Ankara Science University Graduate School of Studies
Business Administration Department

THE EFFECT OF USING AI ON CONSUMER BEHAVIOR

MOHAMMED ABDULLAH ALASHIQ

Master’s Thesis

Ankara, 2025

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DEDICATION

Reaching the top of this work, I would like to share my greatest dedication with those people whose unequaled support and encouragement have gotten me through my entire phase of academia so far.

I’m forever grateful for my beloved Father and Mother and their endless encouragement. Blessed are you for the support, sacrifices, and belief throughout your life in me. Your ceaseless loving words have always driven me most.

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In the end, I dedicate my thesis to all who supported me, giving a valuable advice, a simple kind word that leave a print in this work. I would like to thank all individuals for even quiet encouragement. You contributed to my ascent in this important milestone, however minor it may have been.

My great thanks for you all

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ÖZET

ALASHIQ, Mohammed Abdullah. *Yapay Zekânin Tüketici Davranişina Etkisi*, Yüksek Lisans Tezi, Ankara, 2025

Bu çalışma, özellikle yapay zekâ (YZ) teknolojisinin tüketici davranışı üzerindeki etkilerini ampirik kanıtlar ve teorik çerçeveler üzerinden incelemeyi amaçlamaktadır. Araştırma, dijital ortamlarda yapay zekâ teknolojisinin tüketici karar alma süreçleri üzerindeki davranışsal ve ekonomik etkilerini anlamayı hedeflemektedir. Çalışma, uygulama ortamı olarak Libyalı İslami Banka seçilerek 15 Nisan ile 15 Haziran 2025 tarihleri arasında 391 müşteriyle gerçekleştirilmiştir. Katılımcılar, örneklem yeterliliği ve temsiliyetine dayalı olarak istatistiksel güç analizi ile seçilmiştir. Veri toplama işlemi, demografik profil bilgileri ve YZ kullanımı ile tüketici davranışlarını ölçen geçerli ölçekler içeren yapılandırılmış anketler aracılığıyla yapılmıştır. Kullanılan araçlar, anahtar kavramlar için Cronbach alfa değeri 0.80'in üzerinde olan yüksek güvenilirlik göstermektedir. Veriler, IBM SPSS ve R yazılımlarıyla analiz edilmiş; betimsel istatistikler, Pearson korelasyonu ve çoklu regresyon analizleriyle araştırma hipotezleri test edilmiştir. Elde edilen sonuçlar, YZ kullanımının dijital ortamlarda tüketici davranışını önemli ölçüde etkilediğini göstermektedir. Tüketici davranışı ile etkileşim ($r = .852$) ve YZ kullanımı ile algılanan fayda ($r = .859$) arasında güçlü pozitif ilişkiler bulunmuştur. Regresyon analizleri, YZ kullanımının tüketici davranışı üzerindeki güçlü pozitif etkisini ($\beta = 0.733$, $R^2 = 0.537$) ve güven ile tavsiyenin tüketici çıktıları üzerindeki önemli etkilerini doğrulamıştır. Tüm bulgular, $p < .001$ seviyesinde istatistiksel olarak anlamlıdır. Genel olarak, bu araştırma, YZ formatlarının tüketici deneyimleri ve davranışları üzerindeki dönüştürücü doğasını vurgulamaktadır. Bu bağlamda, YZ araçları ile güven, kişiselleştirme ve etkileşimin tüketici etkileşimini ve memnuniyetini nasıl artırabileceği üzerinde durulmaktadır. Araştırma, YZ entegrasyonundan en iyi şekilde faydalanmak isteyen politika yapıcıları, uygulayıcılar ve araştırmacılar için önemli sonuçlar sunmaktadır.

Anahtar Kelimeler

Yapay Zekâ, Tüketici Davranışı, Güven.

ABSTRACT

ALASHIQ, Mohammed Abdullah. *The Effect of Using AI on Consumer Behavior*, Master's Thesis, Ankara, 2025

This study focuses mainly on the impacts of artificial intelligence (AI) on consumer behavior through empirical evidence and theoretical frameworks. The research aims to understand the behavioral and economic aspects of consumer decision-making in digital environments with respect to artificial intelligence technology. The study was carried out among clients of the Libyan Islamic Bank, which was selected as an accessible application setting for data collection. A descriptive cross-sectional study design targeting 391 clients between April 15 and June 15, 2025, was utilized. Clients were recruited on the basis of statistical power analysis for sample sufficiency and representativeness. Data were collected using structured questionnaires that included demographic profiling and validated scales measuring AI use and consumer behavior. The instruments used showed high reliability, with Cronbach's alpha greater than 0.80 for key constructs. Data were analyzed through IBM SPSS and R software, applying descriptive statistics, Pearson correlation, and multiple regression analyses to test the hypotheses of the study. The results show that AI significantly affects consumer behavior in digital environments. Strong positive associations were discovered between consumer behavior and engagement ($r = .852$), and also between AI use and perceived usefulness ($r = .859$). Regression analyses confirmed the hypothesized relationships, including a strong positive effect of AI use on consumer behavior ($\beta = 0.733$, $R^2 = 0.537$), and significant effects of trust and recommendation on consumer outcomes. All findings were statistically significant at $p < .001$. In general, the research accentuates the transformative nature of AI regarding consumer experiences and behavior. With this perspective, it emphasizes how trust, personalization, and engagement in dealing with AI tools can help consumer interaction and satisfaction in respect of the digital market. This provides significant implications for policymakers, practitioners, and researchers who want to make the best out of AI integration in customer-oriented services.

Keywords

Artificial Intelligence, Consumer Behavior, Trust.

TABLE OF CONTENTS

INDEX OF ABBREVIATIONS

AI	:	Artificial Intelligence
AIT	:	Artificial Intelligence Technology
ANOVA	:	Analysis Of Variance
CESM	:	Consumer Engagement on Social Media
COB	:	Consumer Behavior
CRO	:	Conversion Rate Optimization
CUS	:	Consumer
CUSs	:	Consumers
Digi	:	Digital
HAB	:	Habit
IoT	:	Internet of Things
LLMS	:	Large Language Models
ORG	:	Organization
RSs	:	Relationships
SCE	:	Satisfying Consumer Experience
Sig.	:	Significantly
S-O-R	:	Stimulus-Organism-Response
SM	:	Social Media
TAM	:	Technology Acceptance Model
TEC	:	Technology
TECS	:	Technologies
TPB	:	Theory of Planned Behavior

VIs	**:**	Virtual Influencers
WOM	**:**	word-of-mouth

YÖK

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SECTION 1:
INTRODUCTION

Artificial intelligence (AI) has emerged in recent years as a force that scholars consider transformative across various sectors, particularly those involving digital (Digi) environments. Its integration has significantly (Sig.) impacted consumer behavior (COB), reshaping how consumers interact with Digi platforms and their subsequent decision-making. The rapid advancement of AI technologies has enabled companies to enhance their experiences in this field, which has in turn improved operations within commercial sectors, whether industrial or service organizations (ORGs). This, in turn, has led to improved customer (CUS) service and, consequently, improved overall satisfaction (Bhagat et al., 2022).

Recent business operations using AI within Digi platforms have also created what scholars call a consumer experience revolution. Because it has enabled AI technologies, including machine learning and natural language processing, among others, these technologies help provide highly personalized services to each individual based on their needs. This technology (TEC) can also analyze massive data to predict demand by predicting consumer preferences and then optimize strategies based on the diverse needs of consumers. Studies have shown that personalized recommendations can increase overall consumer satisfaction and subsequent engagement (Bhagat et al., 2022). Overall satisfaction helps companies and ORGs build a brand, which enhances consumer loyalty, followed by repeated interactions. AI has also brought about a gradual shift in engagement strategies for all consumers in Digi contexts. For example, chatbots, used on websites and powered by AI, provide instant assistance to CUSs, answering many of their queries and providing personalized guidance. This use improves consumer experience and thus higher satisfaction (Luo et al., 2021; Nguyen et al., 2022).

Additionally, many strategies, including AI-powered engagement, have had a positive impact on Digi COB. Social media (SM) platforms are used to create personalized campaigns that engage directly with users (Das et al., 2022). The use of AI has also been linked to a significant increase in consumer loyalty. This is because AI processes the data entered through this TEC and then analyzes COB, which in turn leads to increased loyalty and, consequently, increased sales and profitability (Bedi et al., 2022). This TEC, in turn, anticipates future consumer needs (Davenport, 2018; Shankar, 2020; Huang & Rust, 2021; Jin & Gandhi, 2021).

Despite the obvious benefits, using AI may provide problems and ethical issues in establishing CUS confidence (Tiutiu & Dabija, 2023). The future of AI in Digi contexts has enormous possibilities for improving COB. Ongoing research and breakthroughs in AI TEC will continue to impact the Digi world, opening up new possibilities for personalization, engagement, and efficiency. Future research should investigate the long-term effects of AI on COB, the efficacy of various AI applications, and the formulation of ethical norms for AI use. In conclusion, AI has had a substantial influence on CUS behavior in Digi settings by improving customization, engagement, and loyalty. While there are obstacles and ethical concerns to overcome, AI's benefits in altering the CUS experience are apparent. ORGs that effectively use AI technologies can gain a competitive advantage, increase CUS satisfaction, and drive long-term success. While significant progress has been made in understanding how AI affects COB in Digi contexts, several research gaps remain. Current research generally focuses on certain features of AI, such as customization, chatbots, and SM interaction, frequently in isolated contexts or areas. For instance, the impact of AI on impulse behavior has been explored primarily in fashion sectors in India, leaving a gap in understanding this phenomenon across different sectors and cultural contexts (Jain and Gandhi, 2021).

Furthermore, insufficient studies has been conducted on the long-term consequences of AI-driven customization on consumer loyalty, as well as the ethical implications of AI in Digi environments. Studies frequently focus on immediate CUS responses, ignoring possible long-term behavioral changes and trust difficulties that may come from AI interactions (Bedi et al., 2022). Furthermore, there is a need for more extensive study on the integration of AI throughout the full CUS journey, from first interaction to post-use experiences, and its influence on diverse demographics (Kumar et al., 2020; Hoyer et al., 2020; Huang & Rust, 2021). Further study should look at the convergence of AI with new technologies such as augmented reality and the Internet of Things (IoT), as well as how these integrations affect CUS behavior and expectations. Exploring these gaps will allow for a more comprehensive understanding of AI's influence on COB in Digi contexts.

This level of customisation contributes to deeper ties between CUSs and brands, encouraging loyalty and repeat interactions. Furthermore, AI-driven SM engagement methods have positively affected COB, since SM platforms are utilized to construct targeted campaigns and engage people directly (Das et al., 2022).

AI has also been utilized to improve CUS loyalty. ORGs may design more focused programs and give tailored rewards by using AI to assess CUS behavior and preferences. According to studies, AI-driven customisation and better experiences lead to higher loyalty and recurring engagement (Bedi et al., 2022). This is especially important in a competitive Digi economy, where retaining consumers is key to long-term success. Large Language Models (LLMs) are on the rise. Every day, millions of people use these tools to write school essays, summarize text, generate new ideas, and engage with ORGs (Conversational AI models, such as OpenAI's ChatGPT, are powerful because they can create human-like language and facilitate discussions between many types of entities and users. As a result, LLM-powered bots will soon become the primary means by which consumers interact with businesses. While this can considerably simplify interactions since individuals can express their preferences using their normal form of communication, it also raises worries about whether LLMs' capacity to communicate using natural language can be abused to skew decision-making.The promise and risks are plainly seen in the new way CUSs may engage with search engines such as Microsoft's Copilot and platforms such as Amazon and Walmart, who are building LLM-powered assistants to advise users in their purchase search (Mehta and Chilimbi, 2024).

Users may now browse items by directly expressing their preferences, removing the need for rank-based recommendations or advertisements to locate suitable ideas. They can get recommendations by defining the characteristics of the things they want. On the one hand, conversational search eases the strain on CUSs by making it simple to locate items and services. On the other hand, the enhanced powers of LLMs improve their capacity to convince consumers. LLMs may swiftly adjust to requests and may convince CUSs to select more costly options. During a chat, they may learn about your tastes and utilize that knowledge to create unique reasons for you to consume more items. Most crucially, research have demonstrated that they can implicitly convince consumers on a large scale without being recognized. The business model of search engines, SM corporations, and Digi platforms raises concerns (Chen & Tsai, 2023).

Search engines and SM businesses make money via advertising, presenting results depending on the highest-paying vendors and labeling them as adverts. Similarly, for rank-based recommendations, platforms do not always rate their offers based purely on quality or matching tastes. Instead, they may rank items by the income they generate for the platform (which may not be precisely matched with consumer value) (Chen & Tsai, 2023).

The growth of e-commerce in the Digi era has witnessed the integration of AI in many elements, including recommendation systems. Such systems, based on AI, play an essential role in influencing COB by individualizing the process of interaction (Gonçalves et al., 2018; Kolodin et al., 2020). In the recent past, platforms have been using machine learning algorithms more in analyzing COB and predicting preferences (tailoring of recommendations) (Xu et al., 2024). Such advancements not only transform the very nature of Digi interactions but also lead to major changes in the expectations and habits of consumers (Jiang et al., 2019; Ameen et al., 2021). This leads to consumers becoming more accustomed to personalized suggestions, which enhances experiences and affects decisions (Sharma et al., 2022; Riegger et al., 2022).

However, the acceptance of AI-based recommendations will be primarily dependent on whether they feel that such suggestions were helpful to them, and that would influence their decisions (Kim et al., 2021; Rane et al., 2024). This becomes particularly critical in emerging markets, where COB is changing and the Digi sector is under development (Shin, 2021).

The trust consumers have in AI systems also holds an important aspect of the efficiency of recommendation engines. Research has consistently shown that trust Sig. influences consumers' reactions to AI suggestions, particularly in sensitive contexts where privacy and data security concerns are paramount (Choung et al., 2023; Shin, 2021). Trust in AI systems mediates the use of AI-based recommendations and COB, emphasizing the need for honesty and transparency in AI operations (Omrani et al., 2022; Shin, 2021; Hasija & Esper, 2022).

Consumers are likely to accept recommendations made by AI systems and follow through on the suggestions as long as they trust the system to work ethically and safeguard personal data (Pramanik & Jana, 2025; Hasija & Esper, 2022). In addition, an improved AI arsenal has made personalization more precise and, consequently, enhances consumer satisfaction and engagement (Huang & Rust, 2021).

Such developments call for Digi platforms not only to enhance the functionality of their AI systems but also to establish trust and show the value of their recommendations (Tyrväinen et al., 2020). This research analyzes the effect of recommendations by AI, perceived usefulness, and the influence of consumer trust in determining COB in Digi contexts (Shin, 2021; Omrani et al., 2022).

AI is widely regarded as a system that exhibits intelligent behavior by perceiving its environment and performing contextually appropriate actions (Sheikh, Prins, & Schrijvers, 2023). The development of AI-based influencers is made possible through a range of advanced technologies, including machine learning, deep learning, natural language processing, rule-based expert systems, neural networks, and robotics (Davenport, 2018). These AI systems can generate highly realistic human-like features such as facial expressions, gestures, and voices, making virtual influencers appear convincingly human (Sung et al., 2021).

AI-powered technologies commonly used for such applications include virtual bots, avatars, touchscreen kiosks, and physical robots. Among these, AI-based virtual influencers (VIs)—Digi fictional personas used in marketing—are gaining significant popularity, particularly on SM platforms. The rapid advancement of AI, combined with the expansion of the metaverse and SM ecosystems, has facilitated the widespread use of virtual influencers in brand promotion (Jin & Viswanathan, 2024).

Despite extensive evidence that AI-driven personalization, chatbots, and predictive analytics Sig. shape COB in Digi environments, many studies remain confined to mature, high-income markets (Jain & Gandhi, 2021). There is a lack of context-specific insights into how consumers in emerging economies, where technological infrastructure, trust paradigms, and Digi literacy differ, respond to AI interventions. Moreover, current research often overlooks longitudinal shifts in behavior, such as how sustained AI exposure influences trust, loyalty, or impulse buying behavior over time (Bedi et al., 2022). Finally, ethical challenges like algorithmic bias and data privacy are underexplored in non-Western contexts (Tiutiu & Dabija, 2023), calling for deeper investigation into how these factors mediate AI's influence on consumer decisions.

- **Importance of the study**

Understanding the impact of AI on COB in Digi environments is crucial for several reasons. First, AI-powered tools—such as personalization engines, chatbots, and predictive analytics—have been shown to Sig. influence CUS satisfaction, impulse behavior, and loyalty (Dai & Liu, 2024; Jain & Gandhi, 2021). Second, AI's impact spans the entire CUS journey, from awareness and discovery to decision-making and post-experience satisfaction (Bedi et al., 2022). Finally, the study foregrounds the ethical and trust dimensions of AI in Digi contexts, such as transparency, privacy, and algorithmic fairness (Nagy & Hajdu, 2022; Tiutiu & Dabija, 2023).

- **Aim of the study**

The main objective of this study is to examine the impact of AI on COB through the analysis of empirical data and theoretical frameworks. This study provides a comprehensive understanding of the psychological, behavioral, and economic implications of integrating AI into Digi environments.

SECTION 2:
LITERATURE REVIEW

2.1. TECHNOLOGY ACCEPTANCE MODEL (TAM)

2.1.1. Technology Acceptance Model

In the contemporary era of globalization, by the end of 2020, vigilant corporations, whose strategies were implicitly grounded in sustainable operational and implementation practices, had gained immense opportunities to compete effectively across the international platform. The first consideration in rewarding sustainability is that information TEC has been diffused across and therefore integrated into virtually all organizational processes. From then, any consideration of computer system application all over the nation was alien to the strategic approach but now amounts to an operational prerequisite (Akbulut, 2015). This TEC must provide room for companies to enhance their international presence by streamlining processes and improving productivity through IT infrastructure.

In the course of adopting transformational activities, various models have been proposed to provide some conceptual insight on information system adoption in ORGs. Among these models, the TEC Acceptance Model (TAM) developed by Davis in 1986 stands as one of the most widely used paradigmatic approaches to this day. TAM was designed to obtain the acceptance by individual users of computer systems and also attempted to identify psychological and behavioral factors influencing TEC adoption. This model gives a framework to system use from an individual viewpoint, which makes it relevant for multidisciplinary academic research in any technological context (Sheikhshoaei & Oloumi, 2011).

In addition, the Theory of Planned Behavior (TPB) proposed by Ajzen (1991) extended these ideas by incorporating attitudes, subjective norms, and perceived behavioral control, offering a broader explanation of user intentions and behaviors in TEC adoption.

It operates by describing sequences of causal relationships (RSs) that range from an individual's beliefs through attitude, behavior, and ultimately use (Lin et al., 2011). This linear influence diagram emphasizes the inter-relationship between the perceptions of users and their behaviors in adopting technologies. An et al. (2007) emphasized that the model now provides a theoretical framework for linking an individual's decision to use a system with their actual behavior. Hence, this strength and clarity have led to the acceptance of TAM in various clinical studies.

TAM is one of the most widely used theories to this day. The simplicity and wide applicability of TAM encourage usage in differing domains (Aktaş, 2007; Özer et al., 2012). The model posts favorably for those intending to use a TEC when the TAM positively influences their behavior. This is an attitude which is generally formed by two primary beliefs, namely, perceived ease-of-use and perceived usefulness. Chen, Gillinson, and Sherrill (2002) point out that these attitudes in behavioral tendencies-to-use are followed and predict the use, creating an adequate explanatory model of user behavior.

Various factors have come to light through the new adaptations of TAM, including entertainment and satisfaction, which equally affect behavior. According to Göğüş (2014), the addition of such dimensions Sig. increased the ability of this model to explain results, particularly in multimedia or interactive environments. Many diverse studies corroborate these assumptions across various disciplines, confirming that such variables Sig. contribute to the possibility of TEC adoption.

In summary, the TAM provides a satisfactory yet straightforward full model behind any analysis of user acceptance of technological innovations. The fact that it takes into consideration the essential dynamics of user behavior in relation to computer systems has constituted quite a pillar for TEC adoption research. According to Çakır (2009), owing to its conceptual clarity and predictive validity, it becomes an applicable framework to assess user interaction with Digi systems in both organizational and academic settings.

2.1.2. Stimulus–Organism–Response (S-O-R) Model

Mehrabian and Russell developed the Stimulus-Organism-Response (S-O-R) paradigm in 1974, which is a guiding principle of environmental psychology theory and has been applied to organizational behavior and leadership studies. The S-O-R paradigm proposes that an organism's internal feelings or behavior (person) are influenced by its exterior environment (stimuli). This internal processing of the activation might be conscious or unconscious, and it includes perceptions and environmental interpretations that influence one's emotions. This influence elicits an emotion, which leads to a reaction and decision-making. The S-O-R paradigm is a key idea in many global management theories, therefore it is primarily developed and applied in a variety of study domains.

This provides a comprehensive review of the literature on past and current research dimensions of the S-O-R model in branding theory and COB. It links the application of the model in branding theory to its application in organizational behavior and leadership theory. In addition to reviewing the similarities between models used in both research disciplines, three key differences, correlations, and characteristics are constructed and documented. The key factors that distinguish each model are the motivation for its use and purpose, the process of the stages of interaction between stimuli and elements, as well as some moderating variables and factors influencing the decision-making process, such as marketing, branding, or leadership and organizational culture (Hochreiter et al., 2023).

- Theoretical Foundation: S–O–R Model and Advertising Effectiveness

Human behavior in response to environmental stimuli can be systematically interpreted using the Stimulus-Organism-Response (S-O-R) framework, which serves as a foundational model of behavioral science. This framework describes how external environmental cues trigger observable behavior through internal psychological states. The S-O-R model thus provides deep insight into the mediating effects of cognitive and emotional states on the RS between stimulus and behavior, as highlighted by Guo & Chang (2022). This model has been widely used in various fields because it attempts to shed light on behavior in relation to contextual stimuli.

For instance, Asl & Khoddami (2022) successfully used a hybrid model by combining the S-O-R framework with the Theory of Planned Behavior and Consumption Value Theory to explore environmentally responsible COB. Here, the perceived social norms and individual responsibility acted as external stimuli; the emotional values formed the organismic state, while the green behaviors related to the behavioral response. This amalgamation convincingly illustrated the psychological mechanisms by which environmental awareness gets translated into actionable behaviors.

Operating within the S-O-R model, Chen et al. (2023) applied the model with respect to honeymoon tourism. Stimuli were conceptualized as destination attributes, organismic mediators as memorable tourism experiences, and the behavioral decision to revisit as the outcome. The affective memories created during travel emerged as significant predictors of tourists' future behavioral actions.

Similar to Huang (2020), who studied virtual consumer decisions on social networking sites, treating social identity cues as stimuli and cognitive involvement as a mediating factor, showed that the identity-related cues triggered a greater depth of user involvement, which then mediated consumer decisions. Additional contributions from Kumar et al. (2021), Ma et al. (2022), Peng & Kim (2021), and Ric & Benazić (2021) have stretched its application into areas like food consumption, e-commerce, and SM engagement, thereby further augmenting the model's relevance and versatility amid different COB studies.

Within this conceptual framework, advertising appears as a strong and deliberate stimulus aiming to influence attitudes and behavior. In this context, Lou et al. (2023) emphasized that advertising content truly resonates with consumer values and hence can trigger positive internal responses that lead to consumer engagement. Thus, the rise of user-generated content has gained strength to change the entire scenario of consumer persuasion.

User-generated content, such as product reviews and testimonials, has gained Sig. more credibility and informational value compared to traditional advertising methods. Weismueller et al. (2020) have noted that such content lends an additional feel of authenticity and reliability that crucially influences consumer satisfaction and choices. Liu & Zheng (2024) further argue that user-generated content provides richer context and personalized perspectives that consumers find more relatable and trustworthy.

Moreover, the conversion likelihood of users to consumers correlates directly to their perceived richness and credibility of information. Advertising stimuli that are high in quality shall lead to deeper processing in consumers, positively influencing resultant behavior in terms of engagement and adoption decisions. Once again, Wang et al. (2024) asserted that advertising content credibility and clarity Sig. affect consumer engagement and action on Digi marketplace platforms where competing stimuli bombard the consumer.

2.2. AI IN DIGITAL ENVIRONMENTS

AI has evolved into a powerful change agent in the landscape of Digi platforms, affecting the way companies interact with consumers and manage operations. According to Guha et al. (2021), AI is not merely supplemental or used as an operational tool; rather, it is a disruptive TEC in itself. Disruptive technologies are impacting the business landscape itself, as the Digi economy emerges through its own set of disruptive changes. Essentially, the term refers to human-like reasoning imparted to machines, which can learn, analyze and problem-solve through decisions (Ma & Sun, 2020; Schweidel et al., 2023; Vincent, 2021). As part of its integration into Digi service platforms, ORGs are capable of identifying growth opportunities and optimizing the entire performance of their aspects of operations (Oosthuizen et al., 2021). This advanced TEC also renders consumer experiences to be more intuitive and personalized; thereby fundamentally redefining the retention in Digi environments (Ameen et al., 2021).

Among the most significant benefits of AI in Digi contexts is its ability to personalize CUS experiences with remarkable precision. AI tools dynamically personalize content and offers for individual users based on their browsing history, interaction behavior, and CUS profiles, as pointed out by Haleem et al. (2022) and Moreau et al. (2023). Data analysis leads to the understanding of consumer preferences among retailers, which allows targeted recommendations and personalized promotion (Ameen et al., 2021).

Hoyer et al. (2020) made it clear that this level of personalization enhances a CUS's efficiency while interacting online and comfort during experience. Besides that, AI-enabled predictive analytical skills could let Digi platforms step forward in determining possible trends in CUS behavior, projection, and inventory needs (Chaudhuri et al., 2021).

The growing popularization of AI-based applications in Digi services indeed testifies to its wide acceptability and utilitarianism. According to Hagberg et al. (2017), AI technologies are now being more widely deployed for the purpose of streamlining operations, reducing costs, and improving user experiences. Whereas personal AI assistants offer functionalities such as real-time tracking and automated list management, they ensure a seamless, efficient, and satisfying user journey (Pillarisetty & Mishra, 2022).

These tools enhance trust and loyalty through the timely and precise fulfillment of individualistic needs. These works also consider the functional levels above: trust, anthropomorphism, and cognition, which are some of the critical psychological and behavioral variables affected by AI. Easy AI-like systems are believed by Pelau et al. (2024) to have a significant impact on users' decision to trust. When a user finds an AI system easy to use, it becomes more of a factor in their decision to interact with it. Anthropomorphic qualities such as being able to intervene in a human-like way were also found to increase user comfort and perceived trustworthiness (Pelau et al., 2021). As far back as 2021, Skare et al. stated that neuro-management and algorithmic cognition studies are gaining insights into consumer-interface interactions with mobile applications, specifically focusing on ease of TEC adoption. In the same sense, trust in Digi platforms is shaped by how users perceive ease and risk (Lăzăroiu et al., 2020).

On a generic basis, the inclusion of AI in Digi strategies has become a mainstream industry trend. Retail Economics (2019) observed that well over 50% of companies implement AI-enhanced personalization across all communication channels. Matzelle (2024) shows that, of companies in Digi commerce, AI tools are used to afford frictionless user experiences by around 51%. Backing these trends are market forecasts that predict the AI Digi sector will be valued at $9.65 billion in 2024, and grow at a CAGR of 32.17%, hitting $38.92 billion by 2029, according to Mordor Intelligence (2024). The Portuguese Digi sector has indeed picked up the trend of accelerated adoption, with more than 17% of companies employing AI for day-to-day activities, more than double the European average (Lopes, 2023). The same trends will apply to the Portuguese machine learning market, whereby it is estimated to scale to $2.23 billion by 2030, to grow at an 18.14% annual rate (Statista, 2023). Notwithstanding this frantic speed of technological absorption, the populace remains ambivalent. Ribeiro et al. (2022) note that lingering consumer mistrust is an impediment to the full operationalization of AI in Digi environments.

Though numerous studies have explored the AI-induced behavioral alterations in consumers when engaging in Digi environments, several areas in the literature remain unexplored. Tulcanaza-Prieto et al. (2023) suggest that personalization by AI is more likely to enhance user attitudes, experiences, and loyalty toward brands. Nevertheless, the mechanisms of how perceived ease of use shapes these results remain largely unexplored. Chen et al. (2022) establish the overall effect of AI on engagement, but much is left to be studied on the usability aspect of trust and long-term loyalty. Furthermore, in matters of research by Dwivedi et al. (2023), issues such as an understanding of AI bias and its consequences for user behavior have, indeed, become quite important. It would be ideal for future studies to explore the varying nature of ease of use across industries and technological environments, as well as the identification of particular AI attributes concerning consumer choice deliberations (Haleem et al., 2022; Bilal et al., 2024). In developing the most profound understanding regarding

AI usability and its influence on perceptions and behaviors in Digi commerce, it was important, according to Ameen et al. (2021) and Perez-Vega et al. (2021).

Changes and adaptations in Digi platforms have allowed for a very interactive and responsive engagement of users (Kaplan & Haenlein, 2020). Interface simplicity has proven very important in the overall scheme of TEC acceptance (Carter et al., 2020). Users favor systems that are effortless and intuitive (Alalwan, 2020). Perceived ease of use extends to the level of effort CUSs believe they need to exert to use a particular system (Venkatesh & Davis, 2000) and has consistently been shown to influence users' behavioral patterns (Liu et al., 2009; Venkatesh & Davis, 2000).

Further proving that perceived ease-of-use impacts other actions and evaluations made by users concerning new devices, it has to do with effort appraisal by new users and motivation and acceptance (Yang et al., 2017). It can be emphasized that predictably, users' anticipation about a system's usability is usually something that influences them to adopt or reject. Users expect ease of use to become one of the most important aspects to getting them engaged in a brand and retaining its loyalty (Flavián et al., 2006). Apart from pointing out how it affected individual interactions, it will further be referred to in relation to users' willingness to go into Digi actions, as Bayır and Akel (2023) and Pavlou (2003) established. In addition, the perception of ease in the user's mind improves as experience and familiarity with AI tools increase, thereby promoting patterns of long-term use and adoption (Venkatesh & Davis, 2000). According to Monsuwé et al. (2004), enhancement of Digi literacy was positively correlating with consumers' appraisal of the internet as a Digi medium. Thus, this makes ease of use an important dimension on which consumers evaluate and select new TEC for specific purposes (Bayır & Akel, 2023).

2.2.1. Customer Perception in Online Retail Navigation

In comparison with other forms of retail, e-commerce entails specific challenges, especially in that there may be no opportunities for interpersonal interaction, inadequacies to physically check the products, some distance concerns, and even questions of trust regarding the retailer's credibility (Davari et al., 2016; Faqih, 2016). These constraints imply the need for studying how CUSs perceive the online retail environment in a deeper sense. CUS perception, as Digi commerce continues to grow, is therefore becoming a significant factor influencing engagement and satisfaction (Mou et al., 2018). These scholars have further argued that shaping CUS perceptions is at the center of creating value in online environments (Vargo & Lusch, 2004; Zehir et al., 2014).

Several elements Sig. influence how CUSs assess the value of Digi retail platforms (Carlson et al., 2015). Under the experiential flow theory, three dimensions—perceived control, concentration, and cognitive enjoyment—are commonly used as measures of user perception. This control refers to the extent to which an individual perceives their ability to influence the Digi environment and behavior (Kautish & Khare, 2022), as defined by Kautish & Khare (2022) as psychological mastery over a given context. Concentration also plays a significant role in enabling a consumer to focus during their online interaction, particularly in today's context of ever-evolving AI-driven interfaces that respond contextually to user stimuli (Kautish & Khare, 2022). Cognitive enjoyment relates to flow as one experiences intrinsic pleasure from Digi activities, whereas attention to that interaction fades, the sense of self diminishes, and time perception is altered (Kautish & Khare, 2022).

2.2.2. Artificial Intelligence–Enabled Ease of Use and Customer Perception, Experience, and Engagement.

User control over an AI system determines how open users are to accepting such devices (Compeau & Higgins, 1995). Perceived ease of use is directly proportional to TEC acceptance, and in that line, most people are willing to use systems they find easier to deal with and understand (Liang et al., 2020). Simplicity and easy-to-use interfaces related to AI contribute to the perception of increased control, confidence, and autonomy, from the user's viewpoint (Mohr &

Kühl, 2021). When one has perceived limits in decision-making, there is often a negative orientation toward the provider of the TEC (Yan et al., 2022).

Concentration is defined by Moon and Kim (2001) as the user's ability to engross himself by removing distractions from activities. This component is crucial for online consumers who want to successfully do their tasks in complex Digi environments (Kautish & Khare, 2022). Ease of use has been shown to increase concentration levels remarkably and lead users into a flow state as they navigate through AI-powered environments (Akbari et al., 2020; Nguyen et al., 2022).

Emerging literature now also includes investigations related to how Digi technologies provoke mighty emotional responses like awe, a cognitive-emotional response to stimuli that challenge the existing mental models (Chirico et al., 2017; Hinsch et al., 2020). Awe extended environmental processing, stretched time perception, and connectedness (Drinkwater et al., 2022). AI-enabled platforms, through rich immersive experiences, could elicit such, changing once mundane engagements into meaningful interactions (Kautish & Khare, 2022).

In evaluating engagement, scholars usually rely on the dimension of online behavior, which is simply a way of depicting a consumer's decision-making approach to transact through Digi means (Moslehpour et al., 2018). Among the evidence used to show that perceived ease of use has a significant effect on attitudes toward AI, leading to growth in actual COB (Arachchi & Samarasinghe, 2023; Ghosh, 2024; Manis & Choi, 2019; Hsieh & Lee, 2021).

2.2.3. Customer Perception and Customer Experience

Platforms, for a holistic Digi experience, must provide product information and interactive features that stimulate cognitive, emotional, and social involvement

(Kautish & Khare, 2022). AI technologies shape the quality of CUS experience through advanced personalization and intuitive interfaces (Ameen et al., 2021). As a result, the management of CUS experience has become an integral part of organizational strategies and branding (Foroudi et al., 2018).

Temporary losses in the perception of control, for example, in disorganized online experiences, push users into favoring structured environments and more predictable brand experiences (Whitson & Galinsky, 2008; Kay et al., 2009). The perception of control, which brings about an attitude of awe in AI-supported environments, further affects individuals' assessments of the interaction and consideration for future scenarios (Kautish & Khare, 2022; Mueller et al., 2023).

Concentration is associated with performance enhancement and with positive emotional states (Pilgrim et al., 2017). By enabling focused engagement, AI-enabled services stimulate experiences of awe, which are themselves enhancing the overall CUS journey (Kautish & Khare, 2022). For instance, Digi consumers using AI virtual assistants report higher enjoyment and increased emotional responses (Kautish et al., 2023). In a similar vein, Gen Z consumers link cognitive enjoyment with more meaningful and awe-evoking online experiences (Ng et al., 2021).

2.3. CONSUMER BEHAVIOR CONSTRUCTS

2.3.1. Loyalty

Consumer loyalty remains a cornerstone of long-term brand success and sustainable revenue generation. Despite the term’s extensive use in academic and commercial settings, a universally accepted definition remains elusive (Kirillova & Zyk, 2023). Nonetheless, loyalty is generally viewed as a consumer's consistent preference and commitment to a specific brand, often resulting in repeated engagements (Ali et al., 2016; Oliver, 1999; Schiffman & Kanuk, 2003).

In the marketing literature, loyalty is frequently defined as the CUS’s willingness to remain engaged with preferred products or services in the future, despite external pressures or competing offers (Amin et al., 2013; Kursunluoglu, 2014). Oliver (1999) offers a widely endorsed definition, describing loyalty as a "deeply held commitment to continue using or re-engage with a preferred service consistently in the future" (p. 34), regardless of situational factors. This conceptualization integrates both attitudinal and behavioral dimensions of loyalty (Felix, 2014), emphasizing the emotional and action-oriented aspects of consumer allegiance.

Loyalty has been examined from multiple perspectives—attitudinal, behavioral, and composite—depending on the research objectives and context (Chou et al., 2015; Schiffman & Kanuk, 2003). The attitudinal view focuses on consumers' psychological attachment to brands (Casidy & Wymer, 2016), whereas the behavioral perspective emphasizes actual interaction or repeated engagement (Thaichon & Jebarajakirthy, 2016). Composite models integrate both, offering a comprehensive lens through which loyalty can be studied (Prentice & Wong, 2016).

The significance of CUS loyalty lies in its ability to foster sustainable competitive advantage (Murtiasih et al., 2014; Wu & Ai, 2016). Two main types of loyalty are often distinguished: active loyalty, characterized by enthusiastic advocacy such as word-of-mouth (WOM), and passive loyalty, where repeat behavior exists without emotional engagement (Kandampully et al., 2015). In the Digi age, active loyalty is especially valuable, as consumers increasingly rely on user reviews and peer recommendations (Bowen & Chen, 2001). Digi platforms and SM have further enabled loyal CUSs to act as informal brand ambassadors, effectively extending the brand's marketing capabilities (Kandampully et al., 2015).

- **Loyalty Approaches**

Three major frameworks are usually applied in measuring CUS loyalty: attitudinal, behavioral, and integrated or composite (Bowen & Chen, 2001; Chang et al., 2009). These concepts would allow for an appreciation of loyalty in terms of its psychological and behavioral dimensions, with each playing a different role in marketing decision-making (Amin et al., 2013; Rooij, 2015; Ruiz-Mafe et al., 2016).

- **Attitudinal Loyalty**

Attitudinal loyalty is defined as the positive psychological orientation a CUS holds toward a brand or product (Kassim & Abdullah, 2010; Kaura et al., 2015). It is rooted in emotional attachment, cognitive evaluations, and affective responses that build over time (Casidy & Wymer, 2016; Kursunluoglu, 2014). This form of loyalty is linked to factors such as brand allegiance, emotional engagement, and the willingness to continue using or recommending a product (Bowen & McCain, 2015).

Research indicates that attitudinal loyalty often precedes and predicts behavioral loyalty (Lee & Goudeau, 2014), and mediates the RS between service quality and COB (Quach et al., 2016). However, attitudinal loyalty does not always translate into action. For example, a CUS may have favorable views toward a brand but opt for alternatives due to price or availability constraints (Bowen & Chen, 2001).

- **Behavioral Loyalty**

Behavioral loyalty is the consumer practice of repeated engagement or retention of any particular product or service over time and on different occasions (Bowen & Chen, 2001). It often encompasses indicators such as the amount of products CUSs optain, frequency, and the number of visits that they make to an outlet (Chang et al., 2009; Kaura et al., 2015). Behavioral loyalty is also observable and quantifiable, which makes it quite appealing from a managerial point of view. Some scholars say that continuation tendency should be classified as a type of attitudinal loyalty (Lee & Goudeau, 2014), while others recognize it as a behavioral loyalty indicator (Kassim & Abdullah, 2010). It must be highlighted that behavioral loyalty does not imply emotional commitment. A typical example would be a consumer who has regularly engaged with a particular retailer on an ongoing basis, either convenience-driven or simply because they did not have brand affinity (Bowen & McCain, 2015).

- **Composite Loyalty**

Research has shown that most scholars recommend a combination of attitudinal and behavioral mimicking approach to measure loyalty due to the shortcomings of a single approach. Dick and Basu (1994) and Bowen and Chen (2001) recommended a dual-approach view, where the consumer loyalty manifested both emotional commitment and repeat actions. In this case, dual-faceted is referred to as the complexity of consumer loyalty (Taylor et al., 2004).

By treating composite loyalty, attitudes are usually measured concerning continuation willingness and the willingness to share that brand with others (Kaura et al., 2015). This approach has been applied effectively across various fields, including online portfolios (Chen et al., 2016), tourism (Ruiz-Mafe et al., 2016), and fashion (Stathopoulou & Balabanis, 2016).

2.3.2 Impulse Buying as Part of Consumer Behavior

The role of impulse decision-making in Digi environments has increased Sig., as defined by its characteristics of spontaneity and lack of prior planning. Impulse buying mostly occurs in response to emotions rather than conscious decision making (Vohs & Faber, 2003). The same has been followed up by marketing strategies that include Digi loyalty programs targeting such behaviors (Tripathi & Jaiswal, 2023).

Digi loyalty programs offer personalized discounts and time-limited promotions to encourage engagement and foster loyalty. Although impulse buying promotes short-term sales, it is likely to generate user remorse or dissatisfaction when poorly managed (Maqsood & Javed, 2019).

2.3.3 Satisfaction

CUS satisfaction is a salient criterion for evaluating the effectiveness of Digi services and overall user experience. It is generally defined as the extent to which a service fulfills or surpasses CUS expectations (Farris et al., 2010).

High satisfaction levels are thus closely related to enhanced user retention, loyalty, and recommendations. Satisfaction involves cognitive and emotional reactions and signifies perceived value gained from interaction (Godovykh et al., 2020). Satisfaction results when consumers seek to maximize utility through service use based on quality and the emotion experienced during and after interaction. For example, satisfaction from a Digi service when quality or convenience meets consumer expectations can favorably influence subsequent decisions and perceptions (Parboteeah, 2005).

2.3.4 Trust

Trust is crucial for the Digi economy, as it influences consumers' decision-making processes and Digi engagement. Herein, trust diminishes the perceived risks associated and instills confidence in the platforms and the providers, as noted by Lu & Chen (2021) and Zhang et al. (2022). It is the work of McAllister (1995) that identifies the two major types of trust: a cognitive one and an affective one. The first is objective, based on the perception of competence and reliability (Johnson & Grayson, 2005), while the second one is subjective, based on emotional bonding and personal rapport. Cognitive trust can typically be influenced by the evaluation of service quality, platform security, and provider professionalism (Srivastava et al., 2016). Unlike cognitive trust, affective trust is usually related to social bonding, emotional experience, and feelings of closeness to others, especially in the case of interactive Digi environments (Meng et al., 2021; Li et al., 2021). Additionally, both cognitive and affective trusts have been documented to Sig. affect consumer actions, comprising habitual engagement and loyalty (Zhang et al., 2014).

Apart from that, it is often within the emotional mediating that affective trust emerges to establish a RS between cognitive trust and consumer behaviors, further enhancing the psychological and emotional realms of consumer-platform RSs. The rise of influencers and content creators as trust agents further emphasizes the need to integrate the emotional side into Digi marketing strategy (Chen et al., 2019; Ming et al., 2021).

2.4. EMERGING MARKETS FOCUS: LIBYA

Communication Challenges and AI Initiatives. By 2025, Libya is poised to become a strong contender in emerging Digi economies, driven by the rapid development of Digi infrastructure in a constantly changing social, political, and economic environment. Even amidst serious governance challenges and a history of civil unrest, Libya's Digi transformation holds great promise for service innovation, economic diversification, and social resilience (Kemp, 2025; Interlibya, 2025). The Libyan experience demonstrates how digitization can bring about structural change even in fragile environments, provided the right conditions are in place for such change.

2.4.1. Digital Infrastructural Trends and the Case of Adoption

Libya had reformed its Digi connectivity levels by early 2025, well above many countries in this region in some measurements. According to Digi 2025: Libya, the country recorded approximately 14.6 million active mobile cellular connections-representing 197% of the population-meaning that many individuals maintain multiple mobile subscriptions or devices (Kemp, 2025). However, it does not mean absolute access to the internet. A fair share of these connections are limited to basic voice or SMS services, indicating unequal access to the full internet.

Internet penetration has already reached approximately 88.5% of the population, which equates to around 6.57 million, while active SM identities number 6.40 million, which means they constitute 86.3% of the population (Kemp, 2025). These rates represent a society that continues to adopt an increased Digi base in particular urban centers, where mobile broadband coverage and access to requisite Digi devices are more widely available. The speed with which social and mobile technologies have been adopted has opened doors for Digi entrepreneurship, innovative Digi services, and new forms of civic engagement, especially among younger groups.

It has undoubtedly been a recovery and restructuring effort, along with international selective partnerships, which have propelled Libya's advancements in constructing a Digi infrastructure. Investments have targeted specific telecommunications TEC developments, such as constructing fiber optics and extending broadband networks from 4G to 5G. This process resulted in rapid acceleration in adopting Digi TEC, particularly in metropolitan areas, with change yet to be witnessed in rural and peripheral regions, often characterized by minimal infrastructure and limited service delivery (Korhogo Agency, 2025). While progress has been witnessed, infrastructural disparities remain a challenge in ensuring Digi inclusion across the country.

2.4.2. Connectivity Issues, Trust, and Payment Systems

Although the Digi connectivity environment appeared relatively favorable, Libya undertook several systemic efforts to strengthen its Digi ecosystem. The most significant barrier to Digi trust was the lack of confidence, stemming from inadequate cybersecurity measures, limited public awareness of data rights, and an underdeveloped legal framework for Digi governance. Although Law No. 5 of 2022 addressed cybercrime, identity theft, and Digi security, and Law No. 6 of 2022 provided legal guidance on electronic transactions and personal data protection, these laws suffered from weak enforcement. Another detrimental factor is the absence of a centralized data protection authority, along with the lack of a stand-alone data protection law (Dig.Watch, 2024).

Uncertainties in law eroded public trust in Digi services and discouraged private sector participation from venturing into the Digi economy, thereby slowing the brakes on the development of Digi financial services. Most online transactions thus remained heavily reliant on cash or informal arrangements, limiting e-commerce growth and restricting participation in financial inclusion. Furthermore, the unavailability of integrated payment gateways and Digi wallets has resulted in fragmented of consumer experience and reduced opportunities for international e-trade collaborative ventures. In addition to the recurring legal and regulatory hurdles, some logistical and infrastructural bottlenecks—such as inconsistent electricity supply, low Digi literacy rate outside the urban centers, and the absence of standardized Digi IDs—undermined the efficient delivery of Digi services. Addressing these structural challenges is essential for Libya to progress from being digitally connected to being digitally productive (Dig.Watch, 2024).

2.4.3. I Initiatives by Government and Private Sector

There have been initiatives by governments and private sector ORGs to set up AI in Libya. Together with other challenges, Libya made some early steps of considerable importance toward harnessing AI into its Digi strategy. One landmark realization was the issuance of the National AI Policy under the Ministry of Communications and Information in 2025. The policy envisioned the strategic pathways for AI adoption for various public and private sectors. Essentially, the policy included building a Digi infrastructure, including cloud computing capabilities, high-performance computing resources, and secure data storage systems, as well as addressing matters of ethics and regulation, including algorithmic bias, data privacy, and responsible use of automation for public administration, healthcare, and education (Korhogo Agency, 2025).

By these developments, civil society and private initiatives complemented government action. Several capacity-building programs targeting AI were launched, emphasizing youth empowerment. Coding boot camps, training in Digi skills, and entrepreneurship programs were funded by international donors, diaspora professionals, and NGOs. In this regard, the aim was to create a generation of digitally and AI-literate youth who can contribute to the country's long-term innovation agenda (Korhogo Agency, 2025).

Although the AI sector was still embryonic in Libya, having a framework for policy and some initial stages of investment in infrastructure was indicative of a strong commitment toward making AI a national development drive. If nurtured correctly, AI could become the instrument for transforming governance systems, Digi services, public security mechanisms, and healthcare diagnostics in particular, areas that remain underserved.

2.5 RELATIONSHIP AMONG VARIABLES

The configuration among the variables in this study is theoretical and empirical in nature, addressing the consideration of how the AI integration into Digi environments is producing COB. With AI TEC reforming Digi commerce, numerous psychological, behavioral, and experiential factors mediate the effect of such media on outcomes for consumers, including trust, engagement, and satisfaction.

- **Artificial Intelligence (AI) Use and Consumer Behavior (H1)**

AI focuses on COB through personalization, interaction automation, experience optimization, and more. In short, the AI algorithms study consumer preferences, site view history, and usage behavior, returning personalized recommendations and personalized marketing messages. This personalization enhances CUS interaction, satisfaction, and loyalty (Bhagat et al., 2022; Huang & Rust, 2021). Therefore, the practical application of AI in Digi environments is expected to have a positive impact on overall COB.

- **Trust and Conversion Rate Optimization (H2)**

Trust in AI systems is paramount in the execution of CRO strategies. Once consumers trust AI recommendations to be correct, safe, and impartial, they readily act upon them, thereby increasing the efficacy of the whole CRO effort. Trust helps to enhance the platform's credibility and reinforces the user's willingness to convert (Omrani et al., 2022; Choung et al., 2023).

- **AI through CRO and Consumer Confidence (H3)**

AI-enhanced CRO tools raise efficiency, in addition to boosting consumer confidence via consistent personalized experiences in safe environments. Such confidence lowers anxiety levels in decision-making and reaffirms belief in the platform's understanding of their needs (Kim et al., 2021; Gonçalves et al., 2018).

- **Perceived Usefulness of Online Reviews and Consumer Trust (H4)**

AI-positive experiences offered through accurate recommendations, speed in resolving queries through chatbots, and intuitive site navigation yield greater consumer satisfaction; moreover, the perceived usefulness of online reviews Sig. strengthens consumer trust (Bedi et al., 2022; Sharma et al., 2022).

- **Study hypotheses**

This study investigated the interrelationship between AI applications in Digi environments and various dimensions of COB. These variable RSs are based on theoretical and empirical literature on psychological and behavioral influences in the e-commerce environment.

- **AI Use and Consumer Behavior (H1)**

AI applications, such as personalized recommendations, predictive analytics, and virtual assistants, positively affect COB: increasing engagement, enhancing satisfaction, and encouraging loyalty (Bhagat et al., 2022; Huang & Rust, 2021). By delivering contextually relevant content to consumers, these technologies will affect how consumers behave by reducing decision-making efforts (Xu et al., 2024).

H1: There is a significant positive RS between the use of AI and COB.

- **Trust and Conversion Rate Optimization (H2)**

Among other factors, consumer trust is important to the effectiveness of CRO. Trust refers to openness and ethical AI systems that facilitate user trust in platform recommendations and conversion likelihood (Omrani et al., 2022; Zhong et al., 2023).

H2: There is a significant positive RS between Trust and Conversion Rate Optimization (CRO).

- **AI through Conversion Rate Optimization and Consumer Trust (H3)**

By providing personalized experiences and lessening friction in the CUS journey, AI conversion rate optimization tools enhance perceived control and trustworthiness for consumers in online environments, positively contributing to consumer trust (Kim et al., 2021; Gonçalves et al., 2018).

H3: The use of AI through conversion rate optimization (CRO) has a statistically significant positive impact on consumer confidence

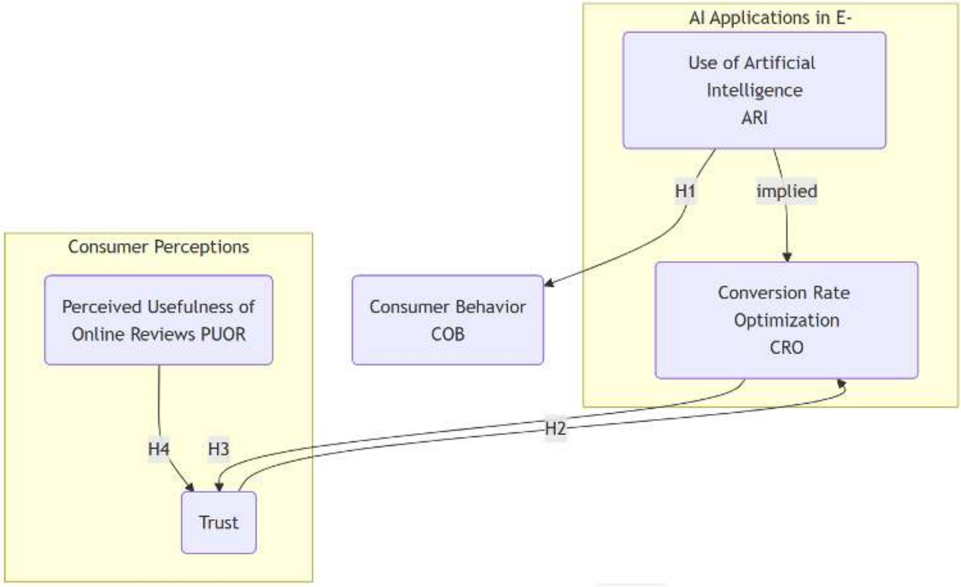
- **Perceived Usefulness of Online Reviews and Consumer Trust (H4)**

Trust is fostered when consumers find online reviews credible, informative, and contextually relevant, especially if AI systems are applied to filter bias and noise (Hasiga and Esper, 2022; Tervanen et al., 2020).

Collectively, these hypothesized RSs emphasize the importance of AI as a facilitator in modern consumer decision-making processes regarding trust, engagement, satisfaction, and other factors, especially in newer Digi markets.

H4: The perceived usefulness of online reviews has a statistically significant positive effect on consumer trust, RS between variables as Figure 1

Figure 1: Research Model.



SECTION 3:
METHODOLOGY

3.1. TYPE OF STUDY

Data was obtained from CUSs of the Libyan Islamic Bank for the purpose of conducting a descriptive cross-sectional study with the purpose of evaluating the RS between the utilization of AI and COB in Digi environments within the context of the study.

The cross-sectional study design is a type of observational research in which both exposures and outcomes are recorded concurrently among chosen individuals. In contrast to case-control studies, which begin by identifying individuals based on their result status, cross-sectional studies recruit participants based on specified inclusion and exclusion criteria independent of exposure or outcome. Once the sample has been created, data collection occurs at a single moment in time, allowing researchers to analyze the prevalence of variables and explore potential correlations within the population without any longitudinal follow-up (Setia, 2016).

The cross-sectional design was chosen for its efficiency in capturing consumer perceptions at a single point in time across a Digi context, using bank CUSs as an accessible and reliable sample.

3.2. STUDY LOCATION AND CHARACTERISTICS

The research was done in a banking setting, with data obtained from Libyan Islamic Bank consumers between 04/15/2025 and 06/15/2025. The bank was chosen as an application environment because of the accessibility and dependability of the participants, and the dimensions examined represent broader Digi COB.

3.3. COMMUNITY AND SAMPLE

The sample size for the study was 391 CUSs of the Libyan Islamic Bank during the data collection period. The sample size was determined based on a 95% confidence interval and a 50% response rate, as shown in Figure 2. The study included CUSs aged 20 years and older who agreed to participate, while those who declined were not included. The bank was selected as a convenient application setting, while the constructs measured reflect broader Digi COB.

Table 1: Sample size calculation for a priori power analysis.

Analysis	**A priori: Compute required sample size**
Input:	
Tail(s)	Two
Effect size d	0.3663518
α error prob	0.05
Power (1 - β error prob)	0.95
Allocation ratio N2/N1	1
Output:	
Noncentrality parameter δ	3.6174342
Critical t	1.9660969
Df (Degrees of freedom)	388
Sample size group 1	195
Sample size group 2	195
Total sample size	391

Table 1 illustrates that the input parameters follow well-established statistical norms. The two-tailed test indicates that researchers are interested in discovering both the positive and negative effects of AI on COB. The effect size (Cohen's d) is 0.3665, indicating a small-to-moderate influence. In a nutshell, it demonstrates a meticulously prepared experimental design to assess the influence of AI on CUS behavior. The computed sample size of 391 offers a solid foundation for deriving accurate and relevant results. The utilization of a modest predicted impact size and strong statistical power illustrates the researchers' dedication to identifying even little changes in CUS behavior caused by AI TEC.

Figure 2: G-Power Analysis.

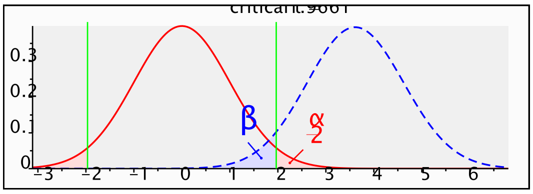


Figure 2 illustrates a basic example of hypothesis testing in inferential statistics using power analysis. Power analysis is critical for determining whether a study has enough statistical power to detect a meaningful effect in the current study of AI's impact on COB. These graphs depict two overlapping probability distributions, which demonstrate the impression of Type I and Type II mistakes. This emphasizes the necessity of properly sized samples, effect size estimation, rigorous study design, and statistical power. This allows academics to offer sound and useful insights on how AI affects consumer involvement and decision-making in Digi ecosystems.

Figure 3: Power curve for estimating sample size.

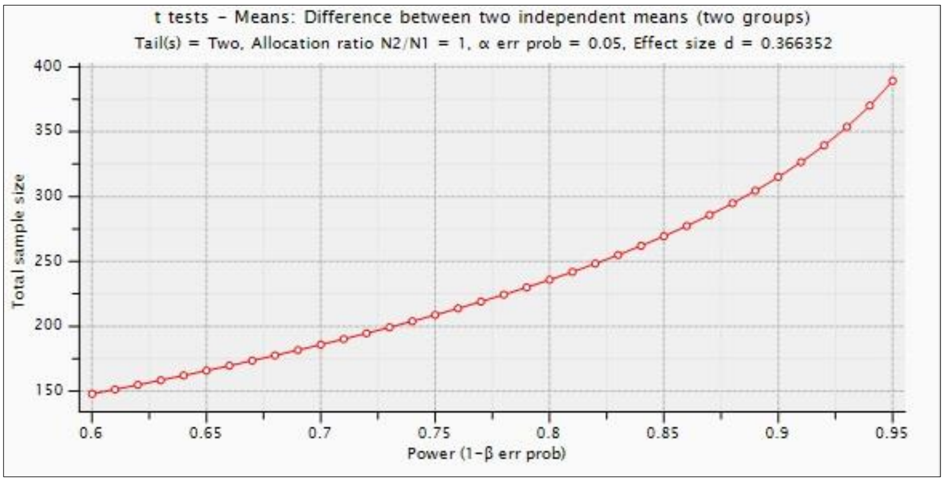


Figure 3 shows the RS between statistical power (probability of error 1 - β) and total sample size in a study on the impact of AI on COB. This power analysis diagram is essential for researchers to make sound design decisions. It enables them to strike a compromise between statistical precision and practical restrictions, such recruitment feasibility and budget. Figure 3 visualizes how different power thresholds impact sample size, providing a clear explanation for selecting a robust design that reduces the probability of Type II errors. Given the nuanced and variable nature of consumer responses to technological interventions, ensuring adequate statistical power is critical for any study evaluating the impact of AI on COB.

3.4. DATA COLLECTION TOOLS

3.4.1. Demographic Data

Demographic data was utilized to establish the participants' characteristics, such as age, gender, education, and occupation (Appendix 1). The participants were CUSs of the Libyan Islamic Bank, chosen as an accessible sample, and the demographic factors give insights applicable to broader Digi COB.

3.4.2. Artificial Intelligence (AI) Use Questionnaire

Nazir et al. (2023) created a tool to assess the application of AI (Capatina et al., 2024). All research items were graded on a 5-point Likert scale, with 1 indicating severe disagreement and 5 indicating strong agreement. Cronbach's alpha values varied between 0.644 to 0.841 (Appendix 1).

3.4.3. Consumer Behavior Creativity Questionnaire

Used to assess COB (Park & Lee, 2009). Ventre and Kolbe (2020) developed a 5-point Likert scale for all research questions, which ranged from 1 (strongly disagree) to 5 (strongly agree). Cronbach's alpha scores range from 0.77 to 0.82 (Appendix 1).

3.5. ETHICAL CONSIDERATIONS

On April 15, 2025, the Libyan Islamic Bank, Tripoli Branch granted ethical approval (Appendix 2). To ensure maximum secrecy, CUS anonymity was maintained. All clients who participated in the study were notified that the survey findings would only be utilized for academic research purposes.

SECTION 4:
FINDINGS

4.1. DATA ANALYSIS

The collected data were analyzed using IBM software. Frequency analysis, mean comparison tests, and correlation analysis were used during the statistical analysis. In addition, kurtosis tests were used to determine the statistical tests used and to ensure that the data conformed to a normal distribution. For mean comparisons, analysis of variance (ANOVA) and t-test were used, depending on the number of groups in the parametric tests. R analysis was used to express the correlation between sub-dimensions. Simple linear regression analysis was also used. The primary analyses were descriptive with regard to the demographic characteristics of the participants. In the descriptive analysis, the qualitative types of descriptive percentages (%) and frequencies (n) were presented together. Thus, these two values could be displayed and combined. Summary statistics were calculated for each score obtained by the researcher on the sub-dimensions of the scale. A 5% margin of error was observed when reviewing the results of the statistical analysis.

4.2. RELIABILITY ANALYSIS

To ensure the accuracy of the study's measurements, an assessment was carried out to determine the consistency of each scale in expressing the intended concept. Cronbach's alpha coefficient was used to determine the internal consistency of the Use AI and COB measures. A reliability score of more than 0.7 is deemed satisfactory, suggesting that the scale generates consistent and trustworthy findings. Table 2 shows the dependability scores for each variable.

Table 2: Reliability values of the scales.

	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**

Use AI	188.3049	737.280	.947	.906
COB	265.8682	1448.006	.799	.827
Artificial Intelligence Technology (AIT)	271.8140	1563.385	.706	.838
Consumer Engagement on Social Media (CESM)	276.3669	1561.186	.743	.837
Conversion Rate Optimization (CRO)	282.6899	1640.318	.762	.843
Satisfying Consumer Experience (SCE)	282.6899	1640.318	.762	.843
Habit (HAB)	290.6822	1712.611	.658	.851
Trust	290.7158	1721.950	.702	.851
Perceived usefulness of online reviews	290.5840	1710.554	.693	.850

Table 2. displays the results of the reliability analysis of the study variables. Cronbach's alpha values were as follows: 0.837 for CESM, 0.838 for AIT, 0.843 for CRO and SCE. Since all values were above 0.70, this confirms that the scales used in the study are reliable and internally consistent.

Table 3: Distribution of study participants according to demographic data.

Items		**Frequency**	**Percent**
Age	20-30	281	71.9
	31-40	60	15.3
	41 and more	50	12.8
Gender	Female	120	30.7
	Male	271	69.3
Education	Primary school or below	51	13.0
	Diploma/high diploma	67	17.1
	Tertiary/University	181	46.3
	Post-graduate or above	92	23.5
Occupation	Professional/consultant	64	16.4
	Academic	171	43.7
	Technician/Operator	156	39.9

Table 3 displays the demographic characteristics of the research respondents. According to the age distribution study, the vast majority of respondents (281, 71.9%) were between the ages of 20 and 30, showing a young predominance. The 31-40 age group came in second, accounting for 15.3%

(60%), and the 41+ age group accounted for 12.8% (50%). In terms of gender, males made up the vast majority of the sample (271, or 69.3%), while females made up 30.7% (120%). This distribution may reflect the better engagement of both genders in AI-related Digi environments or other features unique to the work sector.

The overall education profile indicates that the sample participants were well-educated, with the largest proportion holding a university degree (n = 181, 46.3%), followed by 23.5% (n = 92) with postgraduate qualifications. 17.1% of participants held a diploma or higher (n = 67), while those with only primary education or less comprised 13.0% (n = 51). This data demonstrates that participants, in general, have a good educational foundation, which is likely associated with higher levels of Digi literacy and readiness to work with AI technologies in consumer contexts. Based on occupation, academics occupied the largest segment (n = 171; 43.7%), followed by technicians/operators (n = 156; 39.9%), and finally, professionals/consultants (n = 64; 16.4%). This distribution indicates a wide range of professional and technical expertise among participants, which may promote the wider use of AI-based Digi systems and platforms. As a result of this factor, most participants are young, well-educated individuals with strong engagement from both the academic and technical sectors. These characteristics are important in interpreting the results of this study, particularly regarding participants' Digi proficiency and their exposure to AI applications in consumer and online environments. Therefore, the demographic composition aligns with the study's objectives of understanding the impact of AI on digitally active consumers.

4.3. CORRELATION ANALYSIS

Table 4: Pearson Correlation Matrix Between Using Artificial Intelligence (AI) and Consumer Behavior (COB).

Correlations												
		1	2	3	4	5	6	7	8	9	10	11
ARI	r	1										
	p											
COB	r	.733**	1									
	p	.000										

3.AIT	r	.792**	,512**	1								
	p	.000	.000									
CESM	r	.810**	.590**	.545**	1							
	p	.000	.000	.000								
5.CRO	r	.777**	.564**	.552**	.538**	1						
	p	.000	.000	.000	.000							
6.SCE	r	.777**	.564**	.552**	.538**	1.000**	1					
	p	.000	.000	.000	.000	.000						
7.HAB	r	.701**	.549**	.402**	.432**	.438**	.438**	1				
	p	.000	.000	.000	.000	.000	.000					
9.Trust	r	.638**	.828**	.459**	.507**	.475**	.475**	.462**	.622**	1		
	p	.000	.000	.000	.000	.000	.000	.000	.000			
10. Perceived usefulness of online reviews	r	.621**	.859**	.416**	.488**	.482**	.482**	.516**	.553**	.593**	.587**	1
	p	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	
**. Correlation is significant at the 0.01 level (2-tailed).												

The results in Table 4. indicate strong positive correlations between almost all items, indicating a high level of interconnectedness within the AI-influenced Digi COB framework.

AI use shows the strongest correlations with CESM and ARI ($r = .810$, $p < .01$), also, have correlation with AT and ARI ($r = .792$, $p < .01$), and ARI with CRO ($r = .777$, $p < .01$). This implies that ORGs that effectively use AI are also more likely to experience higher engagement on SM platforms and improved conversions, which is consistent with recent findings (Chatterjee et al., 2021).

The strong positive correlation found between AI and CESM concurs with Luo et al. (2021), who suggested that AI tools (like chatbots and recommendation systems) markedly enhance user engagement and satisfaction on Digi platforms.

Moreover, the data suggested that Satisfactory Consumer Experience (SCE) is strongly tied with CRO ($r = 1.000$); therefore, the two might partially overlap in terms of either conception or quantity. This perfect correlation raises concerns for multicollinearity, but conversely indicates that a good AI-powered user experience translates directly into conversion rates- an observation that Kumar et al. (2020) support.

Trust correlated with behavior (.828), trust correlated with perceived usefulness of reviews (.593), further confirms the importance of credibility in e-commerce as discussed by Pavlou (2003), thus identifying trust as one of the mediators in Digi transactions, stating that a repeat behavior fosters consumer loyalty (Limayem et al., 2007).

4.4. THE RELATIONSHIP BETWEEN THE STUDY VARIABLES

Table 5. Relationship Between ARI and COB

Coefficients[a]									
Hypotheses	Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Result
		B	Std. Error	Beta			Lower Bound	Upper Bound	
H1: There is a significant positive relationship between the use of AI and COB	(Constant)	4.864	1.467		3.315	.001	1.979	7.750	Accept
	ARI	.271	.013	.733	21.117	.000	.246	.296	
R^2= .537 F= 445.940 p=.000									
a. Dependent Variable: COB									

According to Table 5, the coefficient of regression B of ARI is equal to 0.271, meaning that for every unit of increase in this factor, the COB is augmented by approximately 0.271 units provided all other variables remain constant, $p < 0.001$, indicating that the overall regression model is statistically significant. Based on these results, hypothesis H1 is accepted.

The results of the regression analysis show a strong and statistically significant association between ARI and COB, as demonstrated in previous empirical studies that indicate that AI plays a transformative role in shaping and influencing COB, expectations, and decision-making processes. As Chatterjee et al. (2021) and Shankar (2020) have argued, AI-powered technologies, such as recommendation engines, chatbots, and predictive analytics, lead to more personalized, effective, and relevant CUS interactions, resulting in positive behavioral change. The high standardized beta value (β = .733) in the current study supports this claim by identifying the strong impact of AI on behavioral variables.

These findings are further supported by Gursoy et al. (2019), who found that consumers perceive AI-powered services as efficient and responsive, which increases their satisfaction, trust, engagement, and positive behavioral responses. Huang and Rust (2021) also confirmed that AI aids decision-making by reducing information overload and personalizing content presentation, which enhances observable behavioral outcomes. In this study, the R^2 value of 0.537 confirms previous findings. For example, Xu et al.'s (2020) study produced coefficients of determination ranging from 0.45 to 0.60 while analyzing the impact of AI on behaviors in the context of e-commerce, meaning that AI still accounts for a significant portion of the variance in COB outcomes.

Table 6. Relationship Between Trust and CRO

Coefficients[a]										
Hypotheses	Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Result
		B	Std. Error	Beta			Lower Bound	Upper Bound	
H2:There is a significant positive relationship between Trust and Conversion Rate Optimization (CRO).	(Constant)	11.125	.726		15.331	.000	9.699	12.552	Accept
	Trust	.708	.066	.475	10.646	.000	.577	.838	
R^2= .226 F= 113.342 p=.000									
a. Dependent Variable: CRO									

Table 6 reveals a statistically significant positive link between trust and CRO The t =10.646 and p= 0.000 indicate that this association is statistically Sig. at the 0.01 level. Consumer trust accounts for 22.6% of the variance in CRO

(R^2=0.226). The F= 113.342, which is statistically significant at $p < .001$, confirms the overall validity and predictive effectiveness of the model.

Trust is widely accepted in the research as an important factor of online CUS behavior, especially given the Sig. risk is involved with e-commerce, since consumers do not have physical contact with a product prior to purchase. The findings of this study give empirical evidence for this assumption, demonstrating that CUS trust improves conversion rate optimization (CRO) viability.

This conclusion is also very closely aligned with the TEC Acceptance Model (TAM) (Davis, 1989) and its later extensions (e.g., Pavlou, 2003), with the trust factor being the central element influencing perceived usefulness and, therefore, user behavior in Digi transactions. Among other studies, Gefen et al. (2003) corroborated this research and established that trust Sig. influences users' decision to perform transactions electronically, reducing their perception of risk and increasing their confidence in the reliability of the system. In the same vein, Belanche et al. (2012) emphasize that trust increases not only the likelihood of initial engagements but also the loyal behavior in the long term and the efficiency of transaction processes.

The reduction in friction along the conversion pathway that trust offers has also been discussed by Chen and Barnes (2007), whereby trust increases users' willingness to move through the online sales funnel. The current study contributes to this discussion by proving that trust is a predictive variable of CRO, with a standardized beta value of 0.475, meaning there was a difference between higher trust levels and conversion behavior effectiveness.

Zooming in on the marketing, Urban et al. (2009) pointed to trust-enabling design features such as transparent privacy policy, secure payment systems, verified reviews, and reliable CUS support as related to higher conversion rates. Findings resonate with the practical importance of cultivating trust as a pillar of any e-commerce strategy.

Table 7. Regression Analysis of the Impact of Conversion Rate Optimization (CRO) on Consumer Trust

Coefficients[a]									
Hypothesis		Unstandardized Coefficients		Standardized Coefficients	t	p	95.0% Confidence Interval for B		Evaluation
		B	Std. Error	Beta			Lower Bound	Upper Bound	
H3: The use of AI through conversion rate optimization (CRO) has a statistically significant positive impact on consumer confidence	(Constant)	4.731	.568		8.324	.000	3.614	5.849	Accept
	Conversion Rate Optimization (CRO)	.319	.030	.475	10.646	.000	.260	.378	
R^2= .475 F= 148.353 p=.000									
a. Dependent Variable: Trust									

Table 7. The B coefficient (unstandardized) indicates that there is an increase of 0.319 units in consumer confidence for every one-unit increase in conversion rate optimization, keeping all other factors constant. A standard error of 0.030 is considered quite low and therefore, the estimate can be regarded as highly reliable. Furthermore, the t-value of 10.646 with a p=0.000 provides strong evidence that this link is Sig at the p < 0.001 level. Furthermore, the removal of zero from B's 95% confidence interval (0.260 to 0.378) ensures that the impact cannot be attributed to chance.

The standardized beta coefficient (β = 0.475) shows a moderate to strong positive correlation between CRO and CUS confidence. This suggests that in terms of standard deviation, CRO has a statistically significant impact, which helps us evaluate the strength of the effect regardless of the initial measurement scale.

CRO may explain 47.5% of the variance in consumer confidence, as indicated by the coefficient of determination (R^2 = 0.475) for model modification.

Furthermore, the F=148.353, with a p= 0.000, confirms the statistical significance of the overall regression model. Thus, we accept Hypothesis 5. The findings indicate that using AI through conversion rate optimization (CRO) approaches greatly boosts CUS confidence, which supports the overall research purpose of investigating how AI impacts COB.

Table 8. Regression Analysis of the Effect of Perceived Usefulness of Online Reviews on Trust

Coefficients[a]									
		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Result
Hypothesis		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	
H4: The perceived usefulness of online reviews has a statistically significant positive effect on consumer trust	(Constant)	4.831	.414		11.681	.000	4.018	5.644	Accept
	Perceived usefulness of online reviews	.541	.037	.593	14.521	.000	.468	.615	
R^2= .352 F= 210.851 p=.000									
a. Dependent Variable: Trust									

Table 8 reveals a strong, statistically significant positive RS between the variables. A (t = 14.521) and a (p= 0.000) indicate that this RS is highly Sig. at the 0.001 level.

Furthermore, the standardized beta coefficient indicates that the effect size is fairly strong. It is worth noting that the effect size regarding consumers' experience with online reviews as a value would lead to a greater propensity to trust the product, brand, or service associated with the reviews (β = 0.593). The 95% confidence interval for the B coefficient ranges from 0.468 to 0.615, which excludes zero, confirming the reliability of the effect.

The R^2 value of 0.352 in the model fit indicates that approximately 35.2% of consumer trust is explained by consumers' perception of helpful online reviews. Additionally, the F= 210.851 with a p=0.000 confirms that the overall model is Sig.. These statistics support the importance of online reviews in building consumer trust. Helpful reviews lead to increased consumer confidence in a product or service, which enhances the online decision-making process.

Table 9. Summary of Hypotheses

Hypothesis	β	p-value	Evaluation
H1: There is a Sig. A positive RS between the use of AI and COB	0.733	0.000	**Accepted**
H2: There is a Sig. A positive RS between Trust and CRO.	0.475	0.000	**Accepted**
H3: The use of AI through CRO has a Sig. positive impact on CUS confidence.	0.475	0.000	**Accepted**
H4: The perceived usefulness of online reviews has a Sig. positive effect on consumer trust.	0.593	0.000	**Accepted**

In Table 9. All hypotheses in the extended analysis (H1–H4) have been accepted, as each one demonstrated a strong, Sig. RS. This means the evidence strongly supports the idea that these factors (like AI usage, Habit, and Trust) meaningfully influence COB and decisions.

No hypotheses were rejected because each showed a positive and significant RS, and the models were well-fitted with substantial explanatory power. The results provide valuable insights into how habits, AI, and online reviews shape consumer trust and behavior, which is especially relevant in today’s Digi marketplace.

SECTION 5:
CONCLUSION AND SUGGESTIONS

5.1. CONCLUSION

The current study aims to evaluate the impact of AI and its applications, particularly CRO, CESM, and online review systems, on COB, specifically trust. Several statistical TECS, including reliability analysis, correlation, and linear regression, have been used to establish adequate proof of the magnitude of AI's influence on digitally mediated COB.

The study sought to provide a comprehensive understanding of these RSs, grounded in both psychological and behavioral theories and supported by empirical data. The study adds to the growing body of literature highlighting AI's increasing role in shaping modern consumer experiences, particularly in Digi and financial services, by analyzing how AI-driven tools affect COB using data collected from the Libyan Islamic Bank context.

The study used a descriptive cross-sectional study design to collect data from Libyan Islamic Bank clients during a certain time period. This technique enabled the investigation of the links between AI usage and numerous elements of COB in a realistic, real-world situation, without the requirement for long-term tracking. The cross-sectional design also required that data be collected at a particular moment in time, offering a glimpse of the present impact of AI TEC on consumer interactions. The findings represent the current consumer context but are open to additional research in future studies, especially as AI technologies continue to improve and spread.

The primary goal of this study was to assess the psychological, behavioral, and economic effects of AI on COB in Digi environments, using the Libyan Islamic Bank as the application setting. The study sought to determine how AI-driven processes, such as recommendation algorithms, customization tools, and AI-assisted CUS support, influence COB patterns..

In recent years, AI has grown more prevalent in everyday life, altering how CUSs engage with Digi platforms and services. AI is transforming industries such as retail, banking, and e-commerce by powering personalization, CUS support, and product recommendations through advanced algorithms. However, there is still a lack of understanding about the full scope of AI's effects on COB in underexplored markets such as Libya, particularly in banking. This study fills that gap by analyzing data from the Libyan Islamic Bank, providing critical insights into how AI affects consumer trust, engagement, and loyalty in this particular market.

The study was conducted using data collected from the Libyan Islamic Bank, one of the prominent financial institutions in Libya. This setting was chosen because it provides a unique environment where AI is gradually being integrated into banking services, particularly through CUS support systems, personalized banking experiences, and recommendation systems aimed at optimizing consumer experiences. The bank's adoption of AI technologies made it an ideal context for this research, as it allowed the study to directly assess the interaction between AI tools and COB in a financial services setting.

The research design was descriptive and cross-sectional, with the data collected at a single point in time from a sample of 391 CUSs. This design allowed the researchers to examine the prevalence of AI usage and its RS to COB outcomes within the study population. The cross-sectional nature of the study ensured that the RSs between AI use and behavior were assessed based on actual usage patterns at the time, rather than predicting future behaviors, providing a more accurate reflection of the immediate impact of AI technologies on consumer decisions.

The data collection tools were carefully selected to ensure that all relevant variables related to AI and COB were measured accurately. Demographic data such as age, gender, and occupation were collected to understand the characteristics of the bank’s CUSs and how these might influence AI usage and COB. To assess AI usage, a tailored questionnaire was developed based on previous studies that explored AI adoption in consumer-facing industries. Similarly, a COB creativity questionnaire was designed to measure how AI affects consumer engagement and decision-making.

The study used regression analysis to evaluate the RSs between the independent variables (AI usage) and the dependent variables (COB outcomes, including, trust, and engagement). The results from the regression models were crucial in determining whether AI usage had a statistically significant impact on COB in the context of financial services.

The analysis of the data provided clear insights into the RSs between AI usage and several key aspects of COB. The hypotheses formulated at the outset of the study were largely supported by the empirical evidence, and the statistical analyses revealed strong positive RSs between the use of AI and various outcomes related to COB. Below, I will summarize the findings in relation to the hypotheses and discuss their implications.

The study confirmed a strong positive RS between AI usage and COB. This suggests that as AI tools are integrated into consumer-facing services, they Sig. influence consumer decision-making, engagement, and loyalty. The use of AI in personalization, CUS service, and product recommendations was found to enhance consumers’ experiences, leading to increased engagement with the brand and higher levels of satisfaction. These findings are consistent with existing literature that highlights AI’s role in improving CUS experiences by providing tailored recommendations and seamless service delivery.

Trust emerged as a critical factor in the study, with AI tools like automated financial advice and personalized recommendations fostering higher levels of trust in the bank’s services. As trust increased, consumers were more likely to engage in conversion-related actions, such as signing up for new services or repurchasing. This finding reinforces the idea that trust is a key mediator in the RS between AI and COB. Without trust, AI-driven experiences may be perceived as invasive or unreliable, diminishing their effectiveness.

Consumer confidence was Sig. influenced by the bank's use of AI for CRO. Personalized experiences, such as tailored banking services and real-time recommendations, were found to increase consumers' confidence in the brand, making them more likely to engage with the bank and utilize additional services. This is particularly important in financial services, where consumer trust and confidence are paramount for long-term engagement.

This hypothesis was fully supported by the study's findings. AI-powered tools that optimize the consumer experience—whether through personalized services, faster response times, or tailored recommendations—Sig. enhanced the likelihood of CUSs returning to the bank.

AI's ability to foster habitual behaviors was also affirmed in this study. As consumers engage with AI-driven services over time, they develop habits and routines that increase their likelihood of returning to the bank. This is particularly relevant in the Digi era, where ease of access and convenience can lead to habitual interactions with online platforms, reinforcing brand loyalty and increasing the likelihood of repeat business.

Lastly, the study confirmed the important role of online reviews in building consumer trust, especially when AI algorithms are used to recommend reviews that align with a consumer's past behavior and preferences. The conclusion emphasizes that the results reflect the Libyan Islamic Bank sample while simultaneously reflecting the broader Digi environment.

5.2. LIMITATIONS OF THE STUDY

This study offers a meaningful look at how AI influences COB in Digi environments, with data collected from CUSs of the Libyan Islamic Bank, but it's important to recognize its boundaries. Understanding these limitations helps place the findings in the right context and shows where future research can pick up.

First, the study is not limited to banking services but also encompasses Digi COB. This means that the results are shaped by a unique mix of local culture, religious principles, and the Libyan economic environment. Things like trust, habits, and how people perceive usefulness might play out differently in, say, a European commercial bank or a Southeast Asian fintech context. So, while the insights are valuable, we should be cautious about applying them directly to other settings without further testing.

Another point to consider is the research design. Because we collected all the data at one point in time, we can confidently show that certain factors are strongly related—like AI use and COB—but we can't definitively prove that one causes the other. It's like taking a photograph of a moving car: you see where it is, but not how it got there or where it's going next. A longer-term study that tracks CUSs before and after new AI tools are introduced would help solidify those cause-and-effect claims.

Finally, since we relied on the same people to report on both their experiences with AI and their own behaviors, there's a possibility that the strength of some RSs was slightly amplified—a common challenge in survey-based research known as common method bias. We used reliable measurement scales to minimize this, but it's still a factor to keep in mind.

None of these limitations undermine the importance of what we found; instead, they help us interpret the results realistically and point toward interesting questions for next time—like exploring different cultural contexts, using longitudinal tracking, or even integrating actual Digi usage data to complement consumer perceptions.

5.3. SUGGESTIONS

Developing AI-Driven Personalization Strategies: To foster consumer trust and engagement in digital environments, businesses must leverage AI-driven personalization. By harnessing advanced algorithms, businesses can provide personalized product recommendations, dynamic content delivery, and automated support systems that resonate with individual consumer needs. Here’s how businesses can implement these strategies effectively:

Personalized Product Recommendations: AI systems can analyze consumer behavior—such as browsing patterns, past purchases, and preferences—to provide tailored product suggestions in real-time. By delivering what the consumer is most likely to want, AI creates a sense of relevance, improving both the user experience and conversion rates.

Dynamic Content Delivery: Content personalization through AI involves delivering dynamic experiences that adapt based on user behavior and preferences. For example, a website might show different home page layouts, offers, or articles depending on whether the user is a new visitor, a frequent shopper, or someone with a specific interest.

Automated Customer Support Systems: Chatbots and virtual assistants powered by AI can provide quick, 24/7 support. By analyzing customer queries and providing personalized responses, AI-driven support tools build trust by offering immediate, relevant help that aligns with consumer needs.

Fostering Trust-Conducive Behaviors in AI Systems: Trust is a fundamental driver of consumer behavior (COB) in the digital world. AI systems must prioritize transparency, privacy, and credibility to ensure trust-building in consumer-facing processes. Here's how businesses can ensure these aspects:

Transparency: To build consumer confidence, AI systems must be transparent in how data is used, how decisions are made, and how recommendations are formed. Clear communication about the data collection process and AI's role in decision-making allows consumers to feel more in control and less apprehensive about algorithmic processes.

Privacy: AI-driven systems should implement robust privacy protections to ensure that consumer data is securely stored and used ethically. Compliance with regulations like the GDPR (General Data Protection Regulation) is essential to maintain consumer trust, especially in financial institutions and services where data security is paramount.

Credibility: Businesses should ensure that the AI tools they use are accurate and reliable. If consumers encounter errors or inconsistencies in AI-driven recommendations or support, it undermines their trust. Continuous evaluation and refinement of AI systems to improve performance and reliability are essential for maintaining credibility.

Leveraging AI for Social Engagement and Feedback Loops:AI can be a powerful tool for creating and fostering user-generated content (UGC) and building loyalty-based social interactions. These are key strategies for enhancing brand engagement and trust:

Encourage User-Generated Content: AI can help identify trends in customer feedback, reviews, or social media posts and surface relevant user-generated content that enhances brand visibility. By using AI to curate positive UGC, brands can amplify authentic testimonials and experiences, which help build trust.

Loyalty-Based Social Interactions: AI can also personalize loyalty programs based on user data, enabling businesses to deliver customized rewards, exclusive offers, or engagement opportunities that resonate with individual consumers. Over time, this can enhance customer satisfaction and loyalty.

Accounting for Trust in CRO: When integrating AI into the Conversion Rate Optimization (CRO) process, it’s critical to account for trust. Trust-building elements are pivotal for driving successful conversions. Businesses should incorporate the following into their AI-driven CRO strategy:

Secure Payment Options: Ensuring that customers feel their financial transactions are safe is crucial. AI can be used to streamline secure payment processes, detect fraud, and ensure that customers’ personal and payment information is protected.

Reliable Customer Reviews: AI can be employed to analyze and filter reviews for authenticity, ensuring that only genuine customer feedback is presented to potential buyers. This transparency in review systems builds credibility and trust.

On-Time Customer Support: Automated support systems driven by AI can ensure that customers receive timely responses, whether it’s via chatbots, email, or phone. Fast resolution of queries or concerns strengthens trust and encourages conversions.

Longitudinal and Experimental Design for Studying AI's Impact on Consumer Behavior.To comprehensively understand the impact of AI on consumer trust and behavior, businesses and researchers must employ longitudinal and experimental designs:

Longitudinal Studies: These studies track consumer behavior over an extended period to capture the temporality of AI’s influence. For instance, a business could study how the introduction of AI-powered personalization affects trust and consumer engagement over six months or a year.

Experimental Design: Experimental methods allow for causal isolation by testing specific variables and measuring their impact. For example, businesses could conduct A/B tests comparing the effectiveness of AI-driven recommendations versus non-AI alternatives to see how they influence consumer trust and behavior.Implications for Researchers and Practitioners. This research has significant implications for both academics and practitioners:

For Researchers: The findings add to the growing body of knowledge on AI's role in consumer trust and behavior in digital environments. Future research could delve deeper into the long-term effects of AI on consumer loyalty and trust or explore industry-specific AI impacts (e.g., financial institutions vs. e-commerce). For Practitioners: Businesses, especially those in consumer-facing services (e.g., banking, retail, and online services), must integrate AI tools thoughtfully to maximize customer satisfaction, trust, and loyalty. For institutions like Libyan Islamic Bank, AI could play a transformative role in enhancing customer experiences, driving growth, and building stronger RSs with clients.

5.4. CONTRIBUTION OF THE STUDY

While the global debate on AI in Digi consumer environments is growing, most research has focused on Western or developed markets. This study enters lesser-known territory by focusing on data collected from the Libyan Islamic Bank—a context rich with unique cultural, religious, and economic characteristics. We not only ask whether AI influences COB; we also explore how this influence manifests itself in a specific, non-Western environment.

The primary impact of this work is its ability to provide a clear, evidence-based model linking specific AI applications—such as chatbots, personalized offers, and recommendation systems—to the underlying psychological drivers of Libyan consumers, such as trust, habit, and their reliance on social proof. For practitioners and policymakers, our findings provide a practical roadmap, demonstrating which improvements are most likely to resonate with their CUSs (such as improving online experience or building trust). For the academic community, this research contributes to a validated framework that can be tested in other emerging or Islamic markets, helping to build a more nuanced global understanding of the role of AI in the financial sector.

Our findings go beyond theoretical speculation to provide concrete, data-driven insights. The most important contribution of this study is the clear empirical evidence it provides on how AI impacts COB in a real-world setting that has not been adequately researched. We show that in the context of the Libyan market, AI is not just a technological upgrade, but a powerful tool that directly enhances CUS RSs.

The study uncovers the mechanisms behind this effect: AI builds trust through trusted interactions, provides habit-forming convenience, and makes information like online reviews seem more useful. This nuanced understanding is crucial. It means that banks' strategies can now be more nuanced; rather than simply "implementing AI," managers can focus on AI that builds trust or simplifies decision-making.

In essence, this research provides a bridge between TEC and human psychology in a non-Western context. This study provides researchers with a validated model for application elsewhere, and gives practitioners in similar markets an evidence-based guide to using AI not only for efficiency, but also to build deeper, more loyal consumer RSs.

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APPENDIX 1 – ORIGINALITY REPORT

ANKARA BİLİM ÜNİVERSİTESİ

T.C.
ANKARA BİLİM ÜNİVERSİTESİ
LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

Doküman No	ABU-LEE-0012
Yayın Tarihi	00.00.2025
Revizyon Tarihi	
Revizyon No	

MASTER'S THESIS ORIGINALITY REPORT

ANKARA SCIENCE UNIVERSITY
GRADUATE EDUCATION INSTITUTE
BUSINESS ADMINISTRATION DEPARTMENT

Date: 10/10/2025

Thesis Title : **THE EFFECT OF USING AI ON CONSUMER BEHAVIOR**

According to the originality report obtained by myself/my thesis advisor by using the Turnitin plagiarism detection software and by applying the filtering options checked below on 8/10/2025 for the total of 76 pages including the a) Title Page, b) Introduction, c) Main Chapters, and d) Conclusion sections of my thesis entitled as above, the similarity index of my thesis is 18%.

Filtering options applied:

1. ☒ Approval and Decleration sections excluded
2. ☒ Bibliography/Works Cited excluded
3. ☒ Quotes excluded
4. ☐ Quotes included
5. ☒ Match size up to 5 words excluded

I declare that I have carefully read Ankara Bilim University Graduate Education Institute Guidelines for Obtaining and Using Thesis Originality Reports; that according to the maximum similarity index values specified in the Guidelines, my thesis does not include any form of plagiarism; that in any future detection of possible infringement of the regulations I accept all legal responsibility; and that all the information I have provided is correct to the best of my knowledge.

I respectfully submit this for approval.

Date and Signature

Name Surname: Mohammed Abdullah Alashiq

Student No: 235020001

Department: BUSINESS ADMINISTRATION

Program:

ADVISOR APPROVAL

APPROVED.

Prof. Dr. Cem Harun MEYDAN

APPENDIX 2 – ETHICS COMMITTEE PERMISSION

المصرف الإسلامي الليبي
Libyan Islamic Bank

بتاريخ يوم الخميس
الموافق15-ابريل -25

To Whom It May Concern,

Permission to Conduct Academic Survey

Subject: Approval for Research Project

We are writing to confirm that we have received the request from Mr. Mohammed Alashiq, a Business Administration student with registration number 235020001, regarding his intention to conduct a research project at the Islamic Bank of Libya in Tripoli.

We would like to inform you that we have no objections to Mr. Alashiq proceeding with his research project at our institution. We believe this collaboration will be mutually beneficial.

If you require any further information or assistance, please do not hesitate to contact us.

Sincerely,

Marketing Department

Libyan Joint Stock Company
Tripoli Bank Head Quarter
Commercial Register 48861
Capital: 250 million lyd
Fully Paid

شركة مساهمة ليبية
الإدارة العامة للمصرف طرابلس
السجل التجاري 48861
رأس مال المكتتب فيه 250 مليون د.ل
مدفوع بالكامل

أبومليانة مقابل مسجد القدس | طرابلس - ليبيا
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ANKARA BİLİM ÜNİVERSİTESİ

T.C.
ANKARA BİLİM ÜNİVERSİTESİ
Etik Kurul Başkanlığı

Sayı: 2025/32 3/3/2025

Konu: Etik Kurul Onayı

Sayın Mohammed Abdullah Alashiq;

"The Effect of Using Artificial Intelligence on Consumer Behavior" isimli çalışmanız için Ankara Bilim Üniversitesi Etik Kuruluna yaptığınız başvuru 3/3/2025 tarihinde icra edilen etik kurul toplantısında görüşülmüş ve çalışmanın yürütülmesinin Ankara Bilim Üniversitesi Bilimsel Araştırmalar ve Yayın Etiği Yönetmeliği'ne uygun olduğuna oy birliği ile karar verilmiştir.

Prof. Dr. Yavuz Demir
Rektör / Etik Kurulu Başkanı

APPENDIX 3 – QUESTIONNAIRE

Questionnaire

This questionnaire is a part of a scientific study. We invite you to participate in a research entitled "The effect of using AI on consumer behavior" Participation in this study is completely voluntary. Your response to the research will be interpreted as your consent to participate in the research. Personal information obtained from these forms will be kept strictly confidential and will be used for research purposes only.

Mohammed Alashiq

Section 1: Socio-demographic Questionnaire

"Age"	
"Gender"	☐ Female ☐ Male
Education	☐ Primary or below ☐ Secondary ☐ Diploma/high diploma/ associate degree/ ☐ certificates ☐ Tertiary/University ☐ Post-graduate or above
Occupation	☐ Professional/consultant ☐ Academic ☐ Technician/Operator ☐ Clerical/Administrative ☐ Manager/Executive ☐ Others

Section 2: Use Artificial Intelligence (ARI)

Items		5	4	3	2	1
Artificial Intelligence Technology (AIT)	Artificial intelligence applications in digital platforms are useful for the audience, image, and sentiment analysis					
	AR (augmented reality) and VR (virtual reality) are used in digital platforms					
	Audience analysis is a fundamental pillar of digital platform strategies adopted by firms					
	Artificial intelligence technologies use multiple types of customer-related data, such as purchases, sales, or behavioral and demographic data					
	Artificial intelligence tools for brand logo recognition open avenues to analyze digital platform users' interests					
	The employment of automatic image annotation tools may lead to many possible benefits, even for user expectations in digital environments					
	Artificial intelligence techniques lead to classifications and clusters of user-generated content based on variables such as tone, sentiment, or topic					
	Through the sharing of images, users can also express their sentiments, and therefore, digital platform images can offer a rich and useful resource to identify and value users' sentiments					
Consumer Engagement on Social Media (CESM)	Using digital platforms gets me to think about it					
	I think about digital platforms a lot when I am using them					
	Using digital platforms stimulates my interest to learn more about brands					
	I feel very positive when I use digital platforms					
	Using digital platforms websites makes me happy					
	I feel good when I use digital platforms					
	I am proud to use digital platforms					

Conversion Rate Optimization (CRO)	Free trial options or discounts attract me to use digital platforms					
	Flexible return or cancellation policies attract me to use digital platforms					
	Digital promotions and personalized messages influence me to use online services					
	The frequency of promotional or reminder messages on digital platforms has a significant impact on me					
Satisfying consumer Experience (SCE)	Consumer needs for interactive, collaborative, and personalized interactions have been strongly influenced by the rapid development of digital platforms					
	Using digital platforms shows the hedonic behavior of consumers					
	Using digital platforms shows the pragmatic behavior of consumers					
	Using digital platforms shows the sociability behavior of consumers					
	Using digital platforms s shows the usability behavior of consumers					
Habit (HAB)	I frequently use digital platforms for online activities					
	Using digital platforms has become a usual activity for me					
	Whenever I think of online activities, a specific platform comes to my mind					

Section 3: Consumer Behavior (COB) (Ventre; Kolbe, 2020)

1.Strongly disagree 2. Disagree 3. Neutral/Uncertain 4.Agree 5.Strongly agree

Items		5	4	3	2	1
Trust	I am confident in using secured digital platforms to get what I need					
	I feel safe using digital platforms that protects my privacy.					
	I believe a secured digital platform will safeguard my private information.					