TAM and UTAUT in Adopting a Golf App. *Sustainability*, *15(10)*, 8309. https://doi.org/10.3390/su15108309

Kim, M. S., & Hunter, J. E. (1993). Attitude-Behavior Relations: A Meta-analysis of Attitudinal Relevance and Topic. *Journal of Communication*, *43(1)*, 101-142.

Kitsios, F., & Kamariotou, M. (2021). Artificial Intelligence and Business Strategy Towards Digital Transformation: A Research Agenda. *Sustainability*, *13(4), 2025*. https://doi.org/10.3390/su13042025

La Torre, G., Esposito, A., Sciarra, I., & Chiappetta, M. (2019). Definition, Symptoms and Risk of Technostress: A Systematic Review. *International Archives of Occupational and Environmental Health*, *92*, 13-35.

Lai, P. C. (2017). The Literature Review of Technology Adoption Models and Theories for the Novelty Technology. *JISTEM-Journal of Information Systems and Technology Management, 14(1)*, 21-38.

Lazarus, R. S., & Folkman, S. (1984). *Stress, Appraisal, and Coping*. Springer Publishing Company.

Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, *12(1)*, 50.

Lei, C. F., & Ngai, E. W. (2014). The Double-Edged Nature of Technostress on Work Performance: A Research Model and Research Agenda.

Logg, J., Minson, J., and Moore, D. (2019). Algorithm Appreciation: People Prefer Algorithmic to Human Judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Luan, H., Geczy, P., Lai, H., & Li, P. (2020). Challenges and Future Directions of Big Data and Artificial Intelligence in Education. *Frontiers in Psychology*, *11*, 580820.

Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A Comparison of the Theory of Planned Behavior and the Theory of Reasoned Action. *Personality and Social Psychology Bulletin*, *18(1)*, 3-9.

Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What Influences Algorithmic Decision-Making? A Systematic Literature Review on Algorithm Aversion. *Technological Forecasting and Social Change*, *175*. https://doi.org/10.1016/j.techfore.2021.121390

Malone, T. W. (2018). *Superminds: The Surprising Power of People and Computers Thinking Together*. Little, Brown Spark.

Man Tang, P., Koopman, J., McClean, S. T., Zhang, J. H., Li, C. H., De Cremer, D., ... & Ng, C. T. S. (2022). When Conscientious Employees Meet Intelligent Machines: An Integrative Approach Inspired by Complementarity Theory and Role Theory. *Academy of Management Journal*, *65(3)*, 1019-1054. https://doi.org/10.5465/amj.2020.1516

Manstead, A. S., & van der Pligt, J. (1998). Should We Expect More From Expectancy-Value Models of Attitude and Behavior? *Journal of Applied Social Psychology*, *28(15)*, 1313-1316.

Marangunić, N., & Granić, A. (2015). Technology Acceptance Model: A Literature Review from 1986 to 2013. *Universal Access in the Information Society*, *14*, 81-95.

Mason, J. W. (1975). A Historical View of the Stress Field. *Journal of Human Stress*, *1(2)*, 22-36.

Mathieson, K. (1991). Predicting User Intentions: Comparing the Technology Acceptance Model with the Theory of Planned Behavior. *Information Systems Research*, *2(3)*, 173-191.

Matusik, J. G., Ferris, D. L., & Johnson, R. E. (2022). The PCMT Model of Organizational Support: An Integrative Review and Reconciliation of the Organizational Support Literature. *Journal of Applied Psychology*, *107(3)*, 329.

McCarthy, J., Minsky, M., Rochester, N., & Shannon, C. E. (1955). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence. *Dartmouth College*.

McCarthy, J. (2007). What is Artificial Intelligence. *Stanford University*.

McKinsey&Company. (2023a). AI-Powered Marketing and Sales Reach New Heights with Generative AI. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/ai-powered-marketing-and-sales-reach-new-heights-with-generative-ai

McKinsey&Company. (2023b). *How Generative AI Can Boost Consumer Marketing*. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/how-generative-ai-can-boost-consumer-marketing

Meuter, M. L., Ostrom, A. L., Bitner, M. J., & Roundtree, R. (2003). The Influence of Technology Anxiety on Consumer Use and Experiences with Self-Service Technologies. *Journal of Business Research*, *56(11)*, 899-906.

Milicevic, N., Kalas, B., Djokic, N., Malcic, B., & Djokic, I. (2024). Students' Intention Toward Artificial Intelligence in the Context of Digital Transformation. *Sustainability*, *16(9)*, 3554.

Miller, L. E., Bhattacharyya, D., Miller, V. M., Bhattacharyya, M., & Miller, V. (2023). Recent Trend in Artificial Intelligence-Assisted Biomedical Publishing: A Quantitative Bibliometric Analysis. *Cureus*, *15(5)*.

Mogaji, E., Soetan, T. O., & Kieu, T. A. (2020). The Implications of Artificial Intelligence on the Digital Marketing of Financial Services to Vulnerable Customers. *Australasian Marketing Journal (AMJ)*. https://doi.org/10.1016/j.ausmj.2020.05.003

Mokyr, J., Vickers, C., & Ziebarth, N. L. (2015). The History of Technological Anxiety and the Future of Economic Growth: Is this Time Different? *Journal of Economic Perspectives*, *29(3)*, 31-50.

Momani, A. M., & Jamous, M. (2017). The Evolution of Technology Acceptance Theories. *International Journal of Contemporary Computer Research (IJCCR)*, *1(1)*, 51-58.

Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, *2(3)*, 192-222.

Morchid, N. (2020). The Current State of Technology Acceptance: A Comparative Study. *Journal of Business and Management*, *22(2)*, 1-16.

Moya, M., Nabafu, R., Maiga, G., & Mayoka, K. (2017). Attitude and Behavioral Intention as Mediators in Adoption of E-tax Services in Ura, Uganda. *ORSEA JOURNAL*, *6(1)*.

Murgai, A. (2018). Transforming Digital Marketing with Artificial Intelligence. *International Journal of Latest Technology in Engineering, Management & Applied Science*, *7(4)*, 259-262.

Murphy, K., Di Ruggiero, E., Upshur, R., Willison, D. J., Malhotra, N., Cai, J. C., ... & Gibson, J. (2021). Artificial Intelligence for Good Health: A Scoping Review of the Ethics Literature. *BMC Medical Ethics*, *22*, 1-17. https://doi.org/10.1186/s12910-021-00577-8

Nasirpouri Shadbad, F., & Biros, D. (2022). Technostress and Its Influence on Employee Information Security Policy Compliance. *Information Technology & People*, *35(1)*, 119-141.

Nastjuk, I., Trang, S., Grummeck-Braamt, J. V., Adam, M. T., & Tarafdar, M. (2024). Integrating and Synthesizing Technostress Research: A Meta-analysis on Technostress Creators, Outcomes, and IS Usage Contexts. *European Journal of Information Systems*, *33(3),* 361-382.

Neudert, L. M., Knuutila, A., & Howard, P. N. (2020). Global Attitudes Towards AI, Machine Learning & Automated Decision Making.

Nica, E., Stan, C.I., Luțan, A.G., & Oașa, R.Ș. (2021). Internet of Things-Based Real-Time Production Logistics, Sustainable Industrial Value Creation, and Artificial Intelligence-Driven Big Data Analytics in Cyber-Physical Smart Manufacturing Systems. *Economics, Management, and Financial Markets*, *16(1)*, 52-63. https://doi.org/10.22381/emfm16120215

Osgood, C. E., and P. H. Tannenbaum. (1955). The Principle of Congruity in the Prediction of Attitude Change. *Psychological Review*, *62*, 42–55.

Overgoor, G., Chica, M., Rand, W., & Weishampel, A. (2019). Letting the Computers Take Over. *California Management Review*, *61*, 156–186. https://doi.org/10.1177/0008125619859318

Pandey, A., & Chairungruang, S. (2020). Effects Of Organizational Support, Supervisor Support and Coworkers' Interpersonal Helping Behavior On Employee Job Satisfaction: A Case Study In Bangkok, Thailand. *International Journal of Economics, Business and Accounting Research (IJEBAR)*, *4(02)*.

Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding Consumer Adoption of Mobile Payment in India: Extending Meta-UTAUT Model with Personal Innovativeness, Anxiety, Trust, and Grievance Redressal. *International Journal of Information Management*, *54*, 102144. https://doi.org/10.1016/j.ijinfomgt.2020.102144

Peng, Z. (2022). An Empirical Study of Mobile Teaching: Applying the UTAUT Model to Study University Teachers' Mobile Teaching Behavior. *Curriculum and Teaching Methodology*, *5*, 55-70. https://doi.org/10.23977/curtm.2022.050510

Perri, C., Giglio, C., & Corvello, V. (2020). Smart Users for Smart Technologies: Investigating the Intention to Adopt Smart Energy Consumption Behaviors. *Technological Forecasting and Social Change*, *155*, 119991. https://doi.org/10.1016/j.techfore.2020.119991

Peyravi, B., Nekrošienė, J., & Lobanova, L. (2020). Revolutionized Technologies for Marketing: Theoretical Review with Focus on Artificial Intelligence. *Business: Theory and Practice*, *21(2)*, 827-834.

Pirkkalainen, H., Salo, M., Tarafdar, M., & Makkonen, M. (2019). Deliberate or Instinctive? Proactive and Reactive Coping for Technostress. *Journal of Management Information Systems*, *36(4)*, 1179–1212. https://doi.org/10.1080/07421222.2019.1661092

Pitt, C., Eriksson, T., Dabirian, A., & Vella, J. (2018). Elementary, My Dear Watson: The Use of Artificial Intelligence in Marketing Research: An Abstract [Conference session]. New Orleans, LA.

PricewaterhouseCoopers. (2024). *PwC's Global Artificial Intelligence Study*. PwC. https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html

Priyanga, G. (2023). The Effects of Artificial Intelligence on Digital Marketing. *Journal of Visual and Performing Arts Communicating with Communities*, *4(1SE)*, 158-167.

Puriwat, W., & Tripopsakul, S. (2021). Explaining Social Media Adoption for a Business Purpose: An Application of the UTAUT Model. Sustainability, 13(4), 2082. https://doi.org/10.3390/su13042082

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving Language Understanding by Generative Pre-Training.

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The Consequences of Technostress for End Users in Organizations: Conceptual Development and Empirical Validation. *Information Systems Research*, *19(4)*, 417–433. https://doi.org/10.1287/isre.1070.0165

Raisch, S., and Krakowski, S. (2020). A. Acad. Manag. Rev. 46:1. (2020). Artificial Intelligence and Management: The Automation-Augmentation Paradox. *Academy of Management Review*, *46*(1). https://doi.org/10.5465/2018.0072

Ramesh, A., Dhariwal, P., Nichol, A., Chu, C., & Chen, M. (2022). Hierarchical Text-Conditional Image Generation with Clip Latents. *arXiv preprint arXiv:2204.06125*, *1(2)*, 3.

Randall, M. L., Cropanzano, R., Bormann, C. A., & Birjulin, A. (1999). Organizational Politics and Organizational Support as Predictors of Work Attitudes, Job Performance, and Organizational Citizenship Behavior. *Journal of Organizational*

Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, *20(2)*, 159-174.

Ringle, C.M., Wende, S. and Becker, J.M. (2015) SmartPLS 3. SmartPLS GmbH, Boenningstedt. http://www.smartpls.com

Rogers, E. M., & Williams, D. (1983). *Diffusion of Innovations.* The Free Press.

Roh, T., Park, B. I., & Xiao, S. S. (2023). Adoption of AI-Enabled Robo-Advisors in Fintech: Simultaneous Employment of UTAUT and the Theory of Reasoned Action. *Journal of Electronic Commerce Research*, *24(1)*, 29-47.

Rosenberg, M. J. (1956). Cognitive Structure and Attitudinal Affect. *Journal of Abnormal and Social Psychology 53*, 367–372.

Russell, S. J., & Norvig, P. (2003). *Artificial Intelligence a Modern Approach*. Pearson Education.

Sánchez-Prieto JC, O.-M. S., García-Peñalvo FJ. (2016). Informal Tools in Formal Contexts: Development of a Model to Assess the Acceptance of Mobile Technologies Among Teachers. *Computers in Human Behavior*, *55*, 519–528.

Schwarz, A. a. C., W. (2007). (2007). Looking Forward: Toward an Understanding of the Nature and Definition of IT Acceptance. *Journal of the Association for Information Systems*, *8*(4), 230-243.

Seeber, I., Bittner, E., Briggs, R. O., De Vreede, T., De Vreede, G. J., Elkins, A., ... & Söllner, M.. (2020). Machines as Teammates: A Research Agenda on AI in Team Collaboration. *Information & Management*, *57(2), 103174*. https://doi.org/10.1016/j.im.2019.103174

Sharma, A., Sharma, A., Singh, R. K., & Bhatia, T. (2023). Blockchain Adoption in Agri-food Supply Chain Management: An Empirical Study of the Main Drivers Using Extended UTAUT. *Business Process Management Journal*, *29(3)*, 737-756. https://doi.org/10.1108/BPMJ-10-2022-0543

Shi, Y., Siddik, A. B., Masukujjaman, M., Zheng, G., Hamayun, M., & Ibrahim, A. M. (2022). The antecedents of willingness to adopt and pay for the IoT in the agricultural industry: an application of the UTAUT 2 theory. *Sustainability*, *14(11)*, 6640. https://doi.org/10.3390/su14116640

Shneiderman, B. (2020). Human-Centered Artificial Intelligence: Three Fresh Ideas. *AIS Transactions on Human-Computer Interaction*, *12(3)*, 109-124. https://doi.org/10.17705/1thci.00131

Shu, Q., Tu, Q., & Wang, K. (2011). The Impact of Computer Self-Efficacy and Technology Dependence on Computer-Related Technostress: A Social Cognitive Theory Perspective. *International Journal of Human-Computer Interaction*, *27(10)*, 923-939.

Siau, K. L. (2017). Impact of Artificial Intelligence, Robotics, and Machine Learning on Sales and Marketing Impact of Artificial Intelligence, Robotics, and Machine. *Association for Information Systems AIS Electronic Library*.

Singh, B., & Kaunert, C. (2024). Future of Digital Marketing: Hyper-Personalized Customer Dynamic Experience with AI-Based Predictive Models. *In Revolutionizing the AI-Digital Landscape (Productivity Press)*, 189-203.

Siripipatthanakul, S., Limna, P., Sriboonruang, P., & Kaewpuang, P. (2023). Applying the TPB and the UTAUT Models Predicting Intentions to Use Telemedicine Among Thai People During the COVID-19 Pandemic. *International Journal of Computing Sciences Research*, *7(1)*, 1362-1384.

Somosi, Z. (2022). The Role of Artificial Intelligence In Content Creation And Checking Its Effectiveness In The Google Ads Advertising System. *Annals of the University of Oradea, Economic Science Series*, *31(2)*.

Stanford. (2007). *What is AI? / Basic Questions*. http://jmc.stanford.edu/artificial-intelligence/what-is-ai/index.html

Stokel-Walker, C., & Van Noorden, R. (2023). What ChatGPT and Generative AI Mean for Science. *Nature*, *614(7947)*, 214-216.

Stranks, J. (2005). *Stress at Work*. Routledge.

Šumak B, P. M., Heričko M, Šorgo A. (2017). Differences Between Prospective, Existing, and Former Users of Interactive Whiteboards on External Factors Affecting their Adoption, Usage and Abandonment. *Computers in Human Behavior*, *72*, 733–756.

Tandon, U., Kiran, R., & Sah, A. N. (2016). Understanding Online Shopping Adoption in India: Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with Perceived Risk Application. *Service Science*, *8(4)*, 420-437.

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The Impact of Technostress on Role Stress and Productivity. *Journal of Management Information Systems*, *24(1)*, 301-328.

Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The Technostress Trifecta - Techno Eustress, Techno Distress and Design: Theoretical Directions and an Agenda for

Research. *Information Systems Journal*, *29(6)*, 6–42. https://doi.org/10.1111/isj.12169

Tarhini, A., El-Masri, M., Ali, M., & Serrano, A. (2016). Extending the UTAUT Model to Understand the Customers' Acceptance and Use of Internet Banking in Lebanon: A Structural Equation Modeling Approach. *Information Technology & People*, *29(4)*, 830-849.

Tate, M., Evermann, J., & Gable, G. (2015). An Integrated Framework for Theories of Individual Attitudes Toward Technology. *Information & Management*, *52(6)*, 710-727.

Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research*, *6(2)*, 144-176.

Teng, Z., Cai, Y., Gao, Y., Zhang, X., & Li, X. (2022). Factors Affecting Learners' Adoption of an Educational Metaverse Platform: An Empirical Study Based on an Extended UTAUT Model. *Mobile Information Systems*, *2022(1)*, 5479215. https://doi.org/10.1155/2022/5479215

Theodoridis, P. K., & Gkikas, D. C. (2019). How Artificial Intelligence Affects Digital Marketing. In Strategic Innovative Marketing and Tourism: 7th ICSIMAT, Athenian Riviera, Greece.

Thompson, R. L., Higgins, C.A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, *15(1)*, 125-143.

Triandis, H. C. (1971). *Attitude and Attitude Change*. John Wiley and Sons, Inc.

Tsai, T. H., Lin, W. Y., Chang, Y. S., Chang, P. C., & Lee, M. Y. (2020). Technology Anxiety and Resistance to Change Behavioral Study of a Wearable Cardiac Warming System Using an Extended TAM for Older Adults. *PloS one*, *15(1)*, e0227270. https://doi.org/10.1371/journal.pone.0227270

Tsai Y-Y, C. C.-M., Lin H-M, Cheng B-W (2018). Nursing Staff Intentions to Continuously Use a Blended E-learning System from an Integrative Perspective. *Quality & Quantity*, *52(6)*, 2495–2513.

Tyson, A., & Kikuchi, E. (2023). *Growing Public Concern About the Role of Artificial Intelligence in Daily Life*. Pew Research Center. https://www.pewresearch.org/short-reads/2023/08/28/growing-public-concern-about-the-role-of-artificial-intelligence-in-daily-life/

Van Esch, P. (2018). Marketing AI Recruitment: The Next Phase in Job Application and Selection. *Computers in Human Behavior*, *90*, 215–222.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Sykes, T. A., & Zhang, X. (2011). Just What the Doctor Ordered': A Revised UTAUT for EMR System Adoption and Use by Doctors. Proceedings of the 44th Hawaii International Conference on System Sciences (HICSS),

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.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46(2)*, 186-204.

Vishnoi, S. K., & Bagga, T. (2019). Artificial Intelligence Enabled Marketing Solutions: A Review. *Indian Journal of Economics and Business*, *17*, 167–177.

Wang, C., Wu, G., Zhou, X., & Lv, Y. (2022). An Empirical Study of the Factors Influencing User Behavior of Fitness Software in College Students Based on UTAUT. *Sustainability*, *14(15)*, 9720. https://doi.org/10.3390/su14159720

Wang, N., Pynadath, D. V., & Hill, S. G. (2016). Trust Calibration Within a Human-Robot Team: Comparing Automatically Generated Explanations, In 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI). *IEEE.*, 109-116.

Wang, Q., Zhao, G., & Cheng, Z. (2022). Examining the Moderating Role of Technostress and Compatibility in EFL Learners' Mobile Learning Adoption: A Perspective from the Theory of Planned Behaviour. *Frontiers in Psychology*, *13*, 919971. https://doi.org/10.3389/fpsyg.2022.919971

Wang, Q. (2023). The Impact of AI on Organizational Employees: A Literature Review. *Journal of Education, Humanities and Social Sciences*, *19*, 45-53.

Wang, Y. S., Wu, S. C., Lin, H. H., Wang, Y. M., & He, T. R. (2012). Determinants of User Adoption of Web Automatic Teller Machines: An Integrated Model of 'Transaction Cost Theory' and 'Innovation Diffusion Theory'. *The Service Industries Journal*, *32(9)*, 1505-1525.

Wang, Y. Y., & Wang, Y. S. (2022). Development and Validation of an Artificial Intelligence Anxiety Scale: An Initial Application in Predicting Motivated Learning Behavior. *Interactive Learning Environments*, *30(4)*, 619-634.

Wassan, S. (2021). How Artificial Intelligence Transforms the Experience of Employees. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12(10)*, 7116-7135.

Williams, M. D., Dwivedi, Y.K., Lal, B. and Schwarz, A. (2009). Contemporary Trends and Issues in IT Adoption and Diffusion Research. *Journal of Information Technology*, *24*(1), 1-10.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The Unified Theory of Acceptance and Use of Technology (UTAUT): A Literature Review. *Journal of Enterprise Information Management*, *28(3)*, 443-488. https://doi.org/10.1108/JEIM-09-2014-0088

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative Intelligence: Humans and AI are Joining Forces. *Harvard Business Review*, *96(4)*, 114-123.

Wirth, N. I. (2018). Hello Marketing, What Can Artificial Intelligence Help You With? . *Journal of Market Research*, *60*, 435–438. https://doi.org/10.1177/1470785318776841

Wu, M. Y., Chou, H. P., Weng, Y. C., & Huang, Y. H. (2011). TAM-2 Based Study of Website User Behavior - Using Web 2.0 Websites as an Example. *WSEAS Transactions on Business and Economics*, *4(8)*, 133-151.

Wu, T., He, S., Liu, J., Sun, S., Liu, K., Han, Q. L., & Tang, Y. (2023). A Brief Overview of ChatGPT: The History, Status Quo and Potential Future Development. *IEEE/CAA Journal of Automatica Sinica*, *10(5)*, 1122-1136.

Xu, Z., Ge, Z., Wang, X., & Skare, M. (2021). Bibliometric Analysis of Technology Adoption Literature Published from 1997 to 2020. *Technological Forecasting and Social Change*, *170*, 120896.

Xue, L., Rashid, A. M., & Ouyang, S. (2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review. *SAGE Open*, *14(1)*, 21582440241229570.

Yadegari, M., Mohammadi, S., & Masoumi, A. H. (2024). Technology Adoption: An Analysis of the Major Models and Theories. *Technology Analysis & Strategic Management*, *36(6)*(1096-1110).

Yang, K., & Forney, J. C. (2013). The Moderating Role of Consumer Technology Anxiety in Mobile Shopping Adoption: Differential Effects of Facilitating Conditions and Social Influences. *Journal of Electronic Commerce Research*, *14(4)*, 334.

Yen, D. C., Wu, C. S., Cheng, F. F., & Huang, Y. W. (2010). Determinants of Users' Intention to Adopt Wireless Technology: An Empirical Study by Integrating TTF with TAM. *Computers in Human Behavior*, *26(5)*, 906-915.

Yousafzai, S. Y., Foxall, G. R., & Pallister, J. G. (2007). Technology Acceptance: A Meta-analysis of the TAM: Part 1. *Journal of Modelling in Management*, *2(3)*, 251-280.

Yu, L., Chen, Z., Yao, P., & Liu, H. (2021). A study on the Factors Influencing Users' Online Knowledge Paying-Behavior Based on the UTAUT model. *Journal of Theoretical and Applied Electronic Commerce Research*, *16(5),*, 1768-1790. https://doi.org/10.3390/jtaer16050099

Zhang, B., & Allan D. (2019). Artificial Intelligence: American Attitudes and Trends. *Oxford: Center for the Governance of AI, Future of Humanity Institute, University of Oxford* (Available at SSRN 3312874).

Zhang, Y., & Gosline, R. (2023). Human Favoritism, Not AI Aversion: People's Perceptions (and Bias) Toward Creative Content Generated by Ai (ChatGPT-4), Human Experts, and Human-AI Collaboration. *Social Science Research Network (SSRN)*. https://doi.org/10.2139/ssrn,4453958

Zheng, J., & Li, S. (2020). What Drives Students' Intention to Use Tablet Computers: An Extended Technology Acceptance Model. *International Journal of Educational Research*, *102*, 101612. https://doi.org/10.1016/j.ijer.2020.101612

Zhuang, X., Hou, X., Feng, Z., Lin, Z., & Li, J. (Justin). (2020). Subjective norms, attitudes, and intentions of AR technology use in tourism experience: the moderating effect of millennials. Leisure Studies, 40(3), 392–406. https://doi.org/10.1080/02614367.2020.1843692

APPENDICES

Appendix I: Informed Pilot Cover Letter

Dear Informed Pilot Participant,

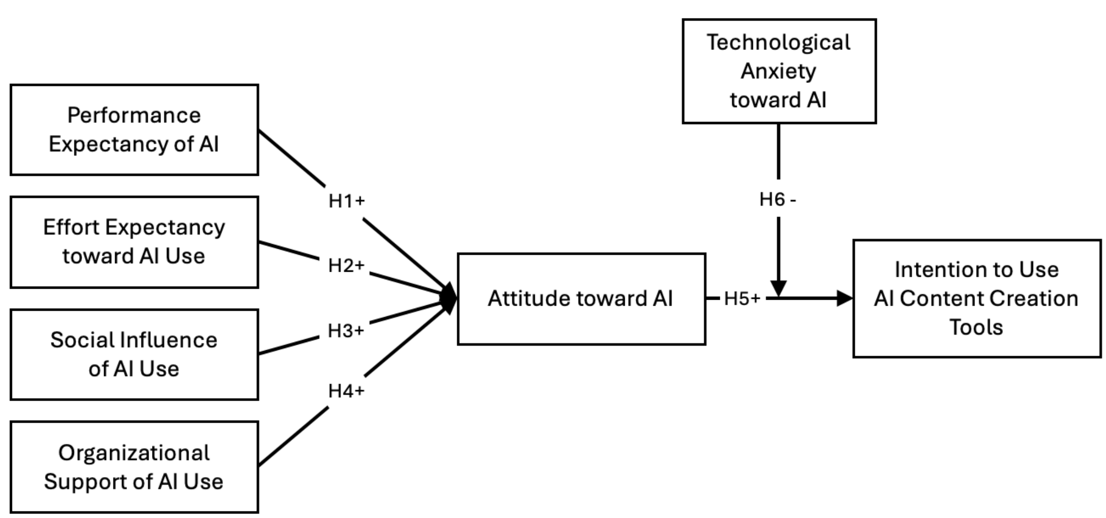
Thank you for your willingness to provide insight regarding the "*Digital Marketer AI Intention*" study.

For the purpose this study, we are requesting your assistance to join other expert panel members in critiquing a draft of the following measurement instrument before it is disseminated for data collection.

Please direct any questions regarding this study or the instructions provided herein to Otis Kopp: okopp001@fiu.edu

<u>Study Overview</u>
To achieve this objective, a measurement model has been proposed (Figure 1) in which the factors influencing the intention of digital marketers to use AI content creation tools are shown.

Figure 1 (Measurement Model for the Intention to Use AI Content Creation Tools):



Instructions for Review of Survey and Related Materials

Review of the Survey

The respondent will be a marketing professional who has worked on a project in the IT industry of the United States. The survey consists of three (3) parts:

1. Qualifier Items
   - Qualifiers refer to questions or statements used to determine if the respondent is eligible to participate in the survey and to ensure that the data collected is based on the intended population of interest.

2. Construct Items:
   - Performance Expectancy (PE)
   - Effort Expectancy (EE)
   - Social Influence (SI)
   - Organizational Support (OS)
   - Attitude Toward AI Use (ATT)
   - Technological Anxiety Toward AI (ANX)
   - Intention to Use AI Content Creation Tools (INT)

3. Control Questions:

   - Control Questions are designed to remove respondents who may affect the overall quality of the data that is collected.

As a reviewer, you are requested to review and evaluate the survey questionnaire. Specifically, you are being asked to evaluate each question, the overall flow of the survey, and provide any additional feedback you may have.

The following reviewer version of the survey contains a list of potential questions along with an input box where you may provide feedback related to each question. Definitions for each construct are also provided. Please consider the following **potential issues** in evaluating each question:

- Is the question clear and understandable?
- Is the question targeted to marketing professionals?
  - Does the question rightly measure the variable of interest?
- Is the question double barreled?
  - Double Barreled Questions cover more than one topic.
  - They are questions that should be broken up into 2 or more different questions.
- Is the question leading?
  - A leading question persuades the respondent to answer a certain way.
- Is the question loaded?

    - A loaded question asks the respondent to rely on their emotions more than the facts.
    - Loaded questions contain “emotive” words with a positive or negative connotation.
- Is the question confusing?
    - A confusing question lacks clarity.
    - The question is difficult to comprehend in the desired/required manner.
- Is the question ambiguous?
    - An ambiguous question is open to more than one interpretation and has a double meaning.
- Is the question easy to understand and answer?
    - Can the respondent easily understand and answer the question given the provided response choices.

Thank you again for your time and feedback.

Best Regards,

Otis Kopp

Otis Kopp
FIU Doctoral Candidate
OKopp001@fiu.edu

Appendix II: IRB Approval

FIU | Research & Economic Development
FLORIDA INTERNATIONAL UNIVERSITY

MEMORANDUM

To:	Dr. George Marakas
CC:	Otis Kopp
From:	Carrie Bassols, BA, IRB Coordinator ceb
Date:	May 7, 2024
Proposal Title:	"C57PREP - Kopp - UNVEILING THE ARTIFICIAL MINDSET: Factors Influencing the Intention to Integrate AI Content Creation Tools into Digital Marketing Workflows"

The Florida International University Office of Research Integrity has reviewed your research study for the use of human subjects and deemed it Exempt via the **Exempt Review** process.

IRB Protocol Exemption #:	IRB-24-0218	**IRB Exemption Date:**	05/07/24
TOPAZ Reference #:	114290		

As a requirement of IRB Exemption you are required to:

1) Submit an IRB Exempt Amendment Form for all proposed additions or changes in the procedures involving human subjects. All additions and changes must be reviewed and approved prior to implementation.
2) Promptly submit an IRB Exempt Event Report Form for every serious or unusual or unanticipated adverse event, problems with the rights or welfare of the human subjects, and/or deviations from the approved protocol.
1) Submit an IRB Exempt Project Completion Report Form when the study is finished or discontinued.

Special Conditions: N/A

For further information, you may visit the IRB website at http://research.fiu.edu/irb.

VITA

OTIS KOPP

2012-2020	B.A. Interdisciplinary Studies Florida International University Miami, Florida
2020-2021	M.Sc. Marketing Florida International University Miami, Florida
2022-2025	Doctor of Business Administration Florida International University Miami, Florida
2024-2025	Undergraduate Instructor Marketing and Logistics Florida International University Miami, Florida