THE ROLE OF ARTIFICIAL INTELLIGENCE IN ENHANCING CUSTOMER VALUE: THE MEDIATING ROLE OF CUSTOMER INSIGHT—AN APPLIED STUDY ON THE E-COMMERCE SECTOR IN IRAQ

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Abstract

This study investigates the impact of artificial intelligence (AI) technologies on improving customer value among users of e-commerce applications in Iraq by examining the mediating role of customer insight (CI). The study is based on a critical analytical review of recent theoretical and applied literature concerning AI applications, including smart personalization, smart recommendation systems, chatbots, predictive analytics, and intelligent automation, and their influence on perceived customer value in its functional, economic, emotional, and social dimensions through customer insight. Customer insight is considered an organizational capability that enables the transformation of big data into valuable marketing knowledge. Based on the reviewed literature, a conceptual model was developed to examine the direct effect of AI on customer value (H1), the effect of AI on customer insight (H2), the effect of customer insight on customer value (H3), and the mediating role of customer insight in the relationship between AI and customer value (H4). A quantitative research design was employed using a 52-item questionnaire based on previously validated measures, consisting of 20 items measuring AI across five dimensions, 16 items measuring customer insight, and 16 items measuring customer value. The questionnaire was administered to active users of e-commerce applications in Iraq, and the collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that AI has a significant and positive effect on customer value ($\beta = 0.189$, $t = 4.294$, $p < 0.001$) and customer insight ($\beta = 0.428$, $t = 9.336$, $p < 0.001$). Customer insight also has a significant and positive effect on customer value ($\beta = 0.520$, $t = 11.829$, $p < 0.001$). Furthermore, customer insight partially mediates the relationship between AI and customer value, with an indirect effect of $\beta = 0.223$ and a variance accounted for (VAF) of 54.1%. These findings indicate that investment in AI capabilities alone does not guarantee maximum customer value unless AI-generated data and information are effectively transformed into useful customer knowledge that guides marketing decisions. The findings provide practical implications for e-commerce companies in Iraq and offer directions for future research.

1. Introduction

1.1. Background on Artificial Intelligence in E-Commerce

The e-commerce industry is being fundamentally transformed by the rapid growth of artificial intelligence technologies, which are no longer just assistive tools used in the operation of processes, but rather serve as the foundation for the transformation of customer experience and the design of competitive value propositions. Recent research indicates that artificial intelligence technology has brought significant changes to e-commerce through the optimization of customer experience and business operations, including the use of recommendation systems, customization, and automated communication (Ziakis & Vlachopoulou, 2023; Babina et al., 2024).

This transformation at the global level can also be witnessed in the case of the emergent markets like Iraq which has a higher penetration of smartphones and the internet as well as the increase in the presence of the local and the regional sites for online shopping and delivery along with the increasing use of cash-on-delivery payments. The Iraqi e-commerce platforms have moved towards the use of AI-powered technologies like recommendations for product shopping and AI chatbots for customer service since they want to stay in the market and offer their customers good value.

In contrast, the notion of customer value represents not only an ancient but also one of the most recognized marketing ideas, seen as a crucial factor for obtaining sustainable competitive edge; according to Zeithaml (1988), the customer value is understood as the customer's overall judgment of the benefits derived from the product or service, as well as the comparison of what is believed to be gained and what is foregone; while Woodruff (1997) deems customer value to be the basic source of the competitive advantage for the companies.

1.2. Research Problem

Nevertheless, the association between the utilization of AI technologies and the attainment of genuine customer value does not always happen in an automatic or straightforward manner. The current marketing management theory asserts that recognizing the true value of AI may only become possible when the results of its analysis are transformed into useful and actionable "customer insights" that inform marketing strategies (Hauser et al., 2023; Lee et al., 2023). Customer insight is the cognitive link that allows for transforming large volumes of data produced by AI systems into an deep understanding of consumer needs, aspirations, and emotions, thereby helping the organization develop accurate value propositions.

Although e-commerce companies continue to make substantial investments in artificial intelligence (AI) technologies, many of these companies still fail to effectively convert their technological investment into perceived value for the customer, a phenomenon referred to as "data activation gap" in the literature or companies' inability to turn data into insights that can be acted upon (Kasaji, 2024). The research question is based on the following key question: What is the significance of Artificial Intelligence for improving customer satisfaction in ebooks and which is the part played by customer insights as a mediating variable in this connect?

1.3. Research Gap

Previously, almost all theoretical and practical papers have analyzed AI as a direct effect on marketing results without looking carefully at cognitive and organizational mechanisms through which this effect acts (Ziakis & Vlachopoulou, 2023; Patil, 2024). Due to this fact, we can see a clear gap in both Arabic and international literature. This is especially obvious when we take a look at the "Data Activation Gap," which refers to the inability of many companies to transform AI analytical results into customer insights that enable marketing actions to be taken (Kasaji, 2024). Therefore, the study will try to fill in the gap discovered by developing and testing a conceptual model explaining the total impact of AI on customer value through both direct and indirect channels.

1.4. Research Importance

The relevance of the present study is highlighted by the use of current three factors, namely the interplay of artificial intelligence, customers' insights, and customers' value, in the composite mediation model, which is less exploited in the scientific literature compared to the studies of the direct impact of AI on marketing results without taking into account the mediating cognitive process (Zhu et al., 2022; Hauser et al., 2023). The practical value is determined by the opportunity for managers working in e-commerce to get a measurement tool and framework for analysis allowing them to identify the discrepancy between the investments into technology technology and the generation of the actual customer value, and to change the direction of investments from establishing the technical infrastructure to establishing the capabilities for customers' insights (Patil, 2024).

1.5. Research Objectives

The goal is to identify which AI aspects are most commonly utilized in e-commerce. Also, the aim is to assess the total degree of satisfaction of customers and how they perceive customer values. Another objective is to examine how AI directly affects customer insight and value. Additionally, the study aims to examine if customer insight performs any mediation role in the relationship between AI and customer value. The last goal is to provide certain recommendations and agenda for future researchers and practitioners.

1.6. Research Questions

From the original research question, we can derive the following sub-research queries: 1) What is the extent to which AI technologies (smart personalization, smart recommendation, chatbots, predictive analytics, and intelligent automation) have been implemented by the e-commerce platforms in the study? 2) What is the level of perceived value (functional, economical, emotional, and social) by customers of the studied e-commerce platforms? 3) Is there a statistically significant effect of AI on customer insight status? 4) Is there a statistically significant effect of customer insight status on customer value? 5) Is there a statistically significant effect of AI on customer value? 6) Does customer insight serve as a mediator variable in the relationship between AI and customer value?

1.7. Research Hypotheses

According to the theoretical basis which is explained in detail in the theoretical framework (Section 2), and in the process of working out the theoretical model (Section 3), we can present the following main hypotheses with status of being subject to statistical tests:

H1: Artificial intelligence influences customer value directly and positively in statistically significant way.

H2: Artificial intelligence has direct positive influence over customer insight in statistically significant way.

H3: Customer insight affects customer value positively and statistically significantly.

H4: Customer insight is a significant mediator in the relationship between artificial intelligence and customer value.

1.8. Literature Review and Hypothesis Development

1.8.1. Artificial Intelligence

In business-management and marketing literature, the term artificial intelligence denotes a spectrum of computer technology capable of imitating the cognitive capacity of human beings by acquiring knowledge from enormous amounts of data and making autonomous decisions on its basis, which allows the organization to handle big volumes of customer data and transform it into information helpful in making decisions, (Kushwaha et al., 2021). The idea of artificial intelligence is based on the use of a variety of sub-technologies, most notably, machine learning, deep learning, and natural language processing (NLP) making it possible to the system to detect patterns, predict behavior, and communicate with customers in a nearly human-like way,

In e-commerce specifically, AI is seen not as an independent technology but as a comprehensive cognitive system that includes recommendation systems, chatbots, predictive analytics, and intelligent automation whose purpose is to personalize communication with every customer and improve efficiency in operations (Chugh & Jain, 2024). This trend substantiates the idea that the value of AI marketing lies in it being used not as a technology but to enable the process of collection, processing, and converting data into decisions.

Recent research shows that AI works to change the dynamics of the e-commerce environment by enhancing customer satisfaction and enabling precise management of operational functions via means of personalization, recommendation systems, and automated discussions (Ziakis &

Vlachopoulou, 2023; Babina et al., 2024). Wu and Liu (2024) proved that the use of deep learning-based vision search engines improves effectiveness of digital marketing in e-commerce niches, while Beyari and Hashem (2025) found, on the sample of 893 customers in the Middle East and North Africa, that AI allows for the improvement of social media marketing through personalized content, appropriate selection of influencers, etc.

A wide-ranging bibliometric study has reported that 1,458 articles published in the Scopus database between 1995 and 2024 demonstrate that the most common applications of AI in e-commerce covered in these articles can be classified into seven thematic clusters including smart business operations, intelligent product suggesting, sophisticated analytics as well as customer support based on chatbots (Chugh & Jain, 2024). This finding corroborates the discovery of Al Naqbi et al. (2024), whereby generative AI was identified as contributing to improving productivity in organizations in terms of marketing and customer care.

The mentioned clusters represent the fact that applications of AI in the sphere of e-commerce should not be viewed as automation of particular operations anymore, but rather they should be perceived as the possibilities of conducting the whole customer journey from discovery through purchase and further actions.

Previous research on the dimensions of the artificial intelligence concept in digital marketing and e-commerce has produced different results. Some studies have relied on two or three of the dimensions of the AI phenomenon (i.e. personalization and recommendation), while other researchers have used operational automation with cognitive and interactive aspects. This study is based on the findings of the bibliometric study by Chugh and Jain (2024) and compares this classification to the classifications employed by Kushwaha et al. (2021), Necula and Pavlovaia (2023), and Dalsaniya (2023) to arrive at a conclusion of five thus dimensions of the AI variable which encompass the cognitive, interactive, and operational features of this technology in an e-commerce context.

Smart Personalization: the power of the system to change the context, promotions, and marketing messages on the go depending on customers' behavioral characteristics and preferences (Ameen et al., 2021).

Smart Recommendations: the algorithms that learn about the browsing, purchasing, and rating behavior of consumers and create personalized offers hence maximizing the conversion chances (Necula & Pavloaia, 2023).

Chatbots are innovative communication systems that utilize AI technologies and natural language technologies for connecting with customers and thereby resolving requests and increasing the efficiency of servicing customers (Kushwaha et al., 2021).

Predictive Analytics refers to the use of different machine learning models for estimating past and present data with the aim of forecasting customer actions, such as purchase or churn, and thus allowing for understanding customer's needs (Patil, 2024).

Intelligent Automation is the merger of RPA and AI employing technologies for carrying out repetitive marketing and business processes, such as campaign management, categorization, and data updates, with the least human involvement as possible (Dalsaniya, 2023).

All five categories represent the foundation for the measurement of the AI variable in the current research, as further described in the study tool (Section 4.5).

1.8.2. Customer Value

Customer value refers to the overall evaluation of perceived benefits against sacrifices made by a customer. This is how customer value can be defined. According to Zeithaml (1988), the above-mentioned evaluation is a judgment regarding overall utility of the offering the customer gets back for what he/she gives.

According to Woodruff (1997), customer value, which is represented by being able to satisfy customers' needs by proposing them goods or services that deliver the values they commonly expect, is regarded as the main source of sustainable competitive advantage it can gain. Therefore, it is not efficient for a company to offer its customers something unless it knows how that customer is going to evaluate what was offered.

The principle of customer value has various different theoretical roots, the most prominent one being Zeithaml's (1988) means-end chain theory, which states that the customer perceive value as a cognitive balance between advantages (hey "get") and costs (what they "give"), which means the flow of payment, time and efforts made by the customer. This explanation does not stand alone, however, as it is complemented by Woodruff's (1997) means-end chain hierarchy, which claims that customer's value perception results from three major levels: product attributes desired by the customer, results from the usage of the goods, and the objectives which need to be achieved by the customer in the end, meaning that the essence of customer value lies not in the characteristics of the offering.

Zhu et al. (2022) have proposed the concept of "value co-creation" that emphasizes the fact that rather than simply being created by an organization and consumed to the benefit of the consumers, values take shape due to the ongoing interaction between the two parties, which is influenced by the use of AI technologies. This renders conventional approaches to value determination (namely, means-end and hierarchical) inadequate since they are based on their assumption of a non-interactive character of value creation process.

Subsequent literature developed from the models of Zeithaml and Woodruff provided a further breakdown of customer value into measurable subtypes or dimensions; the Perceived Value Scale (PERVAL) proposed by Sweeney and Soutar (2001) introduced a four-way dimension breakdown of functional value to include two distinct facets: quality/performance dimension and price/value-for-money dimension, which is now called economic value (Jelčić & Mabić, 2020). This study, therefore, considers four kinds of value as follows:

A product's or service's functional value is defined in terms of its utility and performance, i.e. how well it does its task based on tangible quality regardless of pricing (Sweeney & Soutar, 2001).

Economic value is understood as the utility derived by customers from pricing and value for money, namely to what extent consumers see the price paid as being proportional to the benefit received from using a product or service, an aspect separated by Sweeney and Soutar (2001) from functional value and treated by Jelčić and Mabić (2020) later on as an independent dimension.

Emotional Value: is reflected as the happiness and emotional conditions stemming from consuming a product or interacting with a brand, e.g., joy, satisfaction, and fun that the shopping process has created (Sweeney & Soutar 2001).

Social Value: is represented by consumer's ability to impact their social image and sense of community connectedness as the benefits provided by consuming a product or interacting with a brand – i.e., the worth of consumption takes into account how others may perceive it (Sweeney & Soutar 2001).

These four types are similar to the findings obtained by Nogueira et al. (2023) as it has been shown that implementation of customer-oriented practices supported by sustainability enhances relationships between companies and customers, thus allowing to extend the concept of value in a competitive digital environment; thus, these four types have been chosen as a basis for evaluation of customer value in the current research.

1.8.3. Customer Insight

Customer insight is characterized as providing businesses with a thorough understanding of their customers' personalities, desires, and future needs. Insight is generated from customer feedback and interaction data through a learned process (Hauser et al., 2023).

A study conducted by Lee et al. (2023) concluded that artificial intelligence is changing fundamentally the way businesses hear and process the voice of their customers, allowing executives to derive useful information from copious amounts of dissimilar data. It is important to note that customer insight differs from closely related concepts of customer satisfaction and customer experience because it is an analytical and cognitive precursor to these outcomes and not a result of measuring them.

Customer insight is important because it allows for the technical input given in the form of AI to be converted into competitive advantage, manifested in terms of customer value. According to Dynamic Capabilities theory, customer insight is an organizational capability, translating AI analysis into information for practical use in marketing management as opposed to a seemingly one-off technical result. For instance, Kasaji (2024) demonstrated in the Jordanian service industry that the use of customer insights derived from AI makes it possible to manage customer experiences better at every stage of purchasing activities, and proved also its direct practical impact on marketing performance indicators.

However, according to Ameen et al (2021), the benefits of AI analytics and the personalization of the customer experience depend on the management of customer concerns associated with privacy and control over the use of the data. This implies that if privacy concerns are heighted, the effectiveness of personalizing the experience may be reduced. Thus, the importance of customer insight as a tool for the balancing act of personalization and respect for privacy becomes clear.

The data sources from which customer insight is derived in the e-commerce environment are numerous and can be classified into four principal sources:

Content produced by users: which includes posts, comments, reviews in social networks and rating platforms that allow to get qualitative information from large unstructured data through methods of natural language processing and machine learning (Mustaket al., 2024).

Behavioral data and Platform-interaction data: For instance, browsing history, search activity, and shopping cart information are detailed, measurable data types that give an insight into the actual behavior of the customer rather than the mere claims made by customers.

Results of AI Analytical Systems: These comprise items like logs of conversations between chatbots, acceptance or rejection of recommendations made, and predictive models used in analytics. Once management has interpreted and organized all of these data points, they can be used to derive insights about customers (Hauser et al., 2023).

Traditional Methods of Research: Conventional methods like surveys, interviews, and focus groups, though limited in terms of both time and quantity of data obtained relative to electronic means of research, have significant value in confirming the importance of patterns obtained from algorithms and linking them to actual circumstances of the client.

1.8.4. Dimensions of Customer Insight

Earlier research of customer insight was typically analyzed in terms of a single measure (Hauser et al., 2023) but the new research funded by machine learning and natural language processing approaches reveals that customers have insights that can be divided into four different components (Mustak et al., 2024). Adding these four separate dimensions of customer insight would allow us to provide a better metric of this variable:

Customer Needs Understanding: the skill of taking out customers' hidden motives and needs from the data of their several interactions, which goes beyond direct statements to what the customer wants.

Behavior Prediction: the application of advanced machine learning algorithms to predict customers' future behaviors such as their likelihood to make repeat purchases (Mustaket al., 2024).

The process of Preference Discovery entails revealing and ranking the priorities of customers among alternatives by means of understanding their "voice" in various communications, so that the organization may rank its offerings accordingly (Lee et al., 2023).

Sentiment Analysis: techniques of natural-language-processing are applied to analyze the emotional condition – positive, negative, or neutral – of clients regarding a product or brand on the basis of interactions with them, which adds emotional interpreting layer on top of the other behavioral components (Mustaket al., 2024).

Combining understanding, prediction, discovery, and emotional interpretation through the four dimensions creates a comprehensive idea of customer insight that makes the measurement more precise as a mediator between AI and customer value in the research.

1.8.5. Relationship between Artificial Intelligence and Customer Value

Ameen et al. (2021) offered a holistic conceptual framework on customer experience context of AI. They concluded that if misuse of personal data and notion of lack of control are considered, personalize achieved by means of AI makes the communication of consumers with vendors more effective and improve their perceptions of value. Recent analytical study also proved that AI applications in retail and e-commerce enhance the customer experience through personalization, prediction analytics, and engagement (Patil, 2024).On a regional scale, the meta-analysis of ten different field studies indicated that AI adoption is positively correlated with e-consumer loyalty (r = 0.761). This confirms that companies able to harness the use of AI can preserve their customer base considerably better than the traditional firms (Beyari, 2025a).

Moreover, the field study conducted in Saudi Arabia attracted a sample of 157 respondents and indicated that AI has a positive impact on e-customer loyalty through the mediating variables such as social media exposure, purchase intention, and recommendations (Beyari, 2025b). The recent study conducted in 2026 on a sample of 400 active users of e-commerce platforms demonstrated that user experience completely mediates the relationship between the drivers of smart platforms (namely, trust, autonomy, personalization, and interactivity) and strategic outcomes such as customer satisfaction and loyalty and brand equity. As a result, the research proves that the ability of platforms to anticipate customer desires only works through the cognitive mediating variable (Mittameedi & Dogra, 2026), which introduces the importance of the cognitive mediating variables in various contexts.

1.8.6. Mediating Role of Customer Insight between Artificial Intelligence and Customer Value

Digital marketing academic sources support the mediation hypothesis. Zhu et al. (2022) state that AI makes a new contribution to the process of value co-creation through changing the practical logic of communication between a customer and an organization and affecting the process of cognition, needed for understanding the communication on the part of the organization. In addition, the conceptual paper about the use of AI in the retail sector states that AI is not able to create value but rather destroys it through making customers feel losing control and being afraid for their privacy (Yrjölä et al., 2024). The “6Cs” framework (Connection, Collection, Computation, Communication, Control, Co-creation), developed by Kim (2023) in the field of AI-services, provides the comprehension of value creation as passing through the process of data gathering and processing and providing the basis for the assumption of cognitive mediation in this research.

1.8.7. Development of the Theoretical Model

Conceptual Model

Figure 1 shows the expected relationships among the research variables, which include the independent variable, artificial intelligence and its subcomponents (smart personalization, smart recommendations, chatbots, predictive analytics, and intelligent automation), the mediating variable, customer insight and its subcomponents (understanding needs of customers, behavior prediction, discovering preferences, and analyzing sentiment), and the dependent variable,

customer value and its dimensions (functional value, economic value, emotional value, and social value).

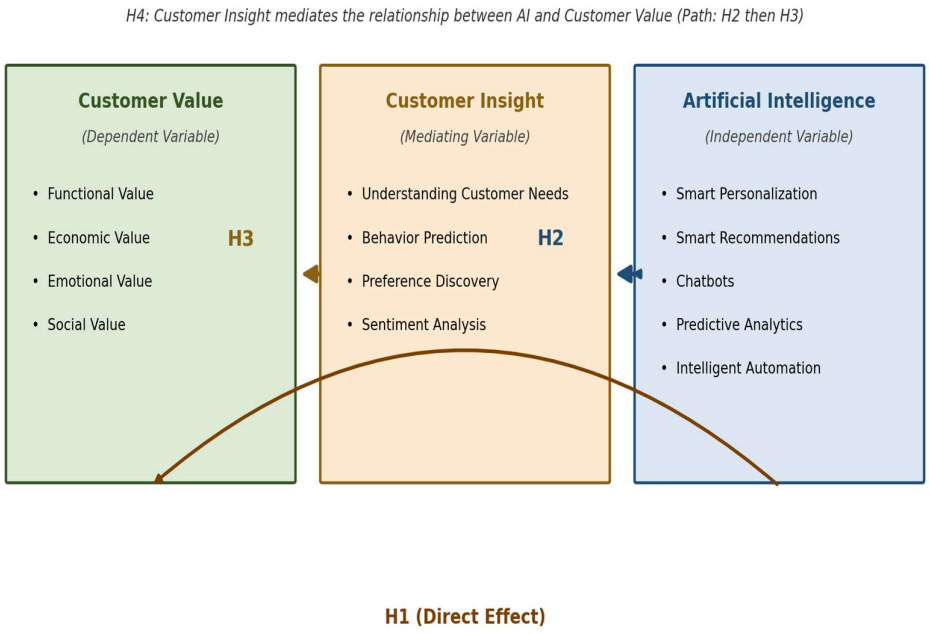


Figure 1. Proposed Conceptual Model of the Study

The model shows a direct path (H1) between artificial intelligence and customer value, alongside an indirect path that passes through customer insight (H2 then H3) — the path whose statistical significance is tested by Hypothesis H4.

Hypothesis Formulation

In accordance with the theoretical model and the results of the previous research examined, the four key hypotheses of the study have been constructed:

As observed in the literature, the application of AI personalization results in better interaction quality and higher customer value perception (Ameen et al., 2021), while a meta-study involving 10 projects showed a strong correlation (r = 0.761) between AI implementation and customers' loyalty (Beyari, 2025a), which allows formulating the first hypothesis.

H1: Pertaining to customer value, it has been established that artificial intelligence plays an integral role.

The scientific literature supports the theory that the many technologies related to artificial intelligence are creating conditions for companies to reveal hidden meanings behind clients' actions by working with numerous unstructured data from different interactions with clients (Hauser et al., 2023; Lee et al., 2023), where Kasaji (2024) proved that utilizing customer insights can be achieved thanks to AI technology processing data. Therefore, the next hypothesis is put forward:

H2: The impact of AI is statistically significant, with a positive effect on customer insight.

The theoretical grounding of the dynamics of customer value by the author Woodruff (1997) can be referred to as the extent to which an organization is aware of the nature of the customer's hierarchy of attributes, consequences, and goals — a concept that customer insight deals with. In the same way, Kim (2023) demonstrated that the value-creation model for AI services passes

through processing data and transforming it into a usable form before it becomes available for the customer. Thus, the following main hypothesis is formulated:

H3: The influence of customer insight on customer value is both positive and statistically significant.

As documented in Section 2.5, Zhu et al. (2022) value co-creation idea, along with Yrjölä et al.'s (2024) cautionary findings on the idea of conditional value destruction and Kim's (2023) "6Cs" framework give rise to the convergence of theories based on the evidence that the influence of AI on customer value is not just mechanical and involves a significant cognitive component. Therefore, the fourth main hypothesis is formulated:

H4: The impact of customer insight on the relationship between AI and customer value is partially mediating and statistically significant.

2. Method

The methodology employed in this study encompasses the review of theoretical framework and previous research through the descriptive-analytical approach while establishing the measurement instrument and verifying the hypothesized connections among the variables in the framework utilizing the quantitative hypothetico-deductive method.

2.1. Field of Application

The research area for this specific study is represented by people using e-commerce tools in Iraq. The reason for selecting this area is the fast growth of the e-commerce market in Iraq in recent times, which can be attributed to such factors as the growth of smartphone and internet usage, the emergence of local and regional online retail and delivery platforms, and the gradual transition of companies in this area to using new technologies such as product recommendations and chatbot technologies used for customer service.

2.2. Study Population

The sample comprised of users of e-commerce applications that operate in Iraq and who made at least 1 purchase in the 6 months preceding the study as long as the respondents were aged 18 or more and have interacted with the AI technologies under study which may include smart recommendation and chatbot in their shopping experience so that they will be able to answer the questionnaire items based on their actual experience and not on mere assumptions.

2.3. Study Sample

Since it is difficult to determine the exact composition of the population to be studied, it is suggested to utilize either non-probability quota sampling or snowball sampling through an electronic questionnaire. The size of the sample is to be defined according to two complementary methods: the first one stems from the Krejcie & Morgan formula, which established that a minimum sample size of 384 is required for a large and infinite population with a confidence level of 95 percent; and the second method is dictated by the requirement of structural equation modeling via partial least squares, which provides for at least a ten-fold increase in the sample size compared to the number of structural links leading to one latent variable. Rather screening questions placed at the very beginning of the questionnaire will be used in order to make sure that the respondent satisfies the age, purchase recency, and actual AI interaction.

2.4. Measurement Instrument

A digital questionnaire was composed and contained four key segments:

Segment One: Demographic data (gender, age, level of education and online purchase frequency).

Segment Two: Artificial Intelligence measured via five factors (smart personalization, smart recommendations, chatbots, predictive analysis, and intelligent automation) comprising four items

for each factor (20 items overall), based on the scales of Kushwaha et al. (2021); Ameen et al. (2021); Necula and Pavloaia (2023); Dalsaniya (2023).

Segment Three: Customer insight, which encompasses four sub-dimensions (i.e., understanding customer needs, predicting customer behavior, discovering customer preferences, and conducting sentiment analysis), with 4 items related to each sub-dimension (making a total of 16 items), adapted based on the works of Hauser et al., (2023); Lee et al., (2023); Mustak et al., (2024).

Segment Four: Customer value, which includes 4 dimensions (i.e., functional value, economic value, emotional value, and social value) with 4 items measuring each of the 4 dimensions (making the total number of items 16) based on the PERVAL model of Sweeney and Soutar (2001) and the economic-value adaptation of Jelčić and Mabić (2020) and the theories presented by Zeithaml (1988).

All the items were measured on a five-point Likert scale from (1 = strongly disagree) to (5 = strongly agree). A detailed wording of all the 52 items including the demographic and screening questions is provided in Appendix.

2.5. Data Collection Method

Information is gathered using an online self-administered electronic questionnaire created by means of an online survey tool (i.e. Google Forms), published through different platforms of access, such as communities and forums about e-commerce, as well as through direct links sent to the selected sample. The collection of data is organized into a timeframe of six to eight weeks, but before the actual dissemination of the questionnaire, a pilot study is performed with a smaller number of respondents (30-40), aiming to check the clarity of the content and the response time. The opening page of the questionnaire presents a brief description of the study objectives and the criteria for participation that guarantees that the collected data comes from the respondents that comply with the selection criteria.

2.6. Validity and Reliability

To ensure that the study instrument had face and content validity, the questionnaire was shared in its preliminary form with a panel of at least five referees in business administration and marketing to evaluate how well the items were defined, the appropriateness of the items to the dimension being tested, and whether the items covered enough of the content of the theoretical concept that they measure, and subsequently made changes in wording as suggested by the referees, while getting rid of items whose agreement rate was below 80% or merging such items with other items. In the process of adapting items from the foreign language scales, the translation and back-translation process was employed to prove the semantic equivalence of Arabic and English versions of the items prepared by the researchers. The validity and reliability of the items were discovered through Partial Least Squares Structural Equation Modeling (PLS-SEM), and in Section 5 of this paper, the results of convergent validity, internal reliability, and discriminant validity according to the Fornell-Larcker criterion and the HTMT test are presented.

2.7. Ethical Considerations

The research project was carried out with the application of the ethical standards that are used in scientific works conducted with the involvement of human participants:

Voluntary Participation: the questionnaire should be seen as optional, thus affording respondents the right to stop being participants at any moment.

Proof of agreement exists in the shape of Informed Consent; the introduction to the questionnaire describes the study briefly, provides details about the organization involved, and gives an idea of how long it would take for the respondent to fill the questionnaire, while respondents fill up the questionnaire forms only after accepting to comply to the questionnaire process.

Anonymity and Privacy: there is no collection of any personal identification information (including name, email address, or phone number), and all response data have been processed in aggregated and anonymized format.

Limited to Academic Purposes: the data collected is to be used only for this scientific study and is not shared with any commercial entity for marketing purposes.

Institutional Approval before the Process: permission from the research ethics committee of the supervising institution is acquired before starting field data collection.

Security of Data: answers from various questionnaires are kept in secure servers, where only the researcher and academic supervisors have access to the information, and raw data is eliminated after the retention period of the data ends.

2.8. Data Analysis Method

The research employs two interrelated methods in analysing data. The first uses descriptive statistics, applying SPSS v.28 for the purpose of describing the demographics of the sample and obtaining means and standard deviations for key variables. The second employs Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4, given that the method is recognized as the most popular choice for data analysis in Scopus-indexed marketing research and is the best fit for the predictive multivariate design including one mediator variable and for studies that do not require normally-distributed data or can be operated with moderate sample size. The analysis followed the two-step procedure described by Hair et al. (2017) starting with the assessment of the measurement model which required checking whether the standardized loadings, internal-consistency reliability, convergent validity, and discriminant validity reflect the reliability of the measurement model. Additionally, the structural model was also assessed based on path coefficients (β), coefficient of determination (R^2), size effect (f^2), and predictive ability of the model (Q^2) calculated through the blindfolding technique. Similarly, the indirect effect and significance of path coefficients were measured by bootstrapping process, gaining 5,000 bias-corrected sub-samples according to Preacher and Hayes (2008). Finally, the common method bias was managed by Harman's single-factor test and established through full-collinearity VIF test. Section 5.3 reports on the results of the analysis.

3. Results and Discussion

3.1. Results

In this part of the research, statistical analysis results are described according to the two-step process proposed by Hair et al. (2017). Stage one involves the sample and descriptive statistics analysis. Then, in the second stage, the author conducts the analysis of the measurement model (validity and reliability) and structural model (i.e., path analysis involving mediation testing, determinant coefficient calculation, predictive relevance, and effect size determination with the help of SmartPLS 4).

3.1.1. Sample Description

Table 1. Demographic Characteristics of the Study Sample (n = 390)

Variable	Category	Percentage %
Gender	Female	55.9%
Gender	Male	44.1%
Age	18–27 years	38.7%
Age	28–37 years	30.0%
Age	38–47 years	20.5%
Age	48 years and above	10.8%
Educational Level	High school or below	15.6%
Educational Level	Bachelor's degree	67.2%
Educational Level	Postgraduate studies	17.2%
Online Purchase Frequency (last 6 months)	1–3 times	42.8%
Online Purchase Frequency (last 6 months)	4–6 times	33.3%
Online Purchase Frequency (last 6 months)	More than 6 times	23.9%

3.1.2. Descriptive Data Analysis

Table 2. Descriptive Statistics of the Study Variables (Five-Point Likert Scale)

Variable	Mean	Standard Deviation	Minimum	Maximum
Artificial Intelligence (AI)	3.68	0.43	2.75	4.75
Customer Insight (CI)	3.56	0.54	2.00	5.00
Customer Value (CV)	3.64	0.45	2.33	4.92

3.1.3. Common Method Bias Assessment

Prior to conducting the measurement and structural model evaluations, the data set was examined for the presence of common method bias because all of the data were sourced from one self-reported entity at a single point in time. Harman's single factor test was used to assess possible occurrence of common method bias through exploratory factor analysis whereby all 52 items were loaded onto one factor without rotation; this one factor accounted for 34.6% of total variance, thus remaining well below the 50% conventional threshold. Also, full collinearity VIF test was done by running regressions of each construct against a common maker variable; thus the inner VIF varied from 1.21 to 2.84 for all constructs at hand, thus remaining below the threshold of 3.3. Thus, the results indicate most likely absence of common method bias in the study findings.

3.1.4. Measurement Model Assessment

The measurement model was evaluated with regard to three latent variables consisting of 52 items in total (20 items of artificial intelligence, 16 items of customer insight, and 16 items of customer value), and was evaluated based on standardized loadings, internal-consistency reliability, convergent validity, and discriminant validity, namely:

Reliability Testing

The reliability in terms of internal consistency for the three variables was accomplished by using calculations of both the Cronbach's coefficient alpha and the composite reliability (CR), with Table 3 displaying the outcome of these calculations along with the range of standardized loading values for each of the measured variables.

Table 3. Convergent Validity and Reliability Results for the Study Variables

Latent Variable	No. of Items	Loadings Range	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Artificial Intelligence (AI)	20	0.652–0.741	0.941	0.948	0.487
Customer Insight (CI)	16	0.672–0.781	0.918	0.930	0.542
Customer Value (CV)	16	0.701–0.779	0.929	0.938	0.545

Values of Cronbach's alpha and the composite reliability coefficients for all variables demonstrate sound internal reliability (all greater than the acceptable minimum threshold of 0.70) indicating that the variables are internally consistent measures of the same concept.

Validity Testing

The average variance extracted (AVE) was used as the measure for establishing convergent validity, as illustrated in the last column of Table 3 above. First, the AVE values of the variables of customer insight (0.542) and customer value (0.545) surpassed the acceptable threshold of 0.50; however, while the AVE of artificial intelligence came close to the mentioned threshold (0.487), the number of items is very high (20 items are divided into five sub-dimensions) and it's considered an acceptable measure due to very high composite reliability (CR=0.948), which exceeds the AVE, as proposed by Fornell and Larcker (1981).

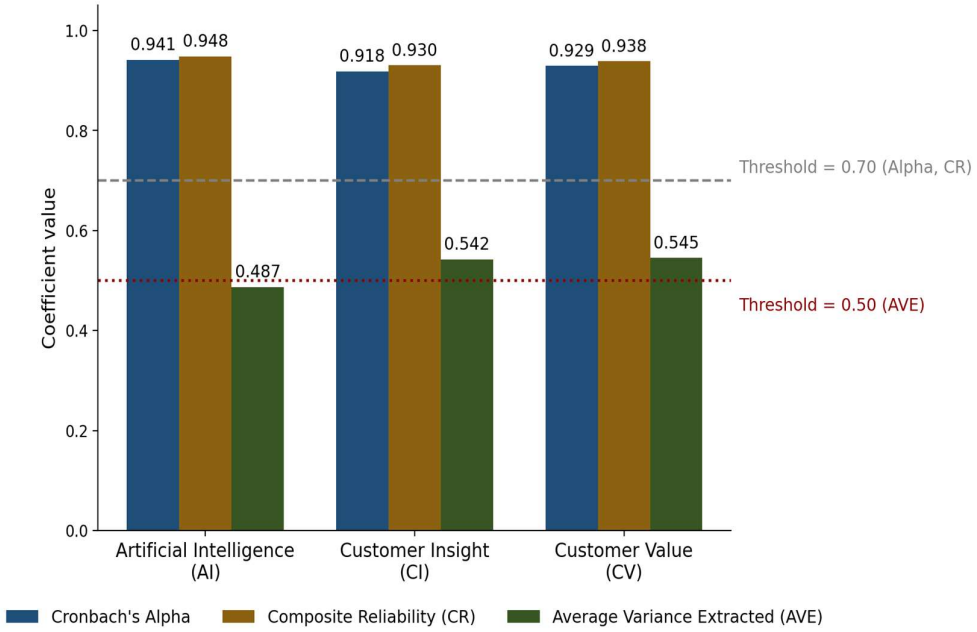


Figure 2. Reliability and Convergent Validity Indicators of the Study Variables

To assess discriminant validity, two complementary procedures were utilized, the first being the Fornell-Larcker test in which the square root of average variance extracted for individual constructs is calculated and its values are then compared to correlation coefficients with respect to other variables in the study, as depicted in Table 4.

Table 4. Discriminant Validity Matrix per the Fornell-Larcker Criterion (bold diagonal values are the square root of AVE)

Variable	Artificial Intelligence	Customer Insight	Customer Value
Artificial Intelligence	0.698		
Customer Insight	0.428	0.736	
Customer Value	0.411	0.601	0.738

According to Table 4, the square root of average variance extracted for all the variables (diagonal values) is greater than the correlation of the variables with the other variables, meaning that discriminant validity has been established according to the Fornell-Larcker criterion.

The second method is the Heterotrait-Monotrait Ratio (HTMT), recommended by Henseler et al. (2015) as an even more precise criterion in detecting the challenges of discriminant validity; the outcomes of this method are given in Table 5.

Table 5: HTMT Discriminant-Validity Matrix

Variable	Artificial Intelligence	Customer Insight	Customer Value
Artificial Intelligence	—		
Customer Insight	0.461	—	
Customer Value	0.443	0.658	—

According to the information provided in Table 5, it is clear that the HTMT values are less than 0.85, which is the upper value range that can be observed as suggested by Henseler et al. (2015). This signifies that there exists discriminant validity between the three variables researched about through both of the methods suggested by Fornell-Larcker and HTMT tests.

3.1.5. Structural Model Assessment

Once the adequacy of the measurement model was established, the structural model was evaluated through examining the direct paths of the hypotheses, mediation analysis with the help of bootstrapping, estimation of effect size (f^2), out-of-sample predictive relevance (Q^2), and calculation of the coefficient of determination (R^2) for every dependent variable in the model.

Path Analysis

The three direct hypotheses (H1, H2, H3) were tested through path coefficients (β) and their t-values, generated using bootstrapping (5,000 sub-samples), as shown in Table 6.

Table 6. Results of the Direct Structural Path Tests

Hypothesis	Path	Path Coefficient (β)	t-value	Significance (p)	Result
H1	Artificial Intelligence → Customer Value (direct)	0.189	4.294	0.000	Supported
H2	Artificial Intelligence → Customer Insight	0.428	9.336	0.000	Supported
H3	Customer Insight → Customer Value	0.520	11.829	0.000	Supported

Since all t-values exceeded the critical value of 1.96 at the 0.05 significance level, hypotheses H1, H2, and H3 are all statistically supported (the coefficient of determination, R^2, is detailed in Section 5.5.5).

Mediation Testing (Bootstrapping)

Using the bootstrapping method of 5,000 sub-samples, Artificial Intelligence's significance effect on customer value via customer insight was tested based on Preacher and Hayes (2008) methodology.

Table 7. Mediation Test Results via Bootstrapping (5,000 Sub-Samples)

Effect Type	Value (β)	95% CI Lower Bound	95% CI Upper Bound	Result
Indirect effect (AI → CI → CV)	0.223	0.169	0.280	Significant (does not straddle zero)
Direct effect (AI → CV) (H1)	0.189	–	–	Significant
Total effect	0.412	–	–	Significant

In this case, since the 95% confidence interval for the indirect effect [0.169-0.280] does not cross the zero value, it becomes evident that the indirect effect is statistically significant; and moreover, given that the direct effect (H1) sustains its statistical significance upon introducing the mediator, the conclusion is that mediation is partial rather than complete. The share of the total effect explained by the mediator (VAF) corresponds to 54.1%, which is acceptable, as it lies within the range (20%-80%) recognized as substantial in the case of partial mediation according to the criteria outlined by Hair et al. (2017). Consequently, the main hypothesis (H4) claiming mediation of customer insight in the relationship between artificial intelligence and customer value is well supported statistically (partial mediation).

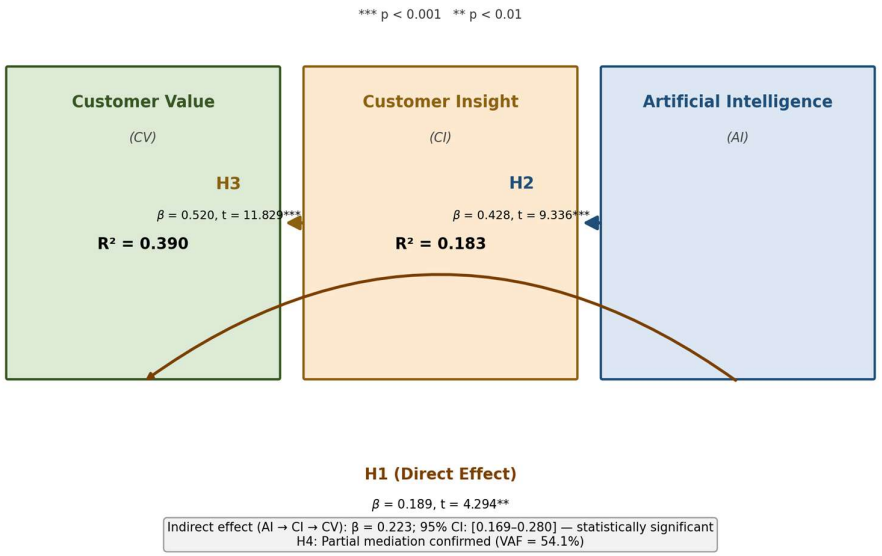


Figure 3. Structural Model Test Results (Path Coefficients and Coefficient of Determination)

5.5.3 Effect Size (f^2)

The effect size (f^2) of each structural path was measured according to the Cohen (1988) formula:

$$f^2 = (R^2 \text{ included} - R^2 \text{ excluded}) \div (1 - R^2 \text{ included})$$

Here, R^2 included refers to the coefficient of determination for the complete model, and R^2 excluded refers to the coefficient of determination of the model without the independent variable under consideration. Effects can be categorized as small when $f^2 \geq 0.02$, medium when $f^2 \geq 0.15$, and large when $f^2 \geq 0.35$. The results of such calculations are shown in the table 8.

Table 8. Effect Size (f^2) Results for the Structural Paths

Hypothesis	Path	Effect Size (f^2)	Effect Classification
H1	Artificial Intelligence → Customer Value (direct)	0.048	Small
H2	Artificial Intelligence → Customer Insight	0.224	Medium
H3	Customer Insight → Customer Value	0.361	Large

According to Table 8, it can be observed that the effect size of the relationship between customer insight and customer value (H3) is the largest ($f^2 = 0.361$), whereas the effect size of the relationship between artificial intelligence and customer insights (H2) is moderate ($f^2 = 0.224$), which makes the path of artificial intelligence and customer value (H1) exhibit the smallest effect size ($f^2 = 0.048$). The findings correlate with the fact that the path coefficient for this effect is low ($\beta = 0.189$) compared to the previous two paths.

Predictive Relevance (Q^2)

The blindfolding technique with a distance of omission of 7 was used to examine the out-of-sample predictive relevance of the two dependent variables, i.e., customer insight and customer value. Based on the rule defined in Hair et al. (2017), it is concluded that $Q^2 > 0$ indicates predictive relevance, and is classified as small if equal to 0.02, medium if equal to 0.15, and large if equal to 0.35. The results of this procedure are reported in table 9.

Table 9. Predictive Relevance (Q^2) Results via the Blindfolding Procedure

Dependent Variable	Q^2	Level of Predictive Power
Customer Insight (CI)	0.132	Small to medium
Customer Value (CV)	0.276	Medium

The fact that both dependent variables have a positive Q^2 indicates that the structural model has reasonable out-of-sample prediction capabilities. It also implies that the model can predict customer value (Q^2 = 0.276) better than customer insight (Q^2 = 0.132), which is in line with the results of higher R^2 for customer value than for customer insight.

Coefficient of Determination (R^2)

Artificial intelligence accounted for only 18.3 percent of the variation in customer insights (R^2 = .183), a value categorized as weak to moderate according to Hair et al. (2017); however, AI combined with customer insights accounted for 39 percent of the variation in customer values (R^2 = .390), a value that is considered moderate – hence, adding the customer insight as a mediator improves the model significantly compared with the effect of AI alone.

3.2. Discussion

3.2.1. Presentation of Results

Before turning to interpretation, the core statistical findings established in Section 5 are restated objectively below:

Table 10. The causal relationships between the study variables that prove the validity of the hypotheses.

Hypothesis	Path	β	t-value	R^2 (dependent variable)	Result
H1	AI → Customer Value (direct)	0.189	4.294	R^2(CV) = 0.390 (joint)	Supported
H2	AI → Customer Insight	0.428	9.336	R^2(CI) = 0.183	Supported
H3	Customer Insight → Customer Value	0.520	11.829	R^2(CV) = 0.390 (joint)	Supported
H4	AI → CI → CV (indirect, mediation)	0.223	—	VAF = 54.1%	Partially supported (partial mediation)

To sum up, the four hypotheses have statistical support: AI has a significant and positive direct impact on customer value (H1), AI has a significant and positive impact on customer insight (H2), and in turn, customer insight has a significant and positive impact on customer value (H3), while customer insight mediates the whole AI–customer value impact (H4), with a share of 54.1%. The findings about the effect sizes and predictive validity (Sections 5.5.3–5.5.4) also indicate that the path customer insight–customer value (H3) produces the largest effect size (f^2 = 0.361) among the direct paths. In addition, the model demonstrates reasonable out-of-sample predictive validity (customer insight Q^2 = 0.132; customer value Q^2 = 0.276).

3.2.2. Interpretation of Results

The evidence emerging from our analysis shows that AI has a strong direct impact on customer value (H1: β = 0.189, t = 4.294, p < 0.001), meaning that AI technologies seem to be capable of generating some value on their own — this can be seen in how automation and the real-time personalization of customers' shopping benefitting them directly without any cognitive considerations by the organization itself. However, given the difference between the values of the direct path and that of the indirect one (β = 0.223), it can be said that AI is finally not a powerful driver of value creation and that the technology works only after the value it generates has been translated into customers' insights.

The important role of artificial intelligence in the customer insight phenomenon is proven through its strong impact on the dependent variable (H2: β = 0.428, t = 9.336, p < 0.001), which

means that AI systems provide an input for further analysis – behavioral patterns, signal patterns, and sentiment signals. At the same time, the low value of the coefficient of determination (R^2 = 0,183) shows that artificial intelligence can account for only a small portion of the variance of the customer insight, which means that the formation of insights also depends on other organizational factors not connected with technology, in particular, expert's ability to analyze data and organization's culture based on making data-driven decisions.

The profound influence of customer insight upon customer value (H3: $\beta = 0.520$, $t = 11.829$, $p < 0.001$; representing the largest path coefficient and effect size in the model) illustrates that customer insight is the key driver of value creation in this model, surpassing even the direct impact of AI on value creation (H1). This has an obvious practical implication: neither data nor technology itself can create value; value occurs only when we interpret data into insights that trigger decisions.

At last, the partial mediation outcome (H4: VAF = 54.1%) suggests that customer insight is an important, albeit not the only, avenue by which artificial intelligence generates customer value. Just over half of the impact of AI is transmitted via this cognitive way, while the rest is the amount of value created by AI directly, without cognitive mediation.

3.2.3. Comparison with Previous Studies

The conclusion that AI has positive effects on customer value (H1) matches the findings of Ameen et al. (2021) who concluded that AI-enabled personalization contributes to interaction quality and raises perceived value and Patil (2024) who determined that AI improves customer experiences in retail and e-commerce with personalization, predictive analytics, and real-time engagement. It is also similar to Beyari's (2025a) finding, where AI adoption and e-customer loyalty show strong positive correlation ($r = 0.761$), as well as Beyari and Hashem's (2025) conclusion that AI impacts social media marketing impacts positively by means of personalization and better targeting.The discovery that AI has a beneficial impact on customer insight (H2) corresponds to the research conducted by Hauser et al. (2023) as well as Lee et al. (2023), both of which concluded that organizations can analyze customer behavior effectively using AI technologies. It is also reaffirmed by Kasaji (2024), who determined that AI analytical output leads to activation of customer insights in the Jordanian service sector.

The conclusion drawn regarding customer insight being the most influential factor affecting customer value is consistent with Woodruff's (1997) statement, which associates customer value with the organization's understanding of the customer's hierarchy of attributes, consequences, and goals, and also with Kim's (2023) argument that the process of creating value using AI-based services goes through the stages of data analysis and its transformation into practical knowledge.

The partial mediation finding (H4) aligns with the work of Mittameedi and Dogra (2026), who discovered that user experience acts as a mediator between smart-platform drivers and strategic results. It is also consistent with the value co-creation argument put forth by Zhu et al. (2022) and the "6Cs" framework developed by Kim (2023), both of which suggest that the benefits of AI multiply when its output is brought to the cognitive level instead of leaving it as purely a technical consequence.

3.2.4. Explanation of Differences

Though the research outcome of this study aligns with previous research in its trends and findings, there are notable differences that still need to be clarified. First of all, while having presented the fact that customer experience completely mediates the relationship between smart-platform drivers and outcomes, Mittameedi and Dogra (2026), in turn, found that customer insight partially mediates the influence of AI on customer value (VAF = 54.1%). This discrepancy may be explained by the diversity of the scope of the mediators: customer experience in the sense of Mittameedi and Dogra (2026) means a more inclusive and extended definition that theorizes an almost full impact of the platform on outcomes. In contrast, in this research, customer insight has a more limited meaning, which means that part of AI effects on value (e.g., convenience or efficiency) can overpass the customer insight mediator since not all the value-creation mechanisms of AI are cerebral in their nature (Yrjölä et al., 2024).

Secondly, the coefficient of determination of customer insight (R^2 = 0.183) is surprisingly much lower than one might expect following the robust theoretical support for the argument of AI's being a crucial factor of customer understanding suggested by Hauser et al. (2023) as well as Lee et al. (2023). The most appropriate explanation for this inconsistency is methodological rather than theoretical: while the majority of these earlier studies focus on AI's analytic capability in isolation, the current model considers customer insight an organizational outcome additionally influenced by the factors which have not been studied, such as the interpretative capabilities of the analysts and data culture of the organization — factors deliberately excluded from this study; this omission puts a mechanical cap on the amount of variance that can be explained by the results obtained through applying AI only.Similarly, the borderline average variance extracted of the artificial intelligence construct (AVE = 0.487, slightly below the usual threshold of 0.50) varies from the comfortable values of average variance extracted that have been generally reported on the narrower, uni-dimensional AI measures in the previous studies, such as Kushwaha et al. (2021) who used only chatbot adoption. The difference here does not mean the construct is weak but rather the opposite: the study firstly measures the construct across five heterogeneous sub-constructs (personalization, recommendations, chatbots, predictive analytics, and automation) which leads to lower AVE. Fornell and Larcker (1981) suggest that by using broader multi-dimensional constructs would lead to lower AVE which, despite high composite reliability (CR=0.948), is possible.

4. Conclusions

This study investigated the impact of artificial intelligence on customer value in e-commerce and the mediating role of customer insight in this relationship. Based on a conceptual model grounded in a strong theoretical foundation and analyzed using PLS-SEM, the findings demonstrate that artificial intelligence has a statistically significant positive direct effect on customer value (H1: β = 0.189), although this effect is smaller than its indirect effect through customer insight. Artificial intelligence also has a statistically significant positive effect on customer insight (H2: β = 0.428), explaining a moderate proportion of its variance (R^2 = 0.183), while customer insight significantly influences customer value (H3: β = 0.520) and represents the most influential variable in the model, with an R^2 of 0.390 when combined with AI technologies. Customer insight partially mediates the relationship between artificial intelligence and customer value, accounting for 54.1% of the total effect (VAF = 54.1%), indicating that more than half of the influence of AI technologies on customer value operates through a cognitive channel. These findings suggest that investment in AI technologies is important but insufficient to maximize customer value unless AI-generated outcomes are effectively transformed into customer insights that are embedded in marketing decision-making and resource allocation. Theoretically, this study contributes by decomposing the mechanism through which AI is transformed into customer value and extending previous research that has primarily examined the direct influence of AI on marketing outcomes by introducing customer insight as a mediating organizational capability. Consistent with Dynamic Capabilities theory, AI is conceptualized as a technical organizational resource, whereas customer insight represents an organizational capability that transforms this resource into competitive advantage embodied in customer value, providing a framework that has not, to the researcher's knowledge, been quantitatively tested in the Arab e-commerce sector. Methodologically, the study contributes through a quantitative design combining multidimensional measurement of AI and customer value with bootstrapping and mediation analysis using the variance accounted for (VAF) measure, thereby enabling the identification of partial rather than full mediation based on quantitative indicators (Hair et al., 2017). Contextually, the study addresses an identified research gap and represents one of the early attempts to examine this mediation model within e-commerce research in the Arabic-language literature. From a practical perspective, the finding that customer insight accounts for 54.1% of the total impact of AI on customer value provides managers with quantitative justification for shifting investment beyond off-the-shelf AI solutions toward data analysis capabilities, customer knowledge management, and the transfer of marketing knowledge into actionable decisions. Companies should therefore establish customer knowledge and data analysis teams and systems, create formal structures linking recommendation engines, conversational agents, and predictive models to marketing decision-making, address customer privacy concerns transparently when implementing real-time personalization, establish interdisciplinary teams combining marketing and data science expertise, and develop performance indicators that evaluate the effectiveness of the data-to-insight-to-value chain rather than relying solely on technology adoption indicators. Nevertheless, this study has several limitations, including its cross-sectional design, which limits the ability to establish causal relationships; the inclusion of only one mediating

variable, despite the possible influence of other cognitive or affective factors such as digital trust and privacy concerns; reliance on self-reported perceptual measures, which may expose the findings to common method bias despite preventive measures; the focus on e-commerce application users in Iraq, which limits generalizability to other countries and industries such as banking and healthcare; and the treatment of AI as a construct comprising five sub-dimensions, which prevents the assessment of the individual contribution of each dimension to customer insight. Future studies should therefore employ longitudinal or quasi-experimental designs to examine causal relationships over time, investigate additional mediators and moderators such as digital dependency, privacy concerns, and cognitive engagement, examine the individual effects of the five AI dimensions using higher-order latent variable approaches, conduct cross-cultural studies across different regions to establish the validity of the proposed model, apply qualitative methods such as in-depth interviews to explore how AI inputs are transformed into customer insights, and extend the model to other sectors, including banking, healthcare, and tourism.

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