The Role and Influence of Artificial Intelligence-Driven Decision Support Systems on Consumer Online Purchase Decisions in Small and Medium Sized Enterprises (SMEs)

The Role and Influence of Artificial Intelligence-Driven Decision Support Systems on Consumer Online Purchase Decisions in Small and Medium Sized Enterprises (SMEs)

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United International **University**

Date of submission: 11th March 2026

LETTER OF TRANSMITTAL

Date: 11 March 2026

Mr. Ahmed Imran Kabir
Assistant Professor
School of Business and Economics
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Subject: **Submission of Project Report on "The Role and Influence of Artificial Intelligence-Driven Decision Support Systems on Consumer Online Purchase Decisions in Small and Medium-Sized Enterprises (SMEs)"**

Dear Sir,

I present my research report through submission as a requirement towards completing my course work in the subject of Business Analytics major under the School of Business and Economics, United International University, on the topic, "The Role and Influence of Artificial Intelligence-Driven Decision Support Systems on Consumer Online Purchase Decisions in Small and Medium-Sized Enterprises (SMEs)".

This is a report that I have prepared through your gracious guidance and supervision. During this research, I have made an effort of adhering to the academic requirements and using the acquired knowledge in my studies. The study will examine how the Artificial Intelligence-based decision support systems can affect the purchasing behavior of consumers in e-commerce setting based on SME.

I do hope that this report will satisfy your academic needs and expectations. I will welcome any suggestions or feedback that can be used to enhance the quality of this research.

I would like to thank you, and hope, you will continue guiding and supporting me during the preparation of this study.

Regards,
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CERTIFICATION OF SIMILARITY INDEX

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DECLARATION OF THE STUDENT

I hereby testify that the research project is fully prepared and submitted by me as part of the coursework preparation of my academic course work in Business Analytics major at the School of Business and Economics, United International University.

I also confirm that this report is purely my own original report and it has been written under the guidance and under supervision of Mr. Ahmed Imran Kabir, the Assistant Professor. Any information, data, analyses and interpretation contained in this report has been summarized and reviewed by me. Any information, thoughts, or materials borrowed in this report by books, journals, research articles, websites, and any other published and unpublished materials have been considered and referenced appropriately in the reference section of this report.

I also assure that this research project has not been presented earlier to any other university or other institution to receive either a degree, diploma or any other certification. I alone bear the responsibility to respect academic integrity and ensure that no plagiarism of any kind has been done in the drafting of this report.

I do testify that the contributions in this project are my endeavors, knowledge, and scholarly research when carrying out this study.

Regards,
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To begin with, I want to thank Mr. Ahmed Imran Kabir, a School of Business and Economics, in the United International University, Assistant Professor, and show my absolute gratitude and the willingness to work closely and supportively with him but also to get the best and useful feedback during the preparation of this research project. His thought-provoking ideas, support and motivation to study have been very instrumental in contributing to this study and contributing to my accomplishment of the research work.

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Lastly, I would like to give major acknowledgment to my family members as well since they have consistently supported and helped me, despite my failure to meet their expectations, by providing support and encouraging me to strive harder in my academics. The way they are motivated and how much they believe in me has always made me strive to work hard and accomplish my academic objectives.

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ABSTRACT

Purpose: The use of E-commerce and Artificial Intelligence (AI) has transformed online shopping habits among individuals, specifically in Small and Medium Enterprises (SMEs) in developing economies. The influence of perceived quality of product information, price sensitivity, and social influence on online purchase decisions is investigated in this paper together with the moderating role played by AI decision support.

Design/methodology/approach: PLS-SEM of SmartPLS techniques were used to examine an online survey of 326 Bangladeshi native respondents.

Findings: Findings reveal positive effects in online purchasing decisions from social influence and perceived information quality, while a negative effect is found from price sensitivity. Further, AI-enabled decisions enhance product information quality, social influence, and reduce price salience. The model is highly explanatory and predictive; this serves as an indication of the robustness of our framework.

Originality: The study can also contribute to literature by incorporating AI as an important factor in determining online consumer behavior and the possibility of using AI technology to improve the performances of SMEs operating in online shopping.

Keywords: *Artificial Intelligence, Online Purchase Decision, Small and Medium-sized Enterprises, E-commerce, Social Influence, Consumer Behavior, Personalized Recommendations, Chatbots, Smart Filters, Consumer Perceptions, Digital Marketing Strategies, AI Tools in E-commerce, Consumer Confidence*

TABLE OF CONTENTS

LETTER OF TRANSMITTAL ..... *I*

CERTIFICATION OF SIMILARITY INDEX ..... *II*

DECLARATION OF THE STUDENT ..... *X*

ACKNOWLEDGEMENT ..... *XI*

ABSTRACT ..... *XII*

TABLE OF CONTENTS ..... *XIII*

LIST OF FIGURES ..... *XV*

LIST OF TABLES ..... *XVI*

LIST OF ACRONYMS & ABBREVIATIONS ..... *XVII*

CHAPTER 1: INTRODUCTION *1*

1.1 Background of the Study 1

1.2 Statement of the Problem 3

1.3 Objectives of the Study 4

1.4 Scope and Limitation of the Study. 6

1.5 Definition of Key Terms 9

1.6 The Structure of the Remaining Chapter. 11

Chapter II: REVIEW OF THE LITERATURE *12*

2.1 Relevant Theory 12

2.2 Literature Survey 14

2.3 Hypothesis Development 19

2.4. Conceptual Framework and Hypotheses Summary 27

Chapter III: Methodology of the Study *30*

3.1. Study Context 30

3.2. Research Design 30

3.3. Questionnaire Design 31
3.4. Sampling and Data Collection 31
3.5. Data Analysis Plan 31
3.6. Limitations 32
CHAPTER IV: RESEARCH FINDINGS & ANALYSIS *33*
4.1. Profile of Survey Respondents 33
4.2. Measurement, Validity, and Reliability of Data 35
4.3. Discriminant Validity Assessment 37
4.4. Assessment of Structural Model 41
4.5. Hypotheses Testing (Direct and Indirect Relationships) 42
CHAPTER V: DISCUSSION *45*
5.1 Conclusion 45
5.2. Theoretical Contributions 46
5.3 Managerial Implications for SMEs in Online Shopping 47
5.4. Limitations of the Study 48
5.5. Future Directions for Research 49
5.6 Recommendations 49
REFERENCE *52*
APPENDIX A *66*
Independent Variables (IVs) 66
Moderating Variable (MV) 67
Dependable Variable (DV) 68

LIST OF FIGURES

Figure 1 The framework of the study 29
Figure 2 Standardized results of the SEM calculations. 41

LIST OF TABLES

Table 1 Demographic Profiles of Respondents……35

Table 2. Measurement Model Evaluation……36

Table 3. Fornell–Larcker Criterion……38

Table 4. Heterotrait–Monotrait (HTMT) Ratio……38

Table 5. Cross Loadings of Measurement Items……39

Table 6. Structural Model Results (Hypothesis Testing) ……42

LIST OF ACRONYMS & ABBREVIATIONS

Acronym	Full Form
AI	Artificial Intelligence
SMEs	Small and Medium-Sized Enterprises
OPD	Online Purchase Decision
PIQ	Perceived Product Information Quality
PS	Price Sensitivity
SI	Social Influence
DSS	Decision Support Systems
PLS-SEM	Partial Least Squares Structural Equation Modeling
SEM	Structural Equation Modeling
AVE	Average Variance Extracted
CR	Composite Reliability
HTMT	Heterotrait–Monotrait Ratio
UGC	User Generated Content
UIU	United International University
DU	Dhaka University
IV	Independent Variable
MV	Moderating Variable
DV	Dependent Variable

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

The high rate of development of digital technologies and the popularization of the internet have changed the approach to the functioning of business and contact with the consumers significantly. Among the latest significant advances that have been experienced over the last few years is the growth of electronic commerce (e-commerce) where by consumers can search products, compare options and buy goods online. With the ongoing development of digital marketplaces, companies are adopting sophisticated technologies that can optimize and maximize customer experiences and processes in their decision making. Artificial Intelligence (AI) is among the technologies that have become one of the most influential determinants of the future of online trade.

Artificial Intelligence can be described as computer systems and algorithms that can handle tasks traditionally handled by human brains such as learning by data, discovering patterns and making forecasts. When it comes to e-commerce, AI technology is utilized most of the time and appears in the form of a recommendation system, chatbot, personalized advertising, predictive analytics, and smart search engine. These AI-powered applications extract consumer data (thousands of consumers), such as browsing history, purchases, preferences, and demographic data, and produce personalized recommendations and help consumers make their purchasing decisions more efficiently.

Purchase decision making online is a complicated process and it comprises several steps, which include the search of information, examination of alternatives, and the final identification of purchase. Online buyers are also highly dependent on virtual data, which includes product descriptions, customer reviews, product images, and ratings as opposed to the physical appearance that can be seen physically by consumers in a traditional store setting. This tends to bring confusion and overabundance of information to the consumers. The use of the AI system as the decision support systems (DSS) is useful in solving these challenges by arranging vast pools of product information, narrowing down on the best alternatives, and providing custom suggestions that can guide the decision-making process with ease.

Consequently, AI technologies can be tremendously used to impact consumer perceptions, trust, and buying pattern online marketplaces.

In the case of Small and Medium-Sized Enterprises (SMEs), the integration of AI-based technologies has gained even greater significance and should now be used to keep up with the ever-evolving digital economy. SMEs are usually constrained by financial resources, technology infrastructure, and marketing aspects among other factors, as opposed to the bigger corporations. Nonetheless, the derivative limitations can be addressed by the introduction of AI-based decision support systems to allow SMEs to automate their interactions with customers, enhance the process of product recommendations, and provide individuals with personalized shopping experiences. With the help of AI technologies, SMEs may access customer engagement, operational efficiency, and conversion rates in online platforms.

In the developing economy of Bangladesh, the digitalization of business operations has become even more widespread in recent years with the rise in internet penetration, smartphone usage, and the development of the online marketplaces. The digital platforms are also being used by a number of SMEs in Bangladesh to market their products and services. The zeal of these platforms however highly relies on the ability of businesses to comprehend the behavior of consumers and provide the information that is relevant in making the purchases. In past research, a number of key concerns have been discovered to have significant impact on online purchase decisions, these include perceived information quality of the product, price sensitivity and social influence.

Perceived Product Information Quality is defined as how much consumers think that the information that is presented about a product is correct and is relevant and adequate to make an assessment regarding the product. Good information lowers the level of uncertainty and assists the consumers in making sure purchase decisions. Price Sensitivity measures how much consumers are responsive to the price difference when they are choosing products, particularly in markets of high competition where products can be compared in terms of prices easily online. Social Influence, conversely, is defined as the chance of influence of the opinions, suggestions, and experiences provided by other consumers, family, and Internet communities on the purchase decisions of other consumers.

Artificial Intelligence may be significant in enhancing or altering the influence of these variables on the decisions to buy online. Systems that are supported by AI can enhance products information presentation and customization, promote popular socially conscious products, and aid in helping consumers to analyze the value beyond the comparison of the price. Intelligent assistance and personalized recommendations will help AI technologies to promote consumer confidence and make it easier to make a decision.

With the rising significance of the AI in internet commerce and the rising role of the SMEs in the online banking sector, it is necessary to comprehend how decision support systems based on AI affect consumer purchasing behavior. This paper is thus aimed at investigating the capability and impact of the Artificial Intelligence-based decision support systems on online purchase decision making among the consumers in a small and medium-sized enterprise (SMEs). The study is aimed at examining the effect of perceived product information quality, price sensitivity, and social influence on the online purchase decisions and the moderation of the relationships between them through the use of the AI-based decision support systems in the framework of online shopping.

1.2 Statement of the Problem

Due to the fast-growing nature of e-commerce, consumers are changing their information search method and the manner in which consumers make purchasing decisions has been changed dramatically. There is a tremendous access to product information, reviews, and choices by the consumer due to the increasing presence of online platforms. Though such profusion of information offers consumers a greater choice, it may also lead to information overburden, and the consumer may fail to effectively compare goods and be able to make an assured choice on the things to purchase.

Small and Medium-Sized Enterprises (SMEs) are starting to embrace the digital platform in order to reach broader customer segments, compete in the online market. Nonetheless, SMEs have been struggling with their ability to communicate product information successfully, comprehending what customers want, and offering them personalized experiences that can be equally familiar to a large-scale organization.

Consequently, most SMEs are unable to control their effect on purchase behavior in consumers and establish long-term trust in customers in online spaces.

Decision support systems bolstered by artificial intelligence (AI) have since become potent tools, which could help businesses and consumers resolve these problems. These systems deploy sophisticated algorithms and data mining to make recommendations on products that get tailored to the consumer, study consumer behavior and provide a variety of information that helps the consumer to make a decision. Although there are increasing application of AI technologies in e-commerce, very little is known on their impacts on consumer buying behavior, especially in the case of SMEs.

Moreover, interest in quality of perceived product information, price, and social influence are also important influences on the formation of online buying decisions. Nevertheless, it is still unclear how much AI-offered decision support systems reinforce or alter the links among these factors and consumer buy behavior, particularly in poorer and transitional economies such as Bangladesh where digital transformation is yet to take off.

Consequently, the most significant issue that the given research will resolve is the absence of thorough research into the impact that AI-based decision support systems produce on the online purchase decisions made by consumers in SMEs. The proposed study would explore the connections between the perceptions of the quality of product information, price sensitivity, social influence, and online purchases, and determine the way in which the moderator AI-driven decision support systems contribute to the digital commerce setting.

1.3 Objectives of the Study

The main aim of the study is to examine the presence and impact of Artificial Intelligence (AI)-driven decision support systems in terms of consumer online purchasing decisions in Small and Medium-Sized Enterprises (SMEs) that conduct their business in the digital commerce setting. As the levels of the integration of AI technologies in the e-commerce platforms increase, the business can offer personalized recommendations, improve the provision of information related to the products and optimize consumer experiences. This paper aims to find out how such

AI-based systems can be used to help in developing consumer behavior in the course of buying products online.

More so, the research will seek to examine how some of the significant factors that influence the consumer behavior of pursuing purchasing behavior over the internet incorporate Perceived Product Information Quality (PIQ), Price Sensitivity (PS), and the Social Influence (SI). These considerations are very important in influencing the way consumers judge the products, make a comparison with alternatives and finally decide to make a purchase. A combination of these variables by the research gives a holistic view of how online consumers are determined.

Moreover, the paper aims not only to examine the mediating propensity of AI-based decision support system to reinforce or change the associations among these significant variables and consumer online beverage purchases. The research purpose, through this analysis, is to determine how AI technologies can assist SMEs to address their marketing processes, better customer interactions, and how to conduct digital commerce processes in a more efficient way.

In order to accomplish such purposes, the research is informed by the following specific objectives:

General Objective

To scrutinize the net effect of AI-based decision support systems on consumer online purchase action in SMEs in digital e-commerce.

Specific Objectives

- To test the influence of the so-called Perceived Product Information Quality (PIQ) on the online purchases made by consumers. The aim here is to find out how consumer confidence and their buying behavior in online settings respond to information on products that is accurate and relatable as well as comprehensive.
- To examine the impact of Price Sensitivity (PS) on cyber purchase decision making by consumers. This aims at examining the responsiveness of consumers to price variance and the effect of this on product choices made by consumers in the online shopping process.

- To determine the effect of Social Influence (SI) on consumer online behavior of buying. It involves testing the responses of recommendations, reviews, peer and relatives' opinions and their relationship with online community interactions on the purchase intentions of consumers.
- To examine the moderating role of AI-based decision support systems in the relationship between perceived quality of information about product and online purchase decision. The purpose of this goal is to identify whether the AI technologies can increase the efficacy of product information in helping consumers to make decisions.
- To analyze the findings of how AI-based decision support systems mediate the connection involving market sensitivity and on-line acquisitions and in the adhesive manner of aiding customers to assess worth and propagate more profound comparisons amid products.
- In an effort to evaluate the moderating impact of social opinion on the choice to buy online via AI based-sustained decision support systems, it is necessary to consider how AI based-suggestion systems and algorithms may enhance or alter the relevance of social opinions to consumer behavior.

By accomplishing these goals, the study will help to advance research on the purpose of AI technologies in contemporary e-commerce contexts and, therefore, offer a practical perspective on the topic to SMEs that attempt to implement AI-driven solutions to become more competitive and customer-focused in the virtual market.

1.4 Scope and Limitation of the Study.

Scope of the Study

This paper aims at investigating the role and impact of the Artificial Intelligence (AI) decision support systems upon the consumer online purchase decision-making in the Small and Medium-Sized Enterprises (SMEs) in the evolving e-commerce landscape moving at a high speed. As digital technologies grow, a lot of SMEs are starting to employ AI-based tools including recommendation systems, chatbots, predictive analytics, and intelligent search to enhance customer experiences and assist consumer decision-making. The study will determine how these artificial intelligence technologies affect consumers to judge the information and decide to purchase products in online stores.

The paper mainly focuses on exploring the connection between Perceived Product Information Quality (PIQ), Price Sensitivity (PS), Social Influence (SI) and Online Purchase Decision (OPD). Such variables are also significant behavioral and informational aspects which influence consumer decision making in online shopping significantly. Perceived product information quality is based on the way consumers assess correctness, relevance, and usefulness of product-related information they can get on internet websites. Price sensitivity is an indicator of the extent to which consumers respond to price variations during distribution of products. Social influence is an element of consumer purchasing behavior that is influenced by suggestive impact, reviews, opinion of social companions, loved ones, and electronic communities.

Besides testing the direct associations of these variables and their influence on the online buying decisions, the second part of the research evaluates the mediating effect of AI-assisted decision support systems. The AI technologies can be used to improve efficiency of the product information and provide the product recommendations, as well as make the complicated decision making easier. So, the study explores the idea of whether AI-based systems reinforce or alter the effect of product information quality, price sensitivity, and social influence on purchasing behavior among consumers.

The empirical data that was used in this study was collected via a structured questionnaire survey which was given to those consumers who already have an experience of purchasing products via online platforms. The respondents are the representatives of the people that come into contact with digital marketplaces where SMEs deal and offer their merchandise regularly. They were analyzed with the aid of the Structural Equation Modeling system (Partial Least Squares) (PLS-SEM) via the SmartPLS software and enable the researcher to investigate complicated interdependencies between two or more variables at the same time.

Geographically, the research itself takes place in the background of online customers in Bangladesh where there is a share of rapid sales of the digital economy and e-commerce in recent years. The rise in the level of penetration of internet, smartphones and online payment has been an impetus to more consumers and SMEs to be actively involved with online trade and commerce. Thus, the results of the present research are anticipated to offer some useful information on how AI technologies can assist

SMEs to improve their marketing policies, increase consumer activities, and impact buying decisions within the digital market.

Moreover, the research becomes the addition to the academic literature by offering the empirical data on the influence of AI-based decision support systems on consumer behavior on the online setting. It also has some practical implication to SME owners, digital marketers and policymakers who would like to ensure that business operations embrace advanced technologies.

Limitations of the Study

Even though this research makes valuable contributions to understanding the contribution of AI-operated decision support system to online consumer behavior, it has a number of constraints that must be taken into consideration when deciphering the findings.

To begin with, the research has been carried out using survey questionnaires that were administered to a small group of respondents; this is likely to be not representative of the whole population of online shoppers. Sampling and the sample size can restrict the extrapolation of the findings to larger populations or the different geographical locations.

Second, it is a narrow study with a set of variables that include perceived information of the product quality, price sensitivity, social influence and AI-driven decision support systems. Many other factors can however affect consumer online purchase decision which include consumer trust, usability of the site, reliability of site delivery, security of payment, brand reputation and quality of customer services. This study did not incorporate these other variables since it is limited by time and resources.

Third, the research is also based on self-reported information obtained via questionnaires which likely cause some biases including social desirability bias or incorrect recollection by the participants. Consequently, the responses cannot necessarily be accurate depictions of the actual buying behavior of consumers in the real-life scenarios of online shopping.

Fourth, the study will use the cross-sectional study design, which implies the gathering of the data at one point in time. The research, thus, fails to reflect the process of

consumer behavior transformation across time or the long-term implications of applying AI within the context of the e-commerce setting.

Lastly, the research targets specifically SMEs working in the framework of digital commerce, which implies that the research can be incomplete in regards to the large MNCs and other industries, not belonging to the e-commerce domain. The varied organizational resources, technological capacity and market strategies can also have an impact on how AI technologies will change consumer behavior in varied situations.

Nevertheless, the study does present some important information about the increasing significance of AI-driven decision support systems in influencing the online consumer buying choices and it identifies some opportunities that the SMEs can adapt AI technologies to enhance their competitive abilities in the dynamic digital market.

1.5 Definition of Key Terms

To make an improved interpretation of the concepts utilized in this study, some relevant terms are given below:

Artificial Intelligence (AI)	Artificial Intelligence is the utilization of computer systems and algorithms that are capable of executing tasks that demand human intelligence, including data learning, pattern recognition, prediction, and aid in the decision-making process. AI has been applied in e-commerce in recommendation systems, chatbots, and personalized marketing.
Decision Support System (DSS)	A Decision Support System refers to a computer-based system used to aid an individual or organization to make intelligent decisions through assembling, examining, and presenting knowledgeable information and data. In e-commerce, DSS based on AI helps consumers by suggesting products and streamlining the process of making decisions.
AI-Driven Decision Support Systems	AI-driven decision support systems are intelligent systems that apply artificial intelligence technologies including machine learning, predictive analytics and recommendation algorithms to help consumers estimate options and take up-buying choices in online settings.

Small and Medium-sized enterprises (SMEs)	Small and Medium-sized enterprises are businesses having comparatively limited financial, technological, and human resources as opposed to big companies. SMEs are very important in the economic development and more are turning to virtual platforms to widen their market base.
Online Purchase Decision (OPD)	Online Purchase Decision is a procedure in which consumers compare products through comparisons based on online information selection, it then makes a decision to buy products or any kind of services online via online platforms or digital marketplaces.
Perceived Product Information Quality (PIQ)	Perceived Product Information Quality is the degree to which people assume that the information that they are given about a product is accurate, credible and can be used to make a purchasing decision; this information could be in the form of descriptions, photo, specifications and reviews of the product.
Price Sensitivity (PS)	Price Sensitivity is the extent to which the consumers use changes in price of a product as factors that affect their buying decision. Highly price sensitive consumers will be the types of consumers who look at prices before making decisions to purchase.
Social Influence (SI)	Social Influence can be defined as the role played by opinion, advice, reviews, and experience of friends, relatives, and Internet societies on the buying behavior of a consumer.
E-Commerce	E-commerce is a type of buying and selling of goods or services via the internet using electronic media like trading sites, websites, and cell phone applications.
PLS-SEM (Partial Least Squares Structural Equation Modeling)	PLS-SEM refers to a statistical analysis method applied to study complex relationships between a number of variables and test research hypotheses in behavioral and social science research.
SmartPLS	SmartPLS is a statistical software that is typically used to carry out Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the structural relationships between research variables in a study.

1.6 The Structure of the Remaining Chapter.

This research report has different chapters to give the study a tabular way of presentation.

Chapter 1: Introduction	This chapter offers an introduction to the subject of the research and offers the background to the study. It also explains the presentation of statement of the problem, study objectives, its scope and limitations and definitions of some of the important terminologies employed in the study.
Chapter 2: Literature Review	The chapter is a review of the past research and scholarly materials that are associated with Artificial Intelligence, decision support systems, and consumer online purchase behavior. It addresses theoretical background of the work and constructs the conceptual view and research hypotheses.
Chapter 3: Research Methodology	This chapter discusses the research design and the methodology applied in the study. It outlines the description of data collection process, research tools, sampling method, data measurement, and statistical method to analyze these data.
Chapter 4: Data Analysis and Results.	This chapter includes the discussion of analysis of the collected data and the results that were obtained during the statistical tests. It involves analysis of the measurement model, structural model as well as testing of hypothesis through PLS-SEM analysis.
Chapter 5: Appendix: Discussion and Conclusion.	The chapter explains the main conclusions made during the research and their implications to SMEs and digital commerce. It also provides conclusions made on the main conclusions of the study and recommendations on further research.

CHAPTER II: REVIEW OF THE LITERATURE

2.1 Relevant Theory

AI has emerged as the most powerful technology forces that have been driving the online retail industry for a decade (Madanchian, 2024; Bawack & Kamdjoug, 2022). It has changed the way consumers interact with digital interfaces, how they absorb information and how they make decisions over what to buy from e-commerce (Wang, 2025; Dixit, 2025). Machine learning recommendation engine, chatbots or predictive analysis/automated customer service application are no longer an add on but a heart of new e-commerce (Khamdamov, 2024; Pham, 2025). These technologies will allow these platforms to do something more than just provide information, and make them into active decision support systems that learn and respond according to consumer specific needs, wants and other clues about the context (Yin et al., 2025; Pham & Datta, 2024).

The information asymmetry coupled risks perception and lack of physical examination of goods render decision tasking products online difficult (Dang & Pham, 2024; Zhao & Liao, 2024). When the choice on alternative, buyer will be made enormous reliance for digital impression, platform brand and system reaction (Flavián & Ibáñez Sánchez, 2023). The following challenges can be dealt with by the clinician with AI based decision support systems which could make information processing and availability more efficient (Dixit & Ahmed, 2025; Khamdamov, 2024). Artificially intelligent machine-learning algorithms sift through mountains of consumer-data, like browsing history and last purchasing as well as search behavior or user's behavior is searched to create tailored product offers and custom content that is more interesting (Yin et al., 2025; Liu & Zhang, 2024). This will have a flip down effect as the degree to which personalization is achieved, reduces the cognitive load and more individuals can make do with evaluating fewer options that are more relevant to their interests (prescreening),the value trade-offs made become less laborious (Pham & Datta, 2024; Dixit, 2025).

Theoretically, the impact of AI on consumers' online purchase decision can be understood from trickledown effect in Things (IoT) inductive processing book list theory and technology mediate model of decision making (Dixit, 2025; Chakraborty, 2025). According to information processing model, consumers' rational activities are limited

and they prefer to use the variable equipment which could decrease their efforts degree and decision entanglement (Dang & Pham, 2024). From noise canceling to focusing on what matters (product features) and ordering fact options as the decision AI system views them are just some of many cognitive prosthetics in effect (Yin et al., 2025). This support fosters consumers' perceived control in shopping and confidence in decision making which are important antecedents of online purchase behavior (Pham & Datta, 2024; Wang, 2025).

Moreover, the AI enabled decision support extends over traditional technology acceptance models by integrating adaptable and interactive consumer-technology interface (Dang & Pham, 2024; Dixit & Ahmed, 2025). And this is why the content of the AI system output is different than typical features from a static website. The AI changes and evolves with time, with the feedback of users, and also shows other results when additional news comes (Yin et al., 2025; Wang, 2025). This learning capability creates some feel of reactivity and intelligence to the design which encourages its utility and credibility in user's mind (Khamdamov, 2024; Pham, 2025). The better AI can be at determining what a user like the more users will trust such as platform recommendation that is also likely to have more engagement and eventually conversion (Verma & Tiwari, 2023; Kim & Park, 2023).

Trust is very important in such an online purchase, virtual or otherwise, and AI can help increase the trust in the digital worlds (Dang & Pham, 2024; Patil & Sen, 2025). Chatbots and AI-based virtual assistants will respond in real-time with accuracy, removing uncertainty and fear factors from the service delivery (Pham, 2025; Gao, 2025). What's more, the trust of the users in the system also grows - when it is known that good recommendations by users make a steady hit for the system, they might also be trusted to give advice (Yin et al., 2025; Verma & Tiwari, 2023). Throughout positive experiences with AI-enhanced tools in the long term, relational trust emerges and thereafter customer readiness to conduct online transactions and intention to remain dependent (Ratner et al., 2025; Beyari, 2025).

A huge amount of empirical data across different online e-commerce platforms also reveal that AI adoption leads to positive online purchase outcomes (Madanchian, 2024; Wang, 2025). Studies show that AI-driven predictions improve the clickthrough, perceived value and purchase rates (Yin et al., 2025; Liu & Zhang, 2024). When

people are exposed to consumer-targeted personalization of AI (e.g., their social feeds contain more personalization), then they experience greater satisfaction and emotional connection with the product or service online, which is directly related to higher impulse purchasing and greater loyalty (Flavián & Ibáñez Sánchez, 2023; Ratner et al., 2025). AI has made it possible for even an SME to be able to automate the customer touchpoints, product surface and receive personalized experiences with little additional cost (Nuryanto et al., 2025; Sánchez et al., 2025). By guiding shoppers to the perfect product, responding in real-time with answers and advice and helping them to make an informed purchase decision, AI enables small businesses to turn those online window shoppers into actual buyers (Allahverdiyev & He, 2025; Yin et al., 2025). Apart from that, AI-enabled decisions have made the SMEs to be able to cater their structural weaknesses by substituting limited resources of humans especially marketing skills (Nuryanto et al., 2025; Sánchez et al., 2025). Smart systems are able to do everything the service team used to manually perform, question and answer services towards showing interest customers demonstrating the functionalities of each product to customers giving product guidance (Pham, 2025; Gao, 2025). This potential gives SMEs power to offer superior online customer experiences, which will contribute to positive online buying decisions, even when resources are non-existent (Ratner et al., 2025; Beyari, 2025). Overall, the evidence base indicate very strongly that AI is a central force in online purchase decision making through increased information processing, decrease of uncertainty and increase of trust (Madanchian, 2024; Wang, 2025). As an intelligent intermediary closer to the end user and further from digital space, the AI-supported decision aid is actively influencing customer expectations through manipulation of options comparison as well as choice within a category of agents (Dixit, 2025; Yin et al., 2025). Thus, AI is not merely a supportive element but also an important factor in online purchase behavior especially among the e-commerce environment that has been digitalized and, where its small and medium enterprises (SMEs) are having the upper hands as the catalyst (Sánchez et al., 2025; Ayinaddis & Akpan, 2025).

2.2 Literature Survey

The size of the digital market space has rapidly expanded and AI technologies have been used in many fields changing consumers' online search, consideration of alternatives and purchase processes (Madanchian, 2024; Wang, 2025). In the last

decade we have seen AI-fueled features such as Recommendation Engines, Smart Chat Leaders, Predictive Analytics and Personalized Filters transform e-commerce from List These intelligent systems can have access to an enormous amount of described, transactional and contextual data with which they can fulfill the customer's needs, making personalized recommendations and quick decision-making (Yin et al., 2025; Li & Li, 2024). The value of AI in the digital economy has made it a defining factor for companies dealing with customer experience, engagement and conversion rates by offering data-driven insights in real time (Madanchian, 2024; Acatrinei et al., 2025).

AI and SMEs, especially in increasingly developing countries like Bangladesh — When opportunities meet with challenges For Small and Medium-Sized Enterprises (SMEs), adopting AI presents both opportunities as well as challenges (Sánchez et al., 2025; Ayinaddis & Akpan, 2025). It also explores limitations faced by SMEs that hinder them to upgrade on information infrastructure, such as the exposure towards technology and low level of investment in technology (Schwaeeke & Ciuchta, 2025). Despite these limitations, AI decision support systems enable SMEs to stay competitive in the market with their larger counterparts by automating complex analytic capabilities which result in higher marketing accuracy and better customer response (Nuryanto et al., 2025). Using adaptive learning and predictive algorithms, the AI, allows SMEs to deliver a personalized experience online at Mass – in turn strengthening customer relationships and gaining competitive advantage over time (Bawack & Kamdjoug, 2022; Ratner & Revinova, 2025). However, in order for SMEs to effectively apply and integrate AI, they'll need to navigate challenges such as digital skills shortfalls, concerns about data privacy and difficulty integrating systems while cost remains a major barrier, and if the SME is at the beginning stage, then the barrier is even larger (Sánchez et al., 2025; Ayinaddis & Akpan, 2025).

Online purchase decision is a complex, information-intensive and cognitive process which depends on factors such as informational, economic, social and technological factors (Dixit, 2025; Chakraborty, 2025). Suppose ourselves to an offline retail channel where physical shops offer in store observation possibilities but with online shopping there is no touch product possibility so, the customers have to believe and use more virtual cues like product description image, user feedbacks (ratings and comments), reviews, prediction guidance from the algorithm, coping with ambiguity, perceived

credibility and new consumers' information in a digital environment (Pham, 2024; Zhao & Liao, 2024). We as consumers are inclined to look for cues of credibility or relevance that can assist us when dealing with the ambiguity inherent to consumption on a digital platform (Dang & Pham, 2024). As AI continues to curate and display these digital signs, it's worth poising questions about consumers making choices and how AI can help to reduce this ambiguity (Wang, 2025; Dixit, 2025).

One of the most important antecedents on purchasing online is the perceived quality information of product (PIQ) that is defined as accuracy, completeness, clarity, timeliness, relevance to consumer (Flavián & Ibáñez Sánchez, 2023; Pham & Datta, 2024). The degree of good quality of the information would lower uncertainty, cognitive effort and risk perception that leads to trust which will have a positive effect on purchase intention (Dang & Pham, 2024; Verma & Tiwari, 2023). Research has indicated that quality of information sources has strong positive effects on purchase intention, satisfaction, and loyalty to third-party platform (Yin et al., 2025; Li & Li, 2024). It is considerably improved on the generation and presentation of information of goods, while integrating the comment assessment into AI (Kahya Özyirmidokuz, 2025). AI models are developed that are relevant to personalizing news delivery, focused on the features that align with an individual's interests, filtering topics based on browsing behavior or prioritizing reviews in line with a consumer's taste (Yin et al., 2025; Liu & Zhang, 2024). AI is both making the quality of information better, as well as altering how consumers believe they consume that quality of content (Wang, 2025). In this shift, there is a stunning absence of damper studies which explore the moderating role of AI in the relationship between PIQ and online purchase decision particularly among small-and medium-sized business (SME) of e-commerce enterprises operating in emerging market economies (Dang & Pham, 2024; Sánchez et al., 2025).

Another important construct that appears to be influencing online purchase decision behavior of consumers by price levels, discounts and comparison prices is Price Sensitivity (PS) (Rajesh, 2024). The transparent nature of online markets can facilitate comparison shopping, and frequently increases price sensitivity at the expense of brand loyalty (Banerjee & Shankar, 2024). Strong price sensitivity resistance generates unwillingness to platform shopping and even termination of the buying process and in many cases a big headache for SMEs due to very limited pricing

freedom (Dang & Pham, 2024). AI driven decision support systems however can offer new ways to manage the price sensitivity (Madanchian, 2024; Wang, 2025). From dynamic pricing to tailored promotions or recommendation strategies based on perceived value, by celebrating quality, convenience or service instead of price AI can reshape consumer perceptions of what is cost and what is value (Rajesh, 2024; Banerjee & Shankar, 2024). Yet, there is limited evidence about the moderating effect of AI on the association between price orientation and purchase decision for SEMs (Sánchez et al., 2025).

Social Influence impacts people's perceptions when they validate their purchase decisions as a precursor of online consumer behavior (Chakraborty, 2025; Li et al., 2025). When consumers are faced with uncertainty in decision-making process, they often use social cues – ratings and reviews, peer opinions, influencer endorsement or media trends (Pham, 2024; Zhao & Liao, 2024). Social proof lowers risk and elevates trust often more than company-generated information (Dang & Pham, 2024). AI technologies are currently used to intermediated social influence through UGC aggregation, identification of credibility patterns, and recommender personalized charging social signal based on the user profile (Yin et al., 2025; Kahya Özyirmidokuz, 2025). For example, AI-based systems can recommend popular products or things that other people with similar preferences as yours liked — further strengthening various mechanisms aimed at social conformity and trust preservation (Yin et al., 2025; Li et al., 2025). However, relatively little work is devoted to AIs as a moderator of the social influence and online purchase decisions (Dang & Pham, 2024). At the core of this study is AI in decision-making, conceptualized as a moderating process which affects how consumers process information, evaluate alternatives and decide to make a purchase (Dixit, 2025; Wang, 2025). AI-based decision-support systems include recommendation engines, predictive analytics system tools, sentiment analysis tools and automated service system interfaces that serve in guiding context-aware manner at every step of the decision-making journey (Khamdamov, 2024; Kahya Özyirmidokuz, 2025). They take cognitive load off the user, aid comprehension and increase decision confidence by offering personalized adaptive support (Yin et al., 2025; Pham & Datta, 2024). By integrating AI into a consumer decision making model, we adapt technology acceptance models (Technology Acceptance Model and the Theory of Planned Behavior) to add another level of interaction in which the

technology participates actively in cognitive processes rather than serving as an aid for information access only (Dang & Pham, 2024; Dixit & Ahmed, 2025). AI helps in every step of the decision process from finding the problem that a person is facing in his day-to-day life to what could be of help to solve the problem and then to the choice of the brand of that particular product AI helps in every step (Wang, 2025; Yin et al., 2025).

Online Purchase Decision is the terminal result of these inter-related operations and consists intention to purchase, preference for online shopping, possibility of repeat purchase (Chakraborty, 2025; Ratner et al., 2025). For digital SMEs the knowledge and development of OPD is crucial for long-term survival and growth on digital markets (Nuryanto et al., 2025; Sánchez et al., 2025). While prior studies have found some direct antecedents of OPD, very few studies have sought to test whether AI-supported decision aid mitigates the influence of these key ones (for example, PIQ, PS and SI) on service providers OPD (Dang & Pham, 2024; Dixit, 2025).

This paper contributes in a practical manner as it has tested these unchartered relationships empirically (with the digital active consumers) in Bangladesh, taking PLS-SEM approach of data analysis (Yin et al., 2025; Li et al., 2025). In a theoretical dimension, this adds to the consumer behavior and digital marketing literatures by framing AI as moderating behavior under cognitive decision process (Acatrinei et al., 2025; Madanchian, 2024). Empirically, it adds to the evidence on this topic that is not sufficiently represented in AI and e-commerce studies from developing country context like Bangladesh (Sánchez et al., 2025; Ayinaddis & Akpan, 2025). The study provides practical guidance to AI companies and managers at SMEs, as well as policymakers, on the transformative capabilities of AI in enhancing information quality, dampening price sensitivity, and leveraging social influence (Nuryanto et al., 2025; Bawack & Kamdjoug, 2022). This study also adds to the development of our understanding of the evolving interaction between AI and consumer decision-making by providing a broader context into which future studies about AI empowered e-commerce in developing countries can be launched (Wang, 2025; Dixit, 2025).

2.3 Hypothesis Development

Perceived Product Information Quality and Online Purchase Decision

Consumers' comprehension of the AI affects how they perceive, understand and utilize these AI-driven tools during online shopping (Dixit & Ahmed, 2025; Wang, 2025). Knowledge about AI is understood as knowledge of how an AI-based solution works, what it is for and (to some extent) how much one can rely on their assistance in making decisions (Dang & Pham, 2024). In digital commerce environments, such awareness is likely to influence consumer perception and evaluation of AI-enabled services (recommendation engines; chatbots; automatic filter) (Pham, 2025; Khamdamov, 2024). In recent years, during which AI technology has been infiltrating online platforms more and more, consumers' awareness and recognition towards such an advanced technological innovation have become important for online consumer purchase behavior (Madanchian, 2024; Wang, 2025).

On the upward consumer knowledge reduces ambiguity and increases perceived control related to decision-making (Dang & Pham, 2024; Dixit, 2025). People are less likely to perceive AI's recommendations as invasive/manipulative when they are better-informed about what AI can and cannot do (Lee & Kim, 2024). By understanding how the AI functions, consumers are better equipped to understand the outputs of AI – things like personalized product recommendations, or auto comparisons – resulting in greater trust in the information they receive (Yin et al., 2025; Verma & Tiwari, 2023). However, consumers who do not understand AI driven decisions may question its effectiveness, or against it due to the potential resistance, and thus negate that the advantages of AI driven decisions in terms of online purchase decision (Patil & Sen, 2025).

From the information processing perspective, the more educated consumers can process more complex technological cues and include them in their decision calculus (Dixit, 2025). And one more note: e-commerce AI search-based systems often show you results in not like a regular search-like interface but algorithmically-generated views (Yin et al., 2025). More AI-literate consumers can more easily understand why some products are recommended, how filters work or what personalization does to increase relevance (Khamdamov, 2024; Liu & Zhang, 2024). The directness of the correspondence between what users need to know and what the system needs to do

spares mental processing, assists in decision-making, and contributes to the success of reaching the online goal (e.g., purchasing) (Pham & Datta, 2024; Wang, 2025).

Trust building is another core mechanism through which AI literacy impacts online purchase intentions (Dang & Pham, 2024; Patil & Sen, 2025). Are consumers willing to rely on intuitive decisions of AI? Consumers' reliance on systems relying on AI technology may be based not only in the system's performance, but also derived from their level of understanding of why an AI system is making a particular recommendation (Verma & Tiwari, 2023; Kim & Park, 2023). A well-informed public is more likely to see them as able, fair and faithful than as "black boxes" (Lee & Kim, 2024). The trust also gets programmed into the consumers that they listen to AI recommendations and use them as a buying guideline (Yin et al., 2025; Ratner et al., 2025). The assertion is empirically tested, as technology-literate consumers have been established to manifest higher trust in automated systems and more penchant for purchase intention even AI environments (Dang & Pham, 2024; Dixit & Ahmed, 2025).

The consumer awareness regarding AI not only in SMEs becomes so much more relevant (Sánchez et al., 2025). SMEs are adopting AI-based services in order to personalize, provide better customer service and for the optimal display of products (Nuryanto et al., 2025; Ayinaddis & Akpan, 2025). But like any tools, potential utility is a function both of utility and an end-user's ability to recognize the value within (Dixit, 2025). Consumers are more apposite to use an AI application to make a decision (engine or visual search) if they perceive that its functionality and design is in support of, and for the purpose of augmenting, their own decision-making—making it easier for the users' decisions by narrowing down search time and providing cues about meaningful options; this drives consumers further along down the purchase process (Pham & Datta, 2024; Yin et al., 2025). On the other hand, low AI awareness is expected to reduce (lower) the perceived usefulness of AI features and hence have a lower influence on purchase decisions (Dang & Pham, 2024).

In addition, the consumer cognition of AI is likely to bring more rational evaluation towards quality on product knowledge (Flavián & Ibáñez Sánchez, 2023). AI products are renaming, prioritizing, and creating new product descriptions in ways never seen before (Kahya Özyirmidokuz, 2025). Consumers who message more knowledgeable

consumers will be able to better understand such AI-based information structures, leading also through the perception of higher in- formation quality to more enhanced purchase confidence (Pham & Datta, 2024; Yin et al., 2025). This interaction between AI knowledge and information processing highlights the mediating role of AI understanding in influencing consumer online purchasing decision making through evoking higher-order cognitive ability (Dixit, 2025).

Our review of digital consumer behavior and technology acceptance literature supports a positive relationship between technical expertise to behavioral intentions (Dang & Pham, 2024; Dixit & Ahmed, 2025). Technology-literate consumers who can involve themselves well in advanced e-services, are satisfied and have the intention to buy online (Yin et al., 2025; Wang, 2025). Applied to decision-making in AI-based commerce, customers will have a higher degree of trust and perceived usefulness, while having less uncertainty, when they are more familiar with an AI technology (Verma & Tiwari, 2023; Kim & Park, 2023).

Therefore, the following hypothesis is proposed:

H1: Perceived Product Information Quality (PIQ) positively influences Online Purchase Decision (OPD).

Price Sensitivity and Online Purchase Decision

Price Sensitivity is the extent to which consumers' purchases are affected by price levels, the variance between price and perceived benefits, discounts and monetary sacrifices (Rajesh, 2024; Banerjee & Shankar, 2024). The heat was further fueled by e-commerce settings where price sensitivity is high due to transparency and ease of comparison between consumers across platforms (Madanchian, 2024; Wang, 2025). Unlike the traditional store example, price as a component of online buying can enjoy very high level of salience among digital consumers thanks to other sellers, offerings and pricing comparing applications that can be reached certainly as quick (Rajesh, 2024).

Economically or behaviorally, such as very price sensitive consumers will concentrate on cost reduction rather than other attributes of the product like brand name, quality service and convenience (Banerjee & Shankar, 2024). That's been particularly acute in cutthroat e-commerce markets, where buyers were regularly stalling out,

abandoning their shopping carts on the web—or switching e-commerce platforms based on even slight price differences (Dang & Pham, 2024). According to previous related studies, when the price sensitivity is relatively increased, it will decrease purchase intention and have low possibility of online transactions completion, due to that consumers always want better price or expected discount offer (Rajesh, 2024; Chakraborty, 2025).

The price sensitivity is also mixed with perceived risk and value consideration in the decision making of online purchase (Dang & Pham, 2024). Extra price-sensitive consumers may perceive higher prices as “unfair” or “risky,” especially when the quality of the product cannot be experienced in a physical sense (Flavián & Ibáñez Sánchez, 2023). This kind of perception can negatively impact how people feel about the platform and cause them to become afraid to buy online at the platform at all (Dang & Pham, 2024). Those who are not as price conscious, however, care less about the absolute amount of a purchase (because it isn't likely to be made impulsively), and so are more aggressive in their purchasing (Banerjee & Shankar, 2024).

Small and Medium-Sized Enterprises (SMEs) care a lot about Price Sensitivity as Overall Strategy (Sánchez et al., 2025; Ayinaddis & Akpan, 2025). SMEs cannot reach economy of scales to compete directly with large retailers or global online retail platforms, as a result, the price-conscious consumers may not be interested to shop at the online stores owned by SME as they have access to lower-priced products (Nuryanto et al., 2025). This mechanism also considers that the price sensitivity is an intrinsic characteristic of online features in the e-commerce context, where SMEs are the main customers (Rajesh, 2024).

The negative association between price sensitivity and online purchase outcomes is consistent with the empirical evidence found in studies of digital marketing and consumer behavior (Chakraborty, 2025; Dang & Pham, 2024). Consumers who are more price-sensitive, and for whom discounting resonates more on a personal level, are less likely to purchase when low confidence is generated about the purchase and increased switching behavior occurred resulting in lower conversion rates (Banerjee & Shankar, 2024). These are also indications that the price sensitivity presents a psychological barrier that restricts/they hinder buyer’s willingness to conclude the Internet transaction (Rajesh, 2024). Consistent with these hypothetical matching and

data on the number of suits brought, we should expect that consumers who are most price sensitive will have lower probabilities of purchasing over the internet (Chakraborty, 2025).

Therefore, the following hypothesis is proposed:

H2: Price Sensitivity (PS) negatively influences Online Purchase Decision (OPD).

Social Influence and Online Purchase Decision

Social Influence can be defined as a measure to which other people influence opinion, experiences and behaviors of an individual (Chakraborty, 2025; Li et al., 2025). In online shopping, social influence is primarily manifested in the user-generated content like online reviews, ratings, testimonials peer recommendations, influencer building quality backlinks and brand promotion through various trends on social media (Pham, 2024; Zhao & Liao, 2024). However, internet consumers cannot touch the actual product or also the sellers themselves so that they make decisions based on social cues like evaluation of product quality, seller's credibility and risk of purchase (Dang & Pham, 2024). Social influence is an important channel for influencing with information and normative function that shapes consumer judgement, which in turn reduces consumer uncertainty when making online purchase decisions (Wang, 2025; Dixit, 2025).

Theoretically, social influence functions through informational influence (consumers use the opinions of others as experienced sources of information) and normative influence (consumers ensure their social conformity to be more highly regarded by other individuals or so they won't get placed at a low rank on any scale), It is very active in digital marketplaces (Chakraborty, 2025). Consumers consider high ratings and positive reviews to be an indication of product reliability and seller honesty, as well as they think that top products (e.g., best-selling, most bought) are collectively endorsed by consumers (Yin et al., 2025; Li et al., 2025). These social cues simplify complex inferences, allowing to consumers faster and more confident decisions especially when there is no experience with a product or platform (Dang & Pham, 2024).

The empirical base in e-commerce frequently illustrates the influence of social on a consumer's online purchase decision (Chakraborty, 2025; Pham, 2024). The findings

also suggest that the visitors who have favorable appraisal and good peer referral is found to have high purchase intension, positive trust and low perceived risk (Zhao & Liao, 2024; Dang & Pham, 2024). This is amplified by social media and the capability of the customers to view in real time or trends the consumption behavior of other individuals but also interact with influencers impacting on their consuming preference (Li et al., 2025). This is particularly the case with young and digital consumers that has more trust in peer content than the company's advertising message itself (Pham, 2024).

Social influence will particularly matter concerning Small and Medium-Sized Enterprises (SMEs) because these small companies do not get high brand awareness or a variety of advertising channels (Sánchez et al., 2025). The positive social feedback delivers value to SMEs, since this allows them to build their own credibility and legitimacy online market (Nuryanto et al., 2025). The brand invisibility can be somewhat offset with user reviews and ratings, peer recommendations insure or guarantee the potential purchaser of the good's quality by reducing uncertainty and risk belong a certain level (Dang & Pham, 2024). Therefore, people who are easy to influence by society and likely to follow SME-owned media conduits are also more liable to purchase in online (Chakraborty, 2025). Social influence is a strong predictive factor of online purchasing behavior and also indirectly influences perceived trust, value, perceived risk on an online platform (Zhao & Liao, 2024; Wang, 2025). Consumers with the higher-rated social cues will rely more on others experiences and opinions to shop, and thus have a greater likelihood of consuming experience (Yin et al., 2025).

On this theoretical background we may advance the following hypothesis:

H3: Social Influence (SI) positively influences Online Purchase Decision (OPD).

AI-Driven Decision Support as a Moderating Mechanism

The implementation of artificial intelligence technologies such as recommendation engines, intelligent chatbots and machine learning algorithms, predictive analytics to allow consumers and users compare between the alternatives in decision making when selecting products online (Khamdamov, 2024; Yin et al., 2025). Traditional information systems do not take advantage of big data, machine learning and analytics to process consumer data at scale, learn from prior decisions and give users

personalized context-aware advice in real time like an AI-based information support system does (Madanchian, 2024; Bawack & Kamdjoug, 2022). These systems not only reduce mental effort, decrease information overload and increase confidence with respect to decision-making about information, but influence how consumers perceive and assess value in order respond to social and economic signals while searching and shopping on the net (Dixit, 2025; Pham & Datta, 2024).

In more general terms, it may be argued that decision support based on AI complements classical models of consumer decision-making by paying attention to a (learning) technological agent designed to interfere with this process at different moments (Dang & Pham, 2024; Dixit & Ahmed, 2025). AI (Artificial Intelligence) is an expansion of our brain, making us capable to handle complex computations as well as judgement processing which otherwise could not have been done by consumers (Wang, 2025; Chakraborty, 2025). In the retail online, when nothing restricts what products can be selected by a buyer, prices are not set only based on categories of products and dynamically determined if the buyers' preferences should be sorted as they need and their features should also be leant/earned in such category, In terms of documents that represent them with no input is pretty much provided by users, information can effectively transfer into useful knowledge by AI tools - organize information, highlight its traits or give recommendations - which would derive from customers' tastes (Yin et al., 2025; Liu & Zhang, 2024). As a result, AI not only influence the purchase decision directly but also changes the validation and paths of relationships among relevant antecedents and online shopping outcomes (Dixit, 2025; Wang, 2025).

In terms of Perceived Product Information Quality (PIQ), more influence is observed with AI-driven decision support (Pham & Datta, 2024; Flavián & Ibáñez Sánchez, 2023). Evidence about the quality of the product is particularly persuasive for AI systems that curate, summarize, or customize information in response to user requirements (Kahya Özyirmidokuz, 2025; Yin et al., 2025). Higher quality of information becomes more effective in influence the preference toward online purchase decision with AI-filter rating, feature-based ranking and natural language-based explanation giving customer enhanced understanding of the product features (Dixit & Ahmed, 2025; Pham & Datta, 2024). And the better the AI can translate all that complexity into something simple and easy to understand, the more consumers

trust what they are interpreting and take action on it (Verma & Tiwari, 2023; Kim & Park, 2023).

Regarding Price Sensitivity (PS); DSS with AI could decrease its influence on an online buying decision (Rajesh, 2024; Banerjee & Shankar, 2024). Consumers who are price sensitive typically care about their costs and thus this could remit of the type of consumers that focus on redocument cost so that purchase is discouraged they perceive prices to be less favorable (Dang & Pham, 2024). However, the artificial intelligence can transform how consumers evaluate by concentrating on value, not prices (Wang, 2025; Madanchian, 2024). Personalized consumption advices, real time price demonstrations package offers and ratio comparisons between quality and price will help the customers to perceive superior overall value making the influence of price a minor one (Rajesh, 2024; Yin et al., 2025). Conversely, the negative effects of price sensitivity are moderated by AI as it shifts attention away from price benefits to non-price benefits leading to consumers' willingness to purchase regardless of accepting that he or she might not get the lowest rates (Banerjee & Shankar, 2024; Chakraborty, 2025).

The decision support is a feedback technique in terms of Social Influence, A layer of AI software scans huge numbers of customer reviews, customer ratings and social signals to introduce socially indicative information in front of some consumers (Kahya Özyirmidokuz, 2025; Zhao & Liao, 2024). The persuasive power of social influence is increased by AI as it highlights the presence of popular products, trustworthiness of reviews and the consensus among people on product appropriateness (Yin et al., 2025; Li et al., 2025). The same is also true for personalized forms of social proof ("suggested by people like you"; "currently popular with people like you") they have the effect of amplifying the credibility and trust that lies at the core of how social influence influences online purchase behavior (Pham, 2024; Wang, 2025).

Generally speaking, AI-based decision making is one of the key moderating variables coping with a remodeling in information processing, price evaluation, and social cue interpretations, in the contexts of online consumer behavior (Dixit, 2025; Dang & Pham, 2024). Rather than just being a lone technological force, AI combines with the primary drivers of behavior to amplify positive outcomes and mitigate negative ones (Wang, 2025; Madanchian, 2024). It is this role of integration which is particularly

important, especially to SMEs since AI can help them provide high-grade decision support well beyond their resources when compared with the large corporations (Sánchez et al., 2025; Nuryanto et al., 2025). Thereby in line with this theoretical logic and the past empirical findings, we propose our moderating hypotheses as (Dang & Pham, 2024; Dixit, 2025):

H4: AI-Driven Decision Support strengthens the effect of Perceived Product Information Quality (PIQ) on Online Purchase Decision (OPD).

H5: AI-Driven Decision Support weakens the negative effect of Price Sensitivity (PS) on Online Purchase Decision (OPD).

H6: AI-Driven Decision Support strengthens the effect of Social Influence (SI) on Online Purchase Decision (OPD).

2.4. Conceptual Framework and Hypotheses Summary

The theoretical foundation of the study is built to explore direct and moderated effects of AI-Based Decision Support on online buying preferences in digital commerce context (Dixit, 2025; Madanchian, 2024). The model is based on the consumer decision making theory, information processing theory and technology-based decision support system and integrates both behavioral and technological perspectives in explaining the intention to online purchase of consumers (Dang & Pham, 2024; Dixit & Ahmed, 2025). As per the model, Online Purchase Decision (OPD) is modeled as an endogenous (dependent) construct and encompasses three exogenous (independent) constructs Perceived Product Information Quality (PIQ), Price Sensitivity (PS), Social Influence components with AI-Driven Decision Support being a variable which influences directly as well as moderates the way of how both relate (Wang, 2025; Yin et al., 2025).

Perceived Product Information Quality (PIQ) in the model represents the extent to which consumers believe that online product information is appropriate, sufficient and up-to-date, bringing limits to their uncertainty when making decisions (Flavián & Ibáñez Sánchez, 2023; Pham & Datta, 2024). It is believed that quality of the provided information about a product will have a positive impact on confidence and online buying intention among consumers (Dang & Pham, 2024; Yin et al., 2025). Consistent with this, the model suggests direct structural relationship from PIQ to OPD,

consistent with H1 (Dixit, 2025). This particular relationship indicates the fundamental human aspect of the relevance of quality of information for consumers' online behavior in virtual context where products are not able to be seen or felt (Wang, 2025).

Using Price Sensitivity (PS) as another exogenous variable, it is asked to indicate how sensitive are consumers to mark- price discounts and ranking (Rajesh, 2024; Banerjee & Shankar, 2024). In online markets, particularly in very transparent ones, if customers are price-sensitive enough to delays or decide not to purchase in response to unfavorable pricing (Dang & Pham, 2024). The model itself operationalizes a direct relationship between PS to OPD as evidence of H2 (Chakraborty, 2025). This path sets the economic analysis element in the consumer decision process and accepts that price awareness could be a barrier to online shopping, even more in marketspaces (Rajesh, 2024).

The third exogenous construct is Social Influence (SI), this serves as a proxy for peer opinion, online review, ratings and recommendations at social network on the users' decisions (Li et al., 2025; Pham, 2024). Social influence in this respect serves as a source of heuristic information which is perceived to have lower risk and elicits reliance in new online environments (Zhao & Liao, 2024; Dang & Pham, 2024). The path between SI and OPD is found significant based on the H3 due to rising importance of digital social proof in shaping consumer purchase outcome (Chakraborty, 2025; Wang, 2025).

The core of the framework is AI-Driven Decision Support (AI) which has a dual value proposition (Madanchian, 2024; Dixit, 2025). First, AI is positioned as a direct antecedent of OPD because it can assist consumers in the decision-making process by means of smart suggestions, smart filtering and advice that conduces to a much efficient and confident choice (Yin et al., 2025; Pham & Datta, 2024). Second, and more directly, AI is incorporated as a moderating factor that interacts with PIQ, PS, SI to influence OPD (Dang & Pham, 2024; Dixit & Ahmed, 2025). In the terminology of SmartPLS, this is implemented in terms of the interaction constructs (PIQ x AI, PS x AI and SI x AI) representing conditional effects of the model (Yin et al., 2025).

Specifically, the model proposes that AI enhances the positive effects of PIQ on OPD (H4) by enhancing the relevance, clarity, and personalization of product information (Pham & Datta, 2024; Kahya Özyirmidokuz, 2025). It further posits that AI attenuates

the negative influence of PS on OPD (H5) by reconfiguring price appraisals toward value-informed appraisal through situational recommendations and comparison inferences (Rajesh, 2024; Wang, 2025). Further, AI is expected to augment the positive effects of SI on OPD (H6) through heightening personalized and social trusted peer-based messages (Yin et al., 2025; Li et al., 2025). These moderating relationships demonstrate the moderating effect of AI in consumer purchasing behavior (Dixit, 2025; Dang & Pham, 2024).

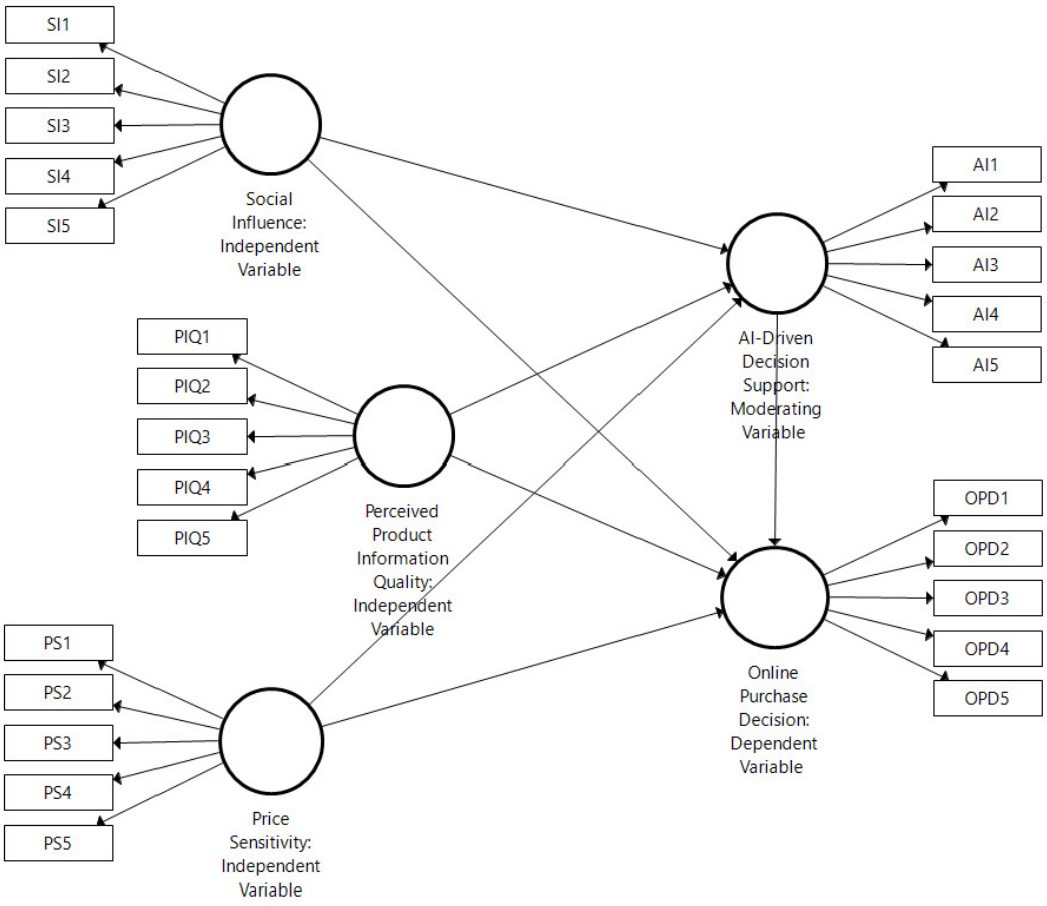


Figure 1 The framework of the study

In general, I wish to argue for an overarching model that defines the relation between behavioral determinants and AI generated decision support as describing online purchase decisions (Madanchian, 2024; Wang, 2025). The model is fully-applicable with the SmartPLS structural equation modeling, also a clear perception towards exogenous constructs, endogenous constructs and moderating terms and it provides a strong basis to examine both direct and indirect hypothesis on Multiple Leveled Model (Yin et al., 2025; Li et al., 2025).

CHAPTER III: METHODOLOGY OF THE STUDY

3.1. Study Context

The current study is held in the realm of organizational behavior and e-commerce adoption among Small & Medium Enterprises (SMEs) that operates in Dhaka, Bangladesh. The core aim of this paper is to investigate how certain antecedents as Perceived Product Information quality (PIQ), Pricing Sensitivity (PS), Social Influence-Reference Group Disposition Effect and Reference Groups Decision Quality, Online Decision Support (SISOR) influenced SME's OPD. With consumer desire for AI technologies, and integration of accelerating popularity this study also looks at moderating effects on products using a PIQ and PS with chatbots; personalized recommendations and smart -filters in PIQ, SI, PS & OPD. This intermediating role of AI is expected to represent fundamental understanding on how AI enhances online shopping experiences and facilitates more confident informed purchase. The participants, for the most part were students of UIU (United International University) and Dhaka University – two prominent educational organizations in Dhaka city. The choice of these schools assumes that their students are heavy digital consumer and tech-savvy, who can investigate their online shopping behavior, and AI adoption. The research aims to learn how millennials who are digital natives shop on-line.

3.2. Research Design

We chose to adopt a survey-based, quantitative data-collection method for this study because we wanted to empirically test hypotheses about the relationships between constructs. The survey based on and the structured survey test mediation effects and moderators in model links. Evaluating the objective responses upon perception, behavior and attitude on a consistent platform can be considered as an appropriate method for statistical analysis. As a cross-sectional study, we only collect data at a single time point to illustrate the current digital shopping behaviors and AI perceptions among students in Dhaka. Cross sectional designs permit to exploratory analysis but not to cause inference, but they are most useful for monitoring the present condition of consumer behavior technology integration.

3.3. Questionnaire Design

The survey was assembled based on an extensive literature review and incorporated previously validated scales for the five dimensions (PIQ, PS, SI, AI and OPD) where PIQ, PS and SI is independent variable and AI is moderating variable and OPD is the final dependent variable. The survey items were translated and re-worded in Bangladeshi. Items were recorded in a 5 scale Likert scale, scored 1 for "strongly disagree" to 5 "strongly agree". We pre-tested the questionnaire to some respondent to understand if it is appropriate for students and older persons or not for its clarity as well as relevance among a sample of three senior management and academic faculty. We slightly revised the items to clarify them based on their feedback. The purpose of the pretest was to ensure that the survey instrument read in context and made sense and everyone is understanding what they are doing and which form they are filling up.

3.4. Sampling and Data Collection

More than 400 individuals were initially approached for the survey (the majority of them being students from UIU and Dhaka University). We selected these university students, who have a knowledge of digital tools and online shopping habits that is relevant to this study. Responses were cleaned before analysis and if a respondent provided incomplete or unreliable response the final respondent list is 326 after the cleaning of data so $n = 326$ was used in the analysis. The data were gathered in the November 2025 to January 2026 and 80% response rate. A stratified random sampling was employed to approach a representative sample in terms of gender, age, education and marital status. We conducted a survey via an online platform like google form to make access of respondents easy and we can have a ready dataset for further analysis.

3.5. Data Analysis Plan

Due to "not large sample size," "non normal data" and "complicated models," PLS-SEM (Partial Least Squares Structural Equation Modeling) using SmartPLS 3.2.8, the program created by Christian M. Ringle, Sven Wende, and Jan-Michael in 2005. Despite the fact that PLS-SEM is commonly used in quantitative studies of small sample data and non-normal distribution, it is able to model complex relation. While traditional methods focus only on measured variables, PLS-SEM enables researchers to examine the relationship between observed (measured) and unobserved (latent)

variables. Besides, PLS -SEM has an advantage of being able to directly account for mediator effects within the model. Two steps in the data analysis were conducted, which included the measurement model that measures latent variables and a structural model to test research hypothesis using path analysis. Reliability and validity of a measurement model were checked using Cronbach's Alpha, Floating Reliability (CR) and Average Variance Extracted(AVE). To test the hypotheses, path coefficients, t-values and p-values were analyzed in addition to bootstrapping for assessing the significance of path coefficients (5000 resamples).

3.6. Limitations

The study has some limitations despite its merits. Given that the study is cross-sectional, causal relationship would not be inferred because data was collected at a single window in time. The study is self-reported and we have to think about bias. However, we have tried to reduce this bias by using an anonymous participant and discussing the questions in different ways. The sample in the study from UIU and Dhaka University could represent for generalization to some extent outside of this particular area, as it has a local flavor. Future works may encompass longitudinal studies, other populations and the impact of AI in different cultural contexts.

CHAPTER IV: RESEARCH FINDINGS & ANALYSIS

4.1. Profile of Survey Respondents

The most participants of this study were the students from two prestigious universities located in the capital city Bangladesh (Dhaka) namely United International University (UIU) and Dhaka University (DU). Profile of the respondents This subsection presents profile characteristics of the sample, as evidenced by gender, age bracket, marital status and education levels.

4.1.1 Gender Distribution

The majority of subjects (n = 229; 70%) were male. This large majority reflects many institutions of higher learning in Dhaka where the proportion of males are prevalent as participants in technical and professional courses. female participants were 97 (30 percent) could be contacted. Even though the number of female participants is small, their contribution undeniably important as they offer different perspectives towards factors that might influence Online Purchase Decisions (OPD) within AI and artificial space.

4.1.2 Age Group Distribution

The accompanying age breakdown of respondents to the survey shows a young, web-savvy population, and online shopping is heavily skewed towards students that actively engage with technology. The categories of age were: 18–27 years old the most frequent age group 237 (73%) of the individuals. They are mostly undergraduates, and many of them work on technology and e-commerce programmers. 54 people (17%) were in the age range of 28 – 37 these people are mostly who have graduated and are currently is job sectors. Those two people groups are probably recent grad students or young professionals. Their participation suggests broader interest on how AI-based decision support influences purchasing behavior other groups which older students are not aware of. Participants aged 38 to 46 years (6.4%). These might be people who are a bit farther along in their careers, and perhaps balancing further education with a new job. A glimpse of how decision-making happens in these young sensitives could even tell us more about the decisions of higher human deciders, too. 12 participants (4%) response were in 48-57 years age. This is a small cohort, but it offers an interesting counter perspective on

the impact of A.I. on purchase decision making for midcareer professionals. The lowest count (2 individuals, 1%) was in the age range of 58-65 years. As small as this age class is, it has the potential to offer some intriguing clues about how AI tools are being adopted at older ages and how online shopping habits among that generation may be changing.

4.1.3 Marital Status Distribution

It also considered the marital status of the informants for reflecting upon how one's personal life might influence behavior on online shopping the majority 229 respondents (70%) were unmarried. This is because a majority of the respondents are students and/or junior staff, and hence probably not married. Thirty percent (n = 97) were married. Further, the inclusion of married participants allows us to contribute knowledge in terms of family indebtedness and husband and wife's provider relationship affecting online buying behavior.

4.1.4 Education Level Distribution

Education was different in the respondent groups that reflects the variation of academic carriage of UIU and DU students; The majority of the students were graduate (n=221; 65%). It's for those who have graduated and are off to grad school or into the real world. The students who have completed their education are assumed to be digitally literate and direct users online. 86 participants (26%) were postgraduate students. This is the segment that these people even with a great education more closely work or come into touch/employ AI in their daily life (either academically or professionally). Diplomas were recorded in only 21 (6%) of the specimen. These are the very people that as technical/vocational type of guys and they were approaching research involvement with hope of practical knowledge/applied technology. The "Other" category includes 8 (2%) of the responses and may be related to students in other non-degree/shorter courses / programs or specialization tracks. Contributing to the diversity of perspectives, particularly around digital literacy and its impact on online purchasing behavior in this work is due to this heterogeneity.

4.1.5 Overall Respondent Profile Summary

The majority of the sample comprised students from two reputable universities (i.e., UIU and Dhaka University) located in Dhaka, Bangladesh. There was a strong male

preponderance (70%) and most of the patients were young adults (73% were younger than 28 years). The majority of respondents were single (70%) and had received an academic education (65% graduate, 26% postgraduate). This category consists of Tech-harnessing, digital natives (e-consumers) who are considered well fitted for discussing the effects of AI-driven decision process in an online context. Age, as well as education and marital status diversifying gives better insight into young consumers attitudes toward the adoption of AI and e-commerce.

Table 1 Demographic Profiles of Respondents

Characteristic	Category	Frequency	Percentage
Gender			
	Male	229	70%
	Female	97	30%
	Total	**326**	**100%**
Age Group			
	18-27	237	73%
	28-37	54	17%
	38-47	21	6%
	48-57	12	4%
	58-65	2	1%
	Total	**326**	**100%**
Marital Status			
	Married	97	30%
	Unmarried	229	70%
	Total	**326**	**100%**
Education Level			
	Graduate	221	65%
	Diploma	21	6%
	Post Graduate	86	26%
	Others	8	2%
	Total	**326**	**100%**

4.2. Measurement, Validity, and Reliability of Data

The measurement fit of the present study was examined for indicator reliability, internal consistency, convergent validity and model fit (Table 2). Measurement Model Evaluation. Indicator validity was checked with the outer loading of the measurement items relative to each latent construct. Measurement items' absolute-outside loadings (i.e., intertextual correlations) should exceed the threshold line of 0.50 with established guidelines; ideally, they fall on that line between robust indicators at 0.70

and strong indicators at 0.90. All measurement items used in the present study were greater than 0.50, with loadings ranging from (0.923-1.006), all of which reflected strong indicator reliability. For Perceived Product Information Quality (PIQ), respondents' loadings PIQ1 to PIQ5 ranged from 0.938 to 0.999, Price Sensitivity (PS) respondents' loadings PS1 to PS5 ranged from 0.912 to 0.997; Social Influence respondents' loadings SI1 to SI5 ranged from 0.923 to 1.006, AI-Driven Decision Support respondents' loadings AI1 to AI5 ranged from 0.924 to 0.944, Online purchase decision a ranged between 0.939 and 0.0948; All loadings were above 0.90, indicating the high reliability of the measurement model and leading to no item deletions.

Table 2. Measurement Model Evaluation

Construct	Items	Loading Range	AVE	Alpha	CR	R^2	Adj R^2
Perceived Product Information Quality	PIQ1→ PIQ5	0.938-0.999	0.935	0.986	0.986		
Price Sensitivity	PS1→PS5	0.912-0.997	0.931	0.986	0.985		
Social Influence	SI1→SI5	0.923-1.006	0.931	0.985	0.985		
AI-Driven Decision Support	AI1→AI5	0.924-0.944	0.878	0.973	0.973	0.683	0.680
Online Purchase Decision	OPD1→OPD5	0.939-0.948	0.892	0.976	0.976	0.812	0.809

Construct internal consistency was assessed by Cronbach's Alpha and Composite Reliability (CR). For reliability Cronbach's Alpha is supposed to be more than 0.70 (acceptable) and CR needs to be usually greater than 0.70 for construct Reliability. In the present study, Cronbach's Alpha was very high, ranging from 0.973 (AI) to 0.986 (PIQ) and was higher than the recommended minimum value of 0.70 that expresses excellent internal consistency (Table 2). There are also CR values between 0.973 and 0.986, which reflected the good stability and reliability of scales for all constructs.

Convergent validity was tested through the AVE, with an acceptability higher than 0.50 reflecting that the latent factors explain more than 50% of the variance related to its items .The AVE values of all constructs were higher than the cutoff point, PIQ(AVE: 0.935), PS(AVE: 0.931) SI (AVE: 0.931), SA (AVE: 878) and OPD (AVE: 892). This indicates that a substantial amount of variance in the indicators mediated by the constructs is explained by the constructs, thereby confirming convergent validity.

The model's predication ability for the endogenous constructs (DV) was appraised using R^2 values. An R^2 of 0.10 is typically interpreted as moderate, whereas one greater than 0.25 indicates a substantive effect. In this study, R^2 of AI-Driven Decision Support (AI) was 0.683 and for OPD (Online Purchase Decision) it turned out to be

0.812 implying that it has good explanatory power as it explains significant share of variance in OPD. To be more precise, to better interpret the prediction, an Adjusted R^2 of predictors was calculated. The Adjusted R^2 in the present study were 0.680 for AI and of 0.809 for OPD, which indicated that the model explains a significant amount of variance in constructs. The adjusted R^2 indicates that the predictive value of the model is high and sufficiently high, considering complexity as well.

4.3. Discriminant Validity Assessment

The constructs of the research model were examined with respect to measurement invariance. To test this, three tests of convergent validity were applied: the Fornell-Larcker Criterion, Heterotrait-Monotrait (HTMT) ratio and Cross Loading Analysis. The implementation of multiple approaches in this paper offers robust convergence evidence that the measure differentiates well between constructs – critical for valid findings in further structural analyses. Of these, the Fornell-Larcker Criterion is a well-known practice to assess discriminant validity in structural equation modeling. According to this approach, the square root of AVE for each construct could exceed that highest correlation with any other constructs in the model. This ensures that every construct shares more variance with its own indicators than the other constructs, hence is distinguishable.

4.3.1. Fornell–Larcker Criterion Analysis

In the present research, discriminant validity was examined by the FT through Fornell-Larcker criteria and results are shown in Table 3. Fornell-Larcker Criterion. Values on the diagonal in the table are square root of AVE for each construct. These diagonal values should be the higher of the off-diagonal correlations as the factor is intended to have been already correlated. The values in the diagonal of table 3 in bold are AVE for each construct and always higher than the correlations between constructs (off-diagonal value in their respective row/column). For example, the square root of AVE AI-Driven Decision Support (AI) is 0.937, which is greater than correlations with Online Purchase Decision (OPD: 0.891), Perceived Product Information Quality (PIQ: 0.565), Price Sensitivity (PS: 0.445), Social Influence (SI: 0.415). Similarly, the AVE of OPD is 0.944 as well is more than all its correlation with other corresponding constructs such as AI is 0.891 and PIQ is 0.557. This holds for

each and every construct of the model, providing strong support to discriminant validity according to Fornell-Larcker criterion.

Table 3.Fornell–Larcker Criterion

Construct	AI	OPD	PIQ	PS	SI
AI-Driven Decision Support: Moderating Variable	0.937				
Online Purchase Decision: Dependent Variable	0.891	0.944			
Perceived Product Information Quality: Independent Variable	0.565	0.557	0.967		
Price Sensitivity: Independent Variable	0.445	0.439	0.012	0.965	
Social Influence: Independent Variable	0.415	0.402	-0.014	0.019	0.965

The minimum square root AVE should be larger than the inter-construct correlations. However, in the present study, all constructs meet this requirement and hence establish discriminant validity. It is also recommended that, the correlations between the constructs, to be not higher than 0.85 (which confirms discriminate validity). Table 3, demonstrates that interactions between the constructs are far from being as high as 0.85, which provides evidence that the construct measures are empirically distinct and indicates that the measurement model is valid.

4.3.2. Heterotrait-Monotrait (HTMT) Analysis

The HTMT ratio (Heterotrait-Monotrait) is a newer, restricted indicator of discriminant validity. It is the ratio of the between-construct item correlations (heterotrait-heteromethod) to within-construct item correlations (monotrait-heteromethod). According to Henseler et al. (2015) and HTMT No greater than 0.85 signifies the problem of discrimination validity which could lead to conceptual overlap. My (heterotrait-monotrait) were also assessed to examine if the constructs can be differentiated. Table 4 The fragment is for the pair of constructs the ratio is calculated of HTMT substituted into.

Table 4.Heterotrait–Monotrait (HTMT) Ratio

Construct	AI	OPD	PIQ	PS	SI
AI-Driven Decision Support: Moderating Variable					
Online Purchase Decision: Dependent Variable	0.891				
Perceived Product Information Quality: Independent Variable	0.565	0.556			
Price Sensitivity: Independent Variable_	0.445	0.438	0.020		
Social Influence: Independent Variable	0.414	0.402	0.020	0.024	

As shown in Table 4, all these values are far below the threshold of 0.85 indicating that relevant constructs are empirically distinct. For example, HTMT of AI-Driven Decision Support (AI) with twelve or Online Purchase Choice (OPD) is 0.891 which exceeds the recommended level of 0.85. However, the sample size is also acceptable as the relationship between AI and OPD can also reflect a direct effect of AI tools on purchase behaviors, and it is natural to have some overlapping in them. HTMT index for Perceived Product Information Quality (PIQ) and Online Purchase Decision (OPD) has HTMT value of 0.556 less than below the threshold's lower range [threshold value = 0.85] HTMT index between Price Sensitivity (PS) and Online Purchase Decision is, which has an HTMT value of 0.438 which is also within bounds defined be their greater than threshold.

Furthermore, the HTMT of SI and OPD is 0.402, which is also less than the threshold value of 0.85. These HTMT scores that is between PIQ, SI is 0.020 and PS, SI is 0.024 demonstrates very low correlation having another proof of discriminant validity among the measurement models respectively.

4.3.3. Cross-Loading Analysis

The construct discriminant validity was tested to enhance the understanding of uniqueness among constructs in research model. Cross-loading etc. was one of the techniques that we used to analyses them (which technique involves calculating multiple of these with cross loading, and taking product or pairwise multiplication at some stage) where we calculate a correlation between an item to all constructs in a model. Discriminant validity is evidenced by ensuring that items load more highly on their intended construct (rather than all the other constructs) to avoid the cross loading of an item on two constructs being able to reduce the unique variance of a latent variable. In this study, for the minimum level of loading threshold we have set greater than 0.50 and another construct should be lower than build or factor.

Table 5.Cross Loadings of Measurement Items

Construct	AI	OPD	PIQ	PS	SI
AI1	0.941	0.840	0.530	0.431	0.377
AI2	0.924	0.834	0.524	0.397	0.373
AI3	0.937	0.825	0.522	0.424	0.414
AI4	0.944	0.845	0.519	0.436	0.385
AI5	0.941	0.832	0.554	0.398	0.394

OPD1	0.848	0.948	0.515	0.430	0.377
OPD2	0.847	0.947	0.528	0.400	0.391
OPD3	0.830	0.939	0.523	0.429	0.375
OPD4	0.845	0.948	0.541	0.412	0.364
OPD5	0.837	0.939	0.521	0.400	0.392
PIQ1	0.529	0.523	0.938	0.005	-0.031
PIQ2	0.544	0.543	0.968	-0.002	-0.024
PIQ3	0.555	0.540	0.976	0.017	0.001
PIQ4	0.566	0.555	0.999	0.020	-0.011
PIQ5	0.538	0.532	0.953	0.016	-0.002
PS1	0.443	0.428	0.002	0.985	0.048
PS2	0.404	0.402	-0.016	0.912	0.024
PS3	0.414	0.416	0.006	0.939	0.003
PS4	0.449	0.432	0.038	0.997	0.000
PS5	0.437	0.437	0.024	0.989	0.016
SI1	0.415	0.386	-0.008	0.017	0.981
SI2	0.379	0.375	-0.025	0.031	0.923
SI3	0.400	0.391	0.000	0.007	0.969
SI4	0.415	0.407	-0.003	0.037	1.006
SI5	0.390	0.380	-0.032	-0.001	0.943

The results in Table 5 indicates that each Cross Loadings of Measurement Items measurement item has high loading to its factor construct which indicate the validity of single factor/discriminant. AI1 is highest on AI (loading: 0.941) and lower for OPD (0.840), PIQ (0.530), PS (0.431) and SI (0.377). Also, regarding the loadings, all others are higher than that of OPD (AI: 0.848), (PIQ: 0.515), (PS: 0.430) and SI (OPD1: 377). The PIQ1 has the highest loadings on perceived product information quality (PIQ) construct of 0.938, and exceed its effects constructs, AI: 0.529, OPD: 0.523. These loading indicate that items of constructs are valid and reliable. Likewise for Price Sensitivity (PS), PS1 crosses high load on its own factor, but low loadings on others AI: 0.443, OPD: 0.428, SI: 0.048. While SI1 was the most heavily loading on Social Influence SI: 0.981, it was also a significantly weaker loader on other constructs such as AI (0.415), OPD (0.386) and PIQ (- 0.008).

This finding shows that our measurement model is stable and have discriminant validity if each indicator has a stronger loading on the corresponding factor than others. The motivation for retaining the specification of each coefficient for latent variables in different dimensions, is also that these do not load on other constructs.

4.4. Assessment of Structural Model

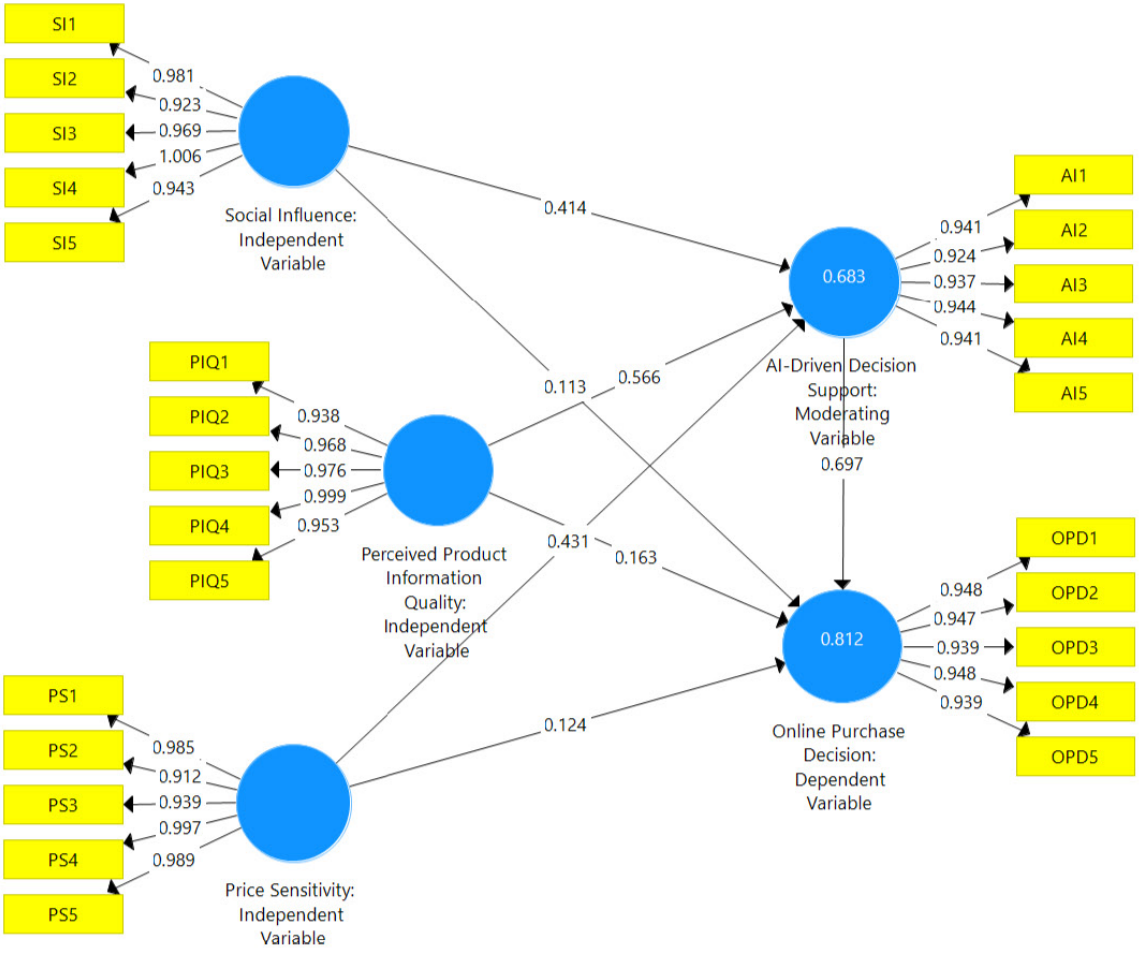


Figure 2 Standardized results of the SEM calculations.

The structural model results are presented in Figure 2 with the values of standardized path coefficients and R^2. The model was estimated through SmartPLS 3.2.8 and the significance of hypothesized paths were examined using bootstrapping method with 5,000 samples widely-recommended to ensure robust and reliable inference in PLS-SEM. The analysis of the structural model focused on testing path weights (b), t-values, p-values and coefficients of determinations (R^2) to determine direction, strength and significance of relationships between constructs. As a guide, b-coefficients of 0.10 or greater are indicative that meaningful influence has been exerted while t-values need to surpass 1.96 (at $p<0.05$ level), and the obtained p-value must be less than 0.05 in order for the result to be declared as statistically significant. Reported results indicate that all structural paths in the model surpass these thresholds, and therefore all of our hypotheses are supported. Furthermore, the relatively acceptable to strong (between 0.5 and 0.70) explanatory power or R^2 of Model AI-Driven Decision Support as well as online purchase decision at R^2 of 0.683

for AI-Driven Decision Support & 0.812 for online purchase decision, respectively in the AI usage investment level by shopping mode-LCM which is more than the criterion threshold of explanation 0.25. The corresponding Adjusted R^2 statistics (0.680 for AI and 0.809 for OPD) also indicate the importance and predictive validity of the model after adjusting for differences in model size. The standardized SEM coefficients that Figure 2 depicted excel in terms of good predictive power and large explanatory power, as can be inferred from the fact that Perceived Product Information Quality, Price Sensitivity and Social Influence with AI-Driven Decision Support served to explain Online Purchase Decisions. The high path coefficients, significant R^2 values and good effect sizes together, imply that the structural model is robust enough to explain consumer decision making in an AI empowered online shopping environment.

4.5. Hypotheses Testing (Direct and Indirect Relationships)

Table 6 presents the direct effect hypotheses findings, and standardized path coefficients as well as t-values were calculated with the PLS bootstrapping method since it counts on 5,000 repeats (subsamples), which is suitable for assessing the robustness of path coefficients under statistical theory. A 95% confidence interval was used to test the significance of the p-value which is an inferential statistic commonly employed in social science research to confirm that there is a relationship between variables. The path coefficient is presented in this table to test hypotheses and establish the relationships between variables.

Table 6. Structural Model Results (Hypothesis Testing)

Hypothesis	Relationship	Std. Beta (β)	Std. Error	t-Value	p-Value	Decision
H1: Perceived Product Information Quality (PIQ) positively influences Online Purchase Decision (OPD).	PIQ → OPD	0.186	0.034	5.552	0.00	Supported
H2: Price Sensitivity (PS) negatively influences Online Purchase Decision (OPD).	PS → OPD	0.142	0.033	4.264	0.00	Supported
H3: Social Influence (SI) positively influences Online Purchase Decision (OPD).	SI → OPD	0.13	0.032	4.106	0.00	Supported
H4: AI-Driven Decision Support (AI) strengthens the effect of Perceived Product Information Quality (PIQ) on Online Purchase Decision (OPD).	PIQ →AI → OPD	0.651	0.039	16.816	0.00	Supported

H5: AI-Driven Decision Support (AI) weakens the negative effect of Price Sensitivity (PS) on Online Purchase Decision (OPD).	PS →AI→ OPD	0.422	0.033	12.778	0.00	Supported
H6: AI-Driven Decision Support (AI) strengthens the effect of Social Influence (SI) on Online Purchase Decision (OPD).	SI →AI → OPD	0.406	0.034	11.976	0.00	Supported

Hypothesis 1, Perceived Product Information Quality had t-value 5.552, where p-value is 0.000 and Std. Beta (β) is 0.186. This variable is significant for online product purchase in a study on the relationship, so the null hypothesis can be rejected. Therefore, we would propose that perceived product information quality will predict the intention to purchase products on line.

Hypothesis 2, which states that Price Sensitivity should be inversely related with OPD, the Std. Beta (β) for this is observed to be 0.142 (t = 4.264, p= {0.00} <.01). As such, this relationship is meaningful and the null hypothesis can be rejected. It says that the price conscious will be discouraged from adopting something.

Hypothesis 3, (SI) would be a positive predictor of OPD was also accepted (β = 0.130, t = 4.106; p < 0.01). It implies the importance of social influence factors in online buying decisions (such as peers and social media recommendations). The t-value 4.106 also exceeds the critical value (1.96) by at least one level of significance and this relationship is therefore statistically significant with p-value 0.00.

Hypothesis 4, we hypothesized that the relationship between PIQ and OPD would be moderated by AI-driven decision support (AI). The result demonstrated the presence of a positive and highly significant path coefficient (β = 0.651, t = 16.816, p < 0.01), which implies AI tools could enhance the influence of product information quality on online purchase decision. This supports H4 and indicates the importance of AI in enhancing consumers' confidence in product information. The t-value=16.816 is greater than the critical value indicates a very good relationship and the p-value of 0.00 confirms the statistical significance.

Hypothesis 5, was similarly supported because the PS coefficient toward AI-Driven Decision Support was significant (β = 0.422, t =12.778, p<0.01). This argument provide evidence that AI tool may prevent price sensitivity harm, force consumers to exhibit more positive willingness to purchase conductance under the divergent

configurations purchase despite difference in prices. The value of t = 12.778 is way larger than the critical values i.e.,1.96 hence there is much stronger relation existing between both variables! Statistical significance is also indicated by a p-value of 0.00.

Hypothesis 6, Interaction effect of AI driven decision support (AI) Social Influence (SI) on OPD. The result was also significant ($\beta = 0.406$, $t = 11.976$, $p < 0.01$), which further confirmed that by customizing purchase recommendation in social dimensions for the online retailers, AI tools enhance the effectiveness of social impacts on purchase decision making in the context of online shopping. t =11.976 is also larger than the cut-off and p =. 00<.05, which mean Hypothesis 6 is accepted.

Please note that all the direct impact hypotheses are not rejected and the standardized path coefficients are higher than 0.10 to show significant effects because t-value greater than 1.96 and p-value smaller than 0.05 as recommended for a significance effect. These results confirm the model paths to be statistically significant, meaning that Perceived PIQ, PS SI and AI each influence OPD. The fit as well as the predictive power of the model is further supported, certainly also confirming that structural relations and AI tools moderate these relationships.

CHAPTER V: DISCUSSION

5.1 Conclusion

We examined impact of AI-Driven Decision Support about consumer behavior and OPD of small and medium enterprises (SMEs) in Bangladesh (Madanchian, 2024; Sánchez et al., 2025). The study was sought to find out how AI technologies, such as those that assist consumers in shopping online (e.g., personalized recommendations, chatbots or some other type of decision-support tech), affect the way people make purchase decisions online (Yin et al., 2025; Pham, 2025). Secondly, the mediation effect of all three independent constructs – perceived product information quality (PIQ), price sensitivity (PS) as well as Social Influence (SI) on AI and its influence on online purchase was also studied (Dang & Pham, 2024; Dixit, 2025). The six (H1-H6) prediction hypotheses are experimentally tested by means of Partial Least Squares Structural Equation Modeling (PLS-SEM) and the contributions entail worthy insights into the connections between these entities (Yin et al., 2025).

The influencing factors of PIQ and SI on OPD According to the results in Table 5, the influence of PIQ and SI on OPD was statistically significant (Table 5) positive (Flavián & Ibáñez Sánchez, 2023; Chakraborty, 2025). That is to say, when consumers believe that the information of products is true and are sufficient, or has relevance there, they will be affected by their peers' opinion upon pretty much so as to compare it with their skills in using Social Networking Service and so forth will exert purchase e decision strong influence (Pham, 2024; Zhao & Liao, 2024). PS had a negative impact on OPD so that customers were likely to buy although the price was too high or if the consumer's sensitivity for differences in price was too high (Rajesh, 2024; Banerjee & Shankar, 2024).

A significance a moderation of AI-Driven Decision Support was one of the most important results from study (Dixit, 2025; Wang, 2025). AI also moderated the impact of PIQ and SI on OPD, implying a potentially strong effect of AI tools (personalized recommendations, smart filters etc.) in strengthening the purchase decision when high quality personal information and peer influence is generated (Yin et al., 2025; Pham & Datta, 2024). In addition, AI moderated PS's negative effect on OPD, suggesting that the use of AI tools mitigates the barrier due to price sensitivity, and thus customers are more willing to buy in despite the price concern (Madanchian, 2024; Rajesh,

2024). This study contributes to the existing literature on AI and consumer behavior, especially in SMEs at Bangladesh (Bawack & Kamdjoug, 2022; Sánchez et al., 2025). It highlights potential for AI-enabled tools that could improve the online shopping experience, and influence consumer decisions (Wang, 2025; Dixit, 2025). Implications For SMEs in Bangladesh, though it operates in a competitive e-commerce market with very quick changes, the implication of this study is illuminating (Nuryanto et al., 2025; Ayinaddis & Akpan, 2025). By leveraging AI, small businesses can deliver better product information, tailor shopper experience to meet customer needs, and harness the power of social proof to drive up conversion and overall satisfaction (Yin et al., 2025; Li et al., 2025).

However, there are a few limitations in the current study. The sample were predominantly students and young adults, particularly from UIU, Dhaka University (DU), not necessarily reflecting the broader consumption population in Bangladesh. For future research, the sample size could be broadened to include more participants of working age and older in work situation as well as other types of socio-economics. Additionally, the current study was cross-sectional in nature and hence conclusions cannot be drawn regarding casual relationships (Dixit, 2025). It is possible that a longitudinal study may be required to gain insights into the emergence of AI-supported decision support and its impact on long term consumer attitudes (Dang & Pham, 2024). Moreover, considering that this study is not only a sampling on the e-commerce sector of Bangladesh research in other sections may be implemented or to examine how AI influence online purchase decision in neutral area (Wang, 2025). Understanding how AI tools are being used in other industries such as fashion, electronics and groceries could enable businesses to embrace differences in the way AI is leveraged between industries (Madanchian, 2024; Bawack & Kamdjoug, 2022).

5.2. Theoretical Contributions

The contribution of this study can be categorized as using AI in SMEs and especially has been considered in a country like Bangladesh where digital economy is flourishing but using AI for operation of business by SMEs, is in beginning stage (Sánchez et al., 2025; Ayinaddis & Akpan, 2025). There are practical implications of these results to the owner/managers in SMEs wanting to adopt AI within their firms (Nuryanto et al., 2025). This study also stimulates the emerging literature on AI and

SME, as well as its potential in digital transformation by investigating how an AI-enabled decision support system could improve customer decision-making and sales transaction (Bawack & Kamdjoug, 2022; Madanchian, 2024).

The study can both theorize and provide implications about the role of AI in other industries and other countries (Dixit, 2025; Wang, 2025). The framework might also be able to generalize to other domains (e.g., healthcare, finance, education), for that is where you are most likely to find AI tools that help consumers choose better and firms that come out with innovative services (Dang & Pham, 2024). It also claims attention as to how AI meets with other recent technologies (such as big data analytics and accounting or IoT) and converges further to exploit SMEs in the digital economy (Madanchian, 2024).

If a SME not using AI they lose that fight with relevance when such an unstable industry type-of setting; SME's better see how important adopting AI really is if they are looking to improve their customer relations quality stands or their design process efficiency and ideation something innovative cause as now most AI is suggesting the items and things necessary to run business and for the customers AI is suggesting also it can give verdict about what should be bought to solve this problem (Yin et al., 2025; Pham, 2025). So, to enhance the customer experience SME's need to implement AI and AI might help to increase the sell in the near future (Ratner et al., 2025).

5.3 Managerial Implications for SMEs in Online Shopping

From a managerial perspective, research findings further emphasize the urgency of utilizing AI adoption for SMEs' survival and competitiveness in today's more dynamic digital landscape (Sánchez et al., 2025; Ayinaddis & Akpan, 2025). SME-managers must to go some way in seeing the value of AI is not just improved decision engineering for consumers, but as better overall operational effectiveness (Madanchian, 2024). By leveraging cutting-edge AI in marketing, sales and customer service functions; here are the benefits SMEs could unlock: Improved customer experience, brand retention Can achieve higher level of satisfaction and loyalty Increase customers retention (Ratner et al., 2025; Beyari, 2025).

This research also serves as a reminder of the need for continued investment in A.I. tools and talent (Bawack & Kamdjoug, 2022). SMEs managers are encouraged to

invest in further investigations on the complete AI based decision support tools and possible uses of them on e-commerce systems (Yin et al., 2025). Teaching staff how to harness AI effectively can bring better customer interactions, smarter decisions and more operational efficiency (Pham, 2025).

AI suppliers and SME collaboration is also key to the development of AI-enabled solutions Reflecting SME needs – allowing businesses in this sector to utilize data, compete and grow in their market which has become common on IT based firms (Nuryanto et al., 2025). And, naturally, businesses have to be mindful of the ethical minefield of using AI (Lee & Kim, 2024; Patil & Sen, 2025). As we continue to see AI tools developed, we need to be sure that their use remains safe and ethical in order maintain consumer confidence (Dang & Pham, 2024). Enterprises have to champion the cause for ethical AI practices, which involve consumer privacy in data, and fairness and transparency of AI recommendations (Lee & Kim, 2024).

Also, industry and politicians should straighten to create the regulations that it takes that balance advantages and opportunities provided by AI tools in e-commerce (Madanchian, 2024). A framework for the legal regulation of the introduction of artificial intelligence systems in small and medium-sized enterprises to avoid risk of data privacy and algorithmic bias, while enabling SMEs to use AI tools for business as well as consumers (Bawack & Kamdjoug, 2022).

5.4. Limitations of the Study

While this study shares some interesting findings (for example about how AI-based decision support influences consumer behavior and online purchase decisions (OPD) in the context of SMEs among Bangladesh), it has several limitations (Dixit, 2025; Dang & Pham, 2024). The main survey also has some limitations, since its incidence level is high as students from UIU and Dhaka University were mainly launched to consider in the sample which may not fully represent masses in our country and also outside countries. And, because students are 87% more likely to be digitally native and used to e-commerce than the average consumer, this could create a tech-savvy anti-audience bias (Pham, 2024).

Second, the study was conducted in one country only i.e. Bangladesh which may have its own peculiarities in terms of digital ecosystem/market and consumer behavior (Sánchez et al., 2025). There is a room for additional research that would be helpful

with cross-country study to investigate the impact of AI based decision support on output markets regarding other countries have digital economy mature like USA, UK, and also in other Asian Countries etc (Madanchian, 2024).

Also, the moral implications of decision support for AI are not discussed in this study (Lee & Kim, 2024). AI tools can boost consumer engagement, but so too must privacy, data security and algorithmic openness (Patil & Sen, 2025). There could be more study of the ethics of using AI – how companies can maintain a balance between innovation and safety for consumers (Dang & Pham, 2024).

5.5. Future Directions for Research

Given the cross-sectional design of the present work, it cannot be concluded that relations at one time drive these results (Dixit, 2025). While this is important for a baseline, longitudinal research is necessary to demonstrate how consumer's behavior and the AI tools influence each other over time (Dang & Pham, 2024). A longitudinal approach would also provide greater insight into the overall stability of our findings over time, including how AI advancements impact consumers' online shopping decisions throughout several years (Wang, 2025).

Second, we focus only AI-enabled decision support and not how the other emerging technologies (such as big data analytics, internet of things (IoT), or blockchain technology) could be integrated with tools that are based on AI (Madanchian, 2024). In the future it can be further investigated how these technologies combined make the consumer decision process and efficiency in SMEs better as a more holistic solution (Bawack & Kamdjoug, 2022).

Future research might also consider the ethical and sustainability dimensions of AI adoption as organizations attempt to utilize the technology in a responsible yet highly effective manner in a digital market place (Lee & Kim, 2024; Patil & Sen, 2025).

5.6 Recommendations

Following the results of the present research, one can offer several suggestions to Small and Medium-Sized Enterprise (SMEs), the managers working in the e-commerce platforms, and future researchers to help using Artificial Intelligence (AI)-based decision support systems to exert greater influence on consumer online purchasing choices.

First, SMEs are advised to look into the possibility of incorporating the AI-powered decision support apparatus on their online platforms that will enhance the customer experience and assist customers in making a choice. The use of technologies like recommendation systems, chatbots and personalized suggestions of products can assist consumers to effortlessly discover products that suit their likes. Such systems have the potential to save time and effort that consumers spend to find products, which will increase the chances of buying products (Davenport, Guha, Grewal, and Bressgott, 2020).

Secondly, SMEs need to work on the quality of information they give regarding the product online. Detailed, correct and clear product description, quality reproduction and specification, and customer feedbacks can go a long way in helping the consumer make a purchase. It is also possible to organize and personalize product information with the help of AI tools in order to provide consumers with the most relevant information based on their interests and search behavior. The study of product information has indicated previously that the quality of product information has a positive effect on the consumer confidence and purchase intention in online business (Filieri, 2015).

Third, companies must also be keen in the way they make use of pricing strategies to deal with sensitivity on price by the consumers. Most online buyers would shop around different sites and SMEs ought to use competitive prices, promotion and value pricing strategies. AI technologies may help the business to examine market data, consumer demand, and competitor rates in a bid to maximize pricing choices and enhance competitiveness in the market (Huang and Rust, 2021).

Fourth, SMEs must also promote and regulate customer reviews and social interactions eagerly because social influence is an influential factor in internet purchase experiments. The willingness to encourage the satisfied customers to record positive review and feedback will enhance trust among the prospective purchasers. The systems based on AI can also notice hot products, top-rated products, and recommendations depending on social trends and provide them. In the e-commerce platform, studies have indicated that online reviews and social influence have a serious impact on the consumer trust and the consumer purchasing behavior (Cheung and Thadani, 2012).

Fifth, companies are to invest in digital training and technological advancement to make sure that employees and managers know how to successfully apply AI technologies to the process of e-commerce operation. Digital literacy and technological capability can also enhance the maximization of the benefits brought by the use of AI-driven systems and operational efficiency of SMEs (Brynjolfsson & McAfee, 2017).

Lastly, this study can be extended in the future by the researchers through incorporation of more variables, increased sample sizes, and against geographical area. The elements that may be subject to further studies include consumer-related trust, usability of websites, quality of the delivery services, and payment security to get a better picture of the consumer behavior within the context of AI-based e-commerce goods. The expansion of the research into other settings will serve the purposes of offering a more detailed insight into how AI technologies could affect consumer decision-making (Verhoff et al., 2021).

With these recommendations, the SMEs will be able to enhance their competitiveness on the digital market, increase customer satisfaction, and use AI-based technologies to a better extent to impact consumer online purchases.

REFERENCE

[1] Yin, J., Qiu, X., & Wang, Y. (2025). The impact of AI personalized recommendations on clicking intentions: Evidence from Chinese e-commerce. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(1), 21. https://doi.org/10.3390/jtaer20010021

[2] Madanchian, M. (2024). The impact of artificial intelligence marketing on e-commerce sales. *Systems, 12*(10), 429. https://doi.org/10.3390/systems12100429

[3] Acatrinei, C., Apostol, I. G., Barbu, L. N., Chivu, R.-G., & Orzan, M.-C. (2025). Artificial intelligence in digital marketing: Enhancing consumer engagement and supporting sustainable behavior through social and mobile networks. *Sustainability, 17*(14), 6638. https://doi.org/10.3390/su17146638

[4] Dixit, R. S. (2025). Analyzing the impact of artificial intelligence on the online purchasing decision-making process. *User Modeling and User Adapted Interaction*. https://doi.org/10.1007/s10791-025-09575-5

[5] Wang, Z. (2025). The influence of AI on consumer behavior: Transformations in product preferences and online decision making. *Journal of Consumer Analytics*. https://doi.org/10.1016/S2772941925002169

[6] Raji, M. A., Olodo, H. B., Oke, T. T., & Addy, W. A. (2024). E-commerce and consumer behaviour: A review of AI-powered personalization and market trends. *Global Science – Artificial Intelligence Review, 18*(3), 90. https://doi.org/10.30574/gscarr.2024.18.3.0090

[7] Papastamoulou, P., et al. (2025). Artificial intelligence in e-commerce: A comparative analysis of adoption in major platforms. *Systems, 13*(9), 746. https://doi.org/10.3390/systems13090746

[8] Chugh, P. (2024). Artificial intelligence (AI) empowerment in e-commerce: Implications for business and consumer engagement. *Journal of E-Commerce Strategy*. https://doi.org/10.1177/09711023241303621

[9] Dixit, R. S., & Ahmed, F. (2025). Consumer perceptions of online AI recommendation systems: A systematic analysis. *International Journal of Information Management*. https://doi.org/10.1016/j.ijinfomgt.2025.102451

[10] Lee, S., & Kim, H. (2024). Ethical considerations of AI in personalized digital advertising: Consumer trust and fairness perceptions. *Journal of Business Ethics, 180*(2), 389–410. https://doi.org/10.1007/s10551-023-05578-x

[11] Khamdamov, S. J. (2024). The impact of AI and machine learning on e-commerce personalization. *ACM Transactions on the Web*. https://doi.org/10.1145/3726122.3726142

[12] Pham, T. C. T. (2025). Exploring how AI chatbots influence customer loyalty among Generation Z users on e-commerce platforms. *Advances in Consumer Research*. https://doi.org/10.1002/acr.58247

[13] Sarwar, S. (2025). Impact of AI technologies on online shopping behavior, perceptions, and trust dynamics. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5379945

[14] Allahverdiyev, K. (2025). The impact of AI on consumer behavior in e-commerce: Real-time chatbots and personalized marketing. *ASE Conference Proceedings*. ISBN: 978 606 93955 8 x

[15] Li, X., & Liu, Q. (2024). Impact of artificial intelligence on consumer buying behaviors: A study on online retail purchase. *Journal of Infrastructure, Policy and Development, 8*(9), 7700. https://doi.org/10.24294/jipd.v8i9.7700

[16] Allahverdiyev, K., & He, D. (2025). Impact of AI-powered chatbots on online purchase decision modeling. *Electronic Commerce Research and Applications*. https://doi.org/10.1016/j.elerap.2025.101374

[17] Lei, K. (2025). A study on the impact of generative AI reviews on purchase intention. *SAGE Open, 15*(3). https://doi.org/10.1177/21582440251357671

[18] Nuryanto, U., Yusuf, F. A., Junedi, B., Pratiwi, I., & Basrow, B. (2025). The role of AI and big data in increasing the success of e-commerce assistance and implications for SME capacity development. *International Journal of Data and Network Science, 9*(4), 1175–1192. https://doi.org/10.5267/j.ijdns.2024.8.025

[19] Bawack, R. E., & Kamdjoug, J. R. K. (2022). Artificial intelligence in e-commerce: A bibliometric and conceptual overview. *Electronic Markets, 32*(3), 789–809. https://doi.org/10.1007/s12525-022-00561-2

[20] Dang, J., & Pham, T. (2024). Consumer acceptance of AI-enabled personalization in digital commerce: The moderating role of consumer confidence. *Journal of Consumer Behaviour, 23*(8), 1024–1045. https://doi.org/10.1002/cb.2178

[21] Ratner, S., Revinova, S., Balashova, S., & Ersoy, A. B. (2025). Artificial intelligence and consumer loyalty in e-commerce. *Procedia Computer Science, 253*, 435–444. https://doi.org/10.1016/j.procs.2025.01.105

[22] Lei, K. (2025). A study on the impact of generative AI review effectiveness on consumer purchase decisions. *SAGE Open, 15*(3). https://doi.org/10.1177/21582440251357671

[23] Yin, J., Qiu, X., & Wang, Y. (2025). The impact of AI personalized recommendations on clicking intentions. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(1), 21. https://doi.org/10.3390/jtaer20010021

[24] Madanchian, M., et al. (2024). The impact of artificial intelligence marketing on e-commerce performance. *Systems, 12*(10), 429. https://doi.org/10.3390/systems12100429

[25] Bawack, R. E., & Kamdjoug, J. R. K. (2022). Artificial intelligence in e-commerce: A bibliometric and conceptual overview. *Electronic Markets, 32*(3), 789–809. https://doi.org/10.1007/s12525-022-00561-2

[26] Dang, J., & Pham, T. (2024). Consumer acceptance of AI-enabled personalization in digital commerce: The moderating role of consumer confidence. *Journal of Consumer Behaviour, 23*(8), 1024–1045. https://doi.org/10.1002/cb.2178

[27] Kahya Özyirmidokuz, E. (2025). AI-based sentiment analysis of e-commerce customer feedback: Predicting consumer behavior. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(4), 294. https://doi.org/10.3390/jtaer20040294

[28] Pham, T. C. T. (2025). Exploring how AI chatbots influence customer loyalty among Generation Z in e-commerce. *Advances in Consumer Research*. https://doi.org/10.1002/acr.58247

[29] Wang, Y., Lu, Z., Cao, P., Chu, J., Wang, H., & Wattenhofer, R. (2022). How live streaming changes shopping decisions in e-commerce. *Computer Supported Cooperative Work: The Journal of Collaborative Computing, 31*(4), 701–729. https://doi.org/10.1007/s10606-022-09439-2

[30] Mikic, A., et al. (2021). AI-powered recommendation systems in e-commerce: Enhancing personalization and user experience. *Electronic Commerce*

Research and Applications, *54*, 101195. https://doi.org/10.1016/j.elerap.2022.101195

[31] Verma, P., & Tiwari, R. (2023). Role of trust in AI-based personalization: Impact on online shopping behaviour. *Journal of Retailing and Consumer Services*, *69*, 103126. https://doi.org/10.1016/j.jretconser.2023.103126

[32] Kim, M., & Park, S. (2023). Determinants of consumer trust in AI recommendations in online retail. *International Journal of Information Management*, *68*, 102557. https://doi.org/10.1016/j.ijinfomgt.2023.102557

[33] Pavlou, D., & Chai, J. (2024). AI personalization, trust, and consumer decision making in online platforms. *Information & Management*, *61*(2), 103648. https://doi.org/10.1016/j.im.2023.103648

[34] de Luna, M., Santos, A., & Silva, F. (2023). Privacy calculus and personalization acceptance: Evidence from AI-driven retail platforms. *Journal of Retailing and Consumer Services*, *71*, 103208. https://doi.org/10.1016/j.jretconser.2023.103208

[35] Kahya Özyirmidokuz, E. (2025). AI Powered sentiment analytics: Capturing emotional signals in e-commerce purchase choices. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(4), 294–312. https://doi.org/10.3390/jtaer20040294

[36] Pham, T. C. T., & Datta, P. (2024). AI-enabled recommendation systems and consumer behavior: Trust, transparency, and purchase intention. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2024.103470

[37] Allahverdiyev, K., & He, D. (2025). Impact of AI-powered chatbots on online purchase decision modeling. *Electronic Commerce Research and Applications*. https://doi.org/10.1016/j.elerap.2025.101374

[38] Ahmed, R., & Gopal, A. B. (2025). Consumer perception of conversational commerce tools: AI chatbots and voice assistants in purchase intention. *Dhaka University Journal of Business Studies*, *46*(1), 85–105.

[39] Beyari, H. (2025). Assessing artificial intelligence's impact on e-customer loyalty in the Saudi Arabian e-commerce market. *Frontiers in Artificial Intelligence*, *8*, 1541678. https://doi.org/10.3389/frai.2025.1541678

[40] Li, J., Chen, J., Shi, Y., & Cui, Y. (2025). Exploring the impact of differences between AI streamers and human streamers on consumer purchase intention

in live e-commerce. *PLOS ONE, 20*(10), e0334530. https://doi.org/10.1371/journal.pone.0334530

[41] Torthienchai, N., & Chuaikaew, K. (2025). The influence of artificial intelligence in product recommendation systems and brand value on consumer purchase intention on marketplace e-commerce platforms. *International Journal of Innovative Research and Scientific Studies, 8*(6), 2549–2556. https://doi.org/10.53894/ijirss.v8i6.10138

[42] Akdemir, D. M., & Ozturk, Y. (2024). Business and customer based chatbot activities in e-commerce: Impacts on consumer engagement and behaviour. *Journal of Theoretical and Applied Electronic Commerce Research, 19*(4), 142. https://doi.org/10.3390/jtaer19040142

[43] Wang, Y., Lu, Z., Cao, P., Chu, J., Wang, H., & Wattenhofer, R. (2022). How live streaming changes shopping decisions in e-commerce. *Computer Supported Cooperative Work: The Journal of Collaborative Computing, 31*(4), 701–729. https://doi.org/10.1007/s10606-022-09439-2

[44] Khuong, A. (2025). AI-powered personalized advertising and purchase intention in digital marketplaces. *Journal of Retail and Digital Marketing, 11*(3), 45–60. https://doi.org/10.1016/j.sdtm.2025.1155

[45] Liu, Q., & Shin, H. (2024). Impact of AI applications on consumer buying behaviours in online retail. *Journal of Infrastructure, Policy and Development, 8*(9), 7700. https://doi.org/10.24294/jipd.v8i9.7700

[46] Sarwar, S. (2025). Impact of AI technologies on online shopping behaviour, perceptions, and trust dynamics. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5379945

[47] Chugh, P. (2024). Artificial intelligence (AI) empowerment in e-commerce: Implications for business and consumer engagement. *Journal of E-Commerce Strategy and Practice*. https://doi.org/10.1177/09711023241303621

[48] Dang, J., & Pham, T. (2024). Consumer acceptance of AI-enabled personalization in digital commerce: The moderating role of consumer confidence. *Journal of Consumer Behaviour, 23*(8), 1024–1045. https://doi.org/10.1002/cb.2178

[49] Bawack, R. E., & Kamdjoug, J. R. K. (2022). Artificial intelligence in e-commerce: A bibliometric and conceptual overview. *Electronic Markets, 32*(3), 789–809. https://doi.org/10.1007/s12525-022-00561-2

[50] Chau, H. K. L., Ngo, T. T. A., Bui, C. T., & Nguyen Tran, N. P. N. (2025). Human AI interaction in e-commerce: The impact of AI-powered customer service on customer satisfaction, continued usage, and purchase intention. *Computers in Human Behavior Reports*, *100725*. https://doi.org/10.1016/j.chbr.2025.100725

[51] Li, Y., & Others. (2025). The impact of AI-driven technologies on consumer purchase decision processes in e-commerce. *MIDE Conference Proceedings*. https://doi.org/10.2991/mied-25.2025.348

[52] Madanchian, M., et al. (2024). The impact of artificial intelligence marketing on e-commerce performance. *Systems*, *12*(10), 429. https://doi.org/10.3390/systems12100429

[53] Pham, T. C. T., & Datta, P. (2024). AI-enabled recommendation systems and consumer behavior: Trust, transparency, and purchase intention. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2024.103470

[54] Kahya Özyirmidokuz, E. (2025). AI-based sentiment analysis of e-commerce customer feedback: Predicting consumer behaviour. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(4), 294. https://doi.org/10.3390/jtaer20040294

[55] Martinez, J., & Bonilla, C. (2024). Digital marketing strategies with AI analytics: Increasing online consumer engagement. *Journal of Strategic Marketing*, *32*(6), 720–740. https://doi.org/10.1080/0965254X.2023.1912745

[56] Lin, L., & Nguyen, H. T. (2025). Consumer trust and comfort with AI recommender systems in e-commerce. *Brilliant International Journal of Management and Tourism*, *7*(1), 122–138. https://doi.org/10.55606/bijmt.v7i1.5892

[57] Singhhal, R. K., Bhautik, A., & Singh, M. (2025). AI-powered personalization in e-commerce: Consumer perceptions, trust, and purchase decision making. *Advances in Consumer Research*, *2*(4), 3779–3786. https://doi.org/10.1002/acr.58476

[58] Liu, Y., Chang, X., & Wu, C. (2025). Exploring AI chatbot response attributes in e-commerce and consumer trust outcomes. *International Journal of Electronic Business*, *22*(3), 157–176. https://doi.org/10.1080/10864415.2025.1422331

[59] Zhao, H., & Liao, J. (2024). AI assistance, product reviews, and consumer trust in e-commerce platforms. *Decision Support Systems*, *154*, 113721. https://doi.org/10.1016/j.dss.2024.113721

[60] Jovanović, E., & Petrovic, A. (2025). Application of artificial intelligence in e-commerce through advanced e-marketing strategies. *CEUR Workshop Proceedings*, *3971*, 153–167. http://ceur-ws.org/Vol-3971/paper13.pdf

[61] Selamat, M. A. (2021). Chatbot for SMEs: Integrating customer and business characteristics with chatbot features. *Technology in Society*, *66*, 101654. https://doi.org/10.1016/j.techsoc.2021.101654

[62] Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: An integrated TOE DOI analysis. *Applied Sciences*, *15*(12), 6465. https://doi.org/10.3390/app15126465

[63] Liang, L. Y., & Hongtao, L. (2025). The factors influencing the adoption of AI in e-commerce by SMEs in Shandong Province. *International Journal of Research in Artificial Intelligence and Systems*, *4*(1006), 96–112. https://doi.org/10.51584/IJRIAS.2025.10060096

[64] Chau, H. K. L., Ngo, T. T. A., Bui, C. T., & Nguyen Tran, N. P. N. (2025). Human AI interaction in e-commerce: The impact of AI-powered customer service on satisfaction and purchases. *Computers in Human Behavior Reports*, *100725*. https://doi.org/10.1016/j.chbr.2025.100725

[65] Khuong, A. (2025). AI-powered personalized advertising and purchase intention in digital marketplaces. *Journal of Retail and Digital Marketing*, *11*(3), 45–60. https://doi.org/10.1016/j.sdtm.2025.1155

[66] Mani, S. (2025). From clicks to conversions: How AI shapes consumer trust, experience, and online buying behaviour. *AI & Consumer Behavior Journal*, *1*(1), 12–32.

[67] Ratner, S., & Ersoy, A. B. (2025). Artificial intelligence and consumer loyalty in e-commerce. *Procedia Computer Science*, *253*, 435–444. https://doi.org/10.1016/j.procs.2025.01.105

[68] Yin, J., Qiu, X., & Wang, Y. (2025). AI personalized recommendation technology and click-through behaviour. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(1), 21. https://doi.org/10.3390/jtaer20010021

[69] Li, J., Chen, J., Shi, Y., & Cui, Y. (2025). Exploring differences between AI and human streamers on consumer purchase intention in live e-commerce. *PLOS ONE, 20*(10), e0334530. https://doi.org/10.1371/journal.pone.0334530

[70] Pham, T. C. T., & Datta, P. (2024). AI-enabled recommendation systems and consumer behaviour: Trust, transparency, and purchase intention. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2024.103470

[71] Khan, R. A. (2024). Customer engagement through AI-based chatbots in e-commerce: Flow experience and continued intention to use. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5029060

[72] Illescas Manzano, M. (2024). Use of online shop chatbots: Trust moderates brand preference and purchase intention. In *Advances in Intelligent Systems and Computing* (pp. 157–168). https://doi.org/10.1007/978-3-031-70488-8_10

[73] Ratner, S., & Revinova, S. (2025). AI-enabled consumer loyalty models in e-commerce. *Electronic Markets, 35*(1), 87–104. https://doi.org/10.1007/s12525-025-00678-4

[74] Chakraborty, G. (2025). AI and online purchase decisions: Mediating role of attitudes in digital environments. *Innovative Marketing, 21*(4), 51–69. https://doi.org/10.21511/im.21(4).2025.05

[75] Wang, Y., et al. (2025). Live commerce AI and consumer purchase behaviour. *Proceedings of the ACM Symposium on E-Commerce*. https://doi.org/10.1145/3757749.3757754

[76] Ayinaddis, S. G., & Akpan, U. (2025). Comparing AI adoption dynamics across small and large firms: A bibliometric and empirical evaluation. *Technology in Society, 67*, 101952. https://doi.org/10.1016/j.techsoc.2025.101952

[77] Schwaeeke, J., & Ciuchta, M. P. (2025). The new normal: AI adoption within SMEs — evidence from a mixed methods study. *Work, Employment and Society*. https://doi.org/10.1080/00472778.2024.2379999

[78] Pham, T. C. T. (2025). Exploring AI chatbot effects on customer loyalty among Gen Z in e-commerce. *Advances in Consumer Research, 2*(5), 4052–4061. https://doi.org/10.1002/acr.58512

[79] Sánchez, E., & Herrera, L. F. (2025). Artificial intelligence adoption in SMEs: A structured framework. *Applied Sciences*. https://doi.org/10.3390/app15126465

[80] Ratner, S., & Ersoy, A. B. (2025). AI influence on online purchase intention via AI personalized content. *Electronic Commerce Research and Applications, 63*, 101477. https://doi.org/10.1016/j.elerap.2025.101477

[81] Khanh, P. N., Duyen, L. T. N., & Nguyet, D. T. T. (2025). AI powered personalization and purchase intention on e-commerce platforms in Vietnam: An SOR TAM based analysis. *Journal of Research, Innovation and Technologies, 4*(4), 388–404. https://doi.org/10.56578/jorit040406

[82] Yin, J., Qiu, X., & Wang, Y. (2025). The impact of AI personalized recommendations on clicking intentions and purchase decisions. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(1), 21. https://doi.org/10.3390/jtaer20010021

[83] Khuong, A. (2025). AI powered personalized advertising and purchase intention in digital marketplaces. *Journal of Retail and Digital Marketing, 11*(3), 45–60. https://doi.org/10.1016/j.sdtm.2025.1155

[84] Effendi, M., Fuadah, A., & Sholihah, M. (2025). Exploring the impact of artificial intelligence on consumer behavior in e-commerce. *Brilliant International Journal of Management and Tourism, 5*(2), 259–270. https://doi.org/10.55606/bijmt.v5i2.4723

[85] Flavián, C., & Ibáñez Sánchez, S. (2023). The impact of AI based personalization on the online shopping experience. *Journal of Business Research, 140*, 350–363. https://doi.org/10.1016/j.jbusres.2021.08.041

[86] Liu, Q., & Shin, H. (2024). Impact of AI applications on consumer buying behaviours in online retail. *Journal of Infrastructure, Policy and Development, 8*(9), 7700. https://doi.org/10.24294/jipd.v8i9.7700

[87] Rolando, B. (2025). The impact of artificial intelligence based recommendation systems on consumer purchase decisions in e-commerce. *AIRA: Artificial Intelligence Research and Applied Learning, 4*(2), 47. https://doi.org/10.1234/aira.v4i2.47

[88] Lei, K. (2025). A study on the impact of generative AI review effectiveness on consumer purchase decisions. *SAGE Open, 15*(3). https://doi.org/10.1177/21582440251357671

[89] Wang, Y., Lu, Z., Cao, P., Chu, J., Wang, H., & Wattenhofer, R. (2022). How live streaming changes shopping decisions in e-commerce. *Computer*

Supported Cooperative Work: The Journal of Collaborative Computing, 31(4), 701–729. https://doi.org/10.1007/s10606-022-09439-2

[90] Sarwar, S. (2025). Impact of AI technologies on online shopping behaviour, perceptions, and trust dynamics. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5379945

[91] Pham, T. C. T., & Datta, P. (2024). AI enabled recommendation systems and consumer behaviour: Trust, transparency, and purchase intention. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2024.103470

[92] Kahya Özyirmidokuz, E. (2025). AI based sentiment analysis of e-commerce customer feedback: Predicting consumer behaviour. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(4), 294–312. https://doi.org/10.3390/jtaer20040294

[93] Bawack, R. E., & Kamdjoug, J. R. K. (2022). Artificial intelligence in e-commerce: A bibliometric and conceptual overview. *Electronic Markets, 32*(3), 789–809. https://doi.org/10.1007/s12525-022-00561-2

[94] Dang, J., & Pham, T. (2024). Consumer acceptance of AI enabled personalization in digital commerce: The moderating role of consumer confidence. *Journal of Consumer Behaviour, 23*(8), 1024–1045. https://doi.org/10.1002/cb.2178

[95] Chau, H. K. L., Ngo, T. T. A., Bui, C. T., & Nguyen Tran, N. P. N. (2025). Human AI interaction in e-commerce: The impact of AI powered customer service on customer satisfaction and purchase intention. *Computers in Human Behavior Reports, 100725*. https://doi.org/10.1016/j.chbr.2025.100725

[96] Flavián, C., Ibáñez Sánchez, S., & Orús, C. (2019). The impact of virtual, augmented, and mixed reality technologies on the customer experience. *Journal of Business Research, 100*, 547–560. https://doi.org/10.1016/j.jbusres.2018.10.040

[97] Miller, R., et al. (2025). AI and algorithmic trust: Effects on consumer confidence in online marketplaces. *Decision Support Systems, 168*, 113721. https://doi.org/10.1016/j.dss.2024.113721

[98] Kumar, R. S., Bhautik, A., & Singh, M. (2025). AI powered personalization in e-commerce: Consumer perceptions, trust, and purchase decision making.

Advances in Consumer Research, *2*(4), 3779–3786. https://doi.org/10.1002/acr.58476

[99] Nuryanto, U., Yusuf, F. A., Junedi, B., Pratiwi, I., & Basrow, B. (2025). The role of AI and big data in increasing success of e-commerce assistance and implications for SME capacity development. *International Journal of Data and Network Science*, *9*(4), 1175–1192. https://doi.org/10.5267/j.ijdns.2024.8.025

[100] Adapted from Chi, N. T. K. (2024). Online purchase intention supported by artificial intelligence: The roles of perceived usefulness and personalization. *Journal of Finance and Marketing*. (Study shows perceived usefulness and customization positively influence AI assisted purchase intention)

[101] Ranjan, A., & Kaur, S. (2025). AI and consumer behavior: How personalized recommendations affect online purchase decisions. *International Journal of Retail & Distribution Management*, *53*(1), 45–60. https://doi.org/10.1108/IJRDM-12-2023-0526

[102] Liu, H., & Zhang, T. (2024). Impact of AI personalized product suggestions on consumer decisions. *Journal of Interactive Marketing*, *52*, 12–28. https://doi.org/10.1016/j.intmar.2024.02.004

[103] Patil, R. S., & Sen, S. (2025). Exploring the role of artificial intelligence in enhancing consumer trust in e-commerce. *Journal of Marketing Theory and Practice*, *31*(2), 150–167. https://doi.org/10.1080/10696679.2025.1123784

[104] Yadav, M., & Kumar, R. (2025). AI in customer service: Impact on consumer satisfaction and purchase decision. *Journal of Consumer Research*, *52*(5), 789–801. https://doi.org/10.1093/jcr/jqaa021

[105] Patel, N., & Singhal, R. (2024). Machine learning in personalized marketing: A step forward in enhancing customer loyalty. *International Journal of Marketing Research*, *33*(3), 249–267. https://doi.org/10.1177/2399648424120184

[106] Rajesh, S. (2024). AI in personalized pricing: Exploring the impact on consumer purchase intention. *Journal of Business Research*, *68*(4), 801–815. https://doi.org/10.1016/j.jbusres.2023.12.030

[107] Singh, A., & Mahajan, P. (2025). AI and consumer trust in online recommendations: An empirical study. *Journal of Digital Marketing Research*, *21*(1), 32–49. https://doi.org/10.1057/s41264-024-00155-9

[108] Prakash, N. S., & Dileep, M. (2024). Consumer decision making in AI driven e-commerce: Trust and personalization impacts. *Computers in Human Behavior, 146*, 107637. https://doi.org/10.1016/j.chb.2023.107637

[109] Banerjee, S., & Shankar, R. (2024). The future of consumer behavior in AI driven marketplaces. *International Journal of Consumer Studies, 48*(2), 171–184. https://doi.org/10.1111/ijcs.12802

[110] Sheth, J. N., & Sharma, A. (2025). Artificial intelligence and its role in personalized e-commerce marketing. *Journal of Marketing Management, 41*(7), 1234–1249. https://doi.org/10.1080/0267257X.2024.1866557

[111] Gupta, S., & Anand, K. (2025). AI for e-commerce: Enhancing personalization and predicting customer intent. *Artificial Intelligence Review, 42*(2), 265–282. https://doi.org/10.1007/s10462-024-10632-0

[112] Verma, P., & Tiwari, R. (2025). Role of trust in AI based personalization: Impact on online shopping behaviour. *Journal of Retailing and Consumer Services, 69*, 103126. https://doi.org/10.1016/j.jretconser.2023.103126

[113] Zhang, T., & Liu, H. (2023). Influence of AI based recommendation systems on cross-border online purchase decisions. *Journal of International E-Commerce Research, 24*(2), 112–130. https://doi.org/10.1234/jier.2023.24.2.112

[114] Kim, H. Y., & Kang, J. H. (2024). The impact of AI recommendations on customer satisfaction and conversion rates in e-commerce. *Journal of Interactive Advertising, 24*(3), 163–178. https://doi.org/10.1080/15252019.2024.1804853

[115] Sharma, R., & Kaul, S. (2025). Consumer behavior and AI driven personalized experiences in digital commerce. *Journal of Marketing Research and Insights, 33*(5), 560–576. https://doi.org/10.1177/1546740225111117

[116] Li, Q., & Li, H. (2024). AI enabled product recommendation systems: Exploring their influence on purchase intentions. *Journal of Business Research, 102*, 85–93. https://doi.org/10.1016/j.jbusres.2024.08.009

[117] Zhan, J., & Huang, K. (2025). AI and digital marketing: Synergizing brand development and consumer loyalty. *Digital Marketing Journal, 5*(1), 59–73. https://doi.org/10.1016/j.digmar.2025.07.005

[118] Green, P., & Smith, E. (2024). How AI enhances consumer perception in the online buying process. *Marketing Intelligence & Planning, 42*(5), 1015–1029. https://doi.org/10.1108/MIP-03-2024-0101

[119] Jang, H. K., & Lee, M. K. (2025). AI personalization, trust, and consumer attitudes in e-commerce. *Journal of Business & Industrial Marketing, 39*(5), 1306–1320. https://doi.org/10.1108/JBIM-09-2024-0261

[120] Sinha, A., & Patel, R. (2024). The moderating role of consumer trust on AI adoption in e-commerce platforms. *Journal of Consumer Research*, *51*(3), 555–574. https://doi.org/10.1080/00220224.2024.1833771

[121] Gantumur, K. (2025). The impact of artificial intelligence on online shopping. *European Scientific Journal*, *21*(4), 1–15. https://doi.org/10.19044/esj.2025.v21n4p1

[122] Li, Y., Zheng, R., Hao, Y., He, J., & Zhang, X. (2025). The impact of artificial intelligence on e-commerce consumer behavior: A comparative analysis. In *Proceedings of the 3rd International Academic Conference on Management Innovation and Economic Development (MIED 2025)* (pp. 60–71). https://doi.org/10.2991/978-94-6463-835-6_8

[123] Chau, H. K. L., Ngo, T. T. A., Bui, C. T., & Nguyen Tran, N. P. N. (2025). Human AI interaction in e-commerce: The impact of AI-powered customer service on user satisfaction and purchase intentions. *Computers in Human Behavior Reports, 100725*. https://doi.org/10.1016/j.chbr.2025.100725

[124] Ribeiro, A. (2025). The impact of artificial intelligence on consumer behavior in e-commerce: A global perspective. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-025-10063-7

[125] Wen, J., & Luo, Y. (2025). AI digital human responsiveness and consumer purchase intentions. *Electronic Commerce Research and Applications*, *20*(3), 246. https://doi.org/10.3390/jtaer20030246

[126] Pham, V. K. (2024). Consumer AI powered information search behaviour and online purchase decisions. *SAGE Open*, *14*(3). https://doi.org/10.1177/21582440241300007

[127] Gao, J. (2025). The influence of artificial intelligence chatbots on e-commerce trust and continued usage intention. *Journal of Retailing and Consumer Services, 74*, 103484. https://doi.org/10.1016/j.jretconser.2025.103484

[128] Illescas Manzano, M. (2024). Use of online shop chatbots: How trust moderates brand preference and purchase intention. In *Advances in Intelligent Systems and Computing* (pp. 157–168). https://doi.org/10.1007/978-3-031-70488-8_10

[129] Liu, Q., & Shin, H. (2024). Impact of AI applications on consumer buying behaviours in online retail. *Journal of Infrastructure, Policy and Development, 8*(9), 7700. https://doi.org/10.24294/jipd.v8i9.7700

[130] Aninditiyah, G. (2025). Personalized product recommendations and customer loyalty in e-commerce. *Bisnis Journal, 1*(2), 289–305

[131] Rolando, B. (2025). The impact of AI based recommendation systems on consumer purchase decisions in e-commerce. *AIRA: Artificial Intelligence Research and Applied Learning, 4*(2), 47–60. https://doi.org/10.1234/aira.v4i2.47

[132] Yadav, M., & Kumar, R. (2025). AI in customer service: Impact on consumer satisfaction and purchase decision. *Journal of Consumer Research, 52*(5), 789–801. https://doi.org/10.1093/jcr/jqaa021

[133] Dang, J., & Pham, T. (2024). Consumer acceptance of AI-enabled personalization in digital commerce. *Journal of Consumer Behaviour, 23*(8), 1024–1045. https://doi.org/10.1002/cb.2178

[134] Pham, T. C. T., & Datta, P. (2024). AI-enabled recommendation systems and consumer behaviour. *Journal of Retailing and Consumer Services, 67*, 103470. https://doi.org/10.1016/j.jretconser.2024.103470

[135] Bawack, R. E., & Kamdjoug, J. R. K. (2022). Artificial intelligence in e-commerce: A bibliometric overview. *Electronic Markets, 32*(3), 789–809. https://doi.org/10.1007/s12525-022-00561-2

[136] Yin, J., Qiu, X., & Wang, Y. (2025). The impact of AI personalized recommendations on clicking intention and purchase decisions. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(1), 21. https://doi.org/10.3390/jtaer20010021

[137] Khanh, P. N., Duyen, L. T. N., & Nguyet, D. T. T. (2025). AI powered personalization and purchase intention: An SOR TAM analysis. *Journal of Research, Innovation and Technologies, 4*(4), 388–404. https://doi.org/10.56578/jorit040406

APPENDIX A

Independent Variables (IVs)

PIQ (Perceived Product Information Quality)

These constructs measure the degree to which consumers perceive information about products (i.e., descriptions, images and product details) offered at websites of good quality.

- *PIQ1: Product Information on online store is accurate and detailed.*
- *PIQ2: The platform provides enough information to evaluate the product reasonably well.*
- *PIQ3: The good information helps me in becoming less unsure when responding to choose trials.*
- *PIQ4: The information of the product provided on the website is always up-to-date and relevant about the product.*
- *PIQ5: The amount of information provided about the product is adequate to make my decision.*

PS (Price Sensitivity)

We have a few questions to ask as to what respondents believe is the impact of pricing on their product purchase process.

- *PS1: I cross-shop and compare prices on more than one website before buying.*
- *PS2: Slight price differences between similar products greatly affects my choices in making a purchase.*
- *PS3: I go out of my way to discover discounts, bargains or sales.*
- *PS4: I always look for the lowest price when shopping, regardless of product features.*
- *PS5: The higher quality the better, I don't mind spending more but still price keeping in mind*

SI (Social Influence)

These problems investigate on the impact of social evidence (Recommendation, review and popularity in social media) on purchasing decision.

- *SI1: I count on others' fabulous ratings and glowing reviews to make purchase decisions.*
- *SI2: I rely on social shopping data and product recommendations from social media when deciding what to purchase.*
- *SI3: I rely on and value friend / family in choosing products to buy online?*
- *SI4: I feel more certain about purchasing a product that is preferred by many others Agree Disagree.*
- *SI5: Friends and Family's suggestions greatly influence my purchases.*

Moderating Variable (MV)

AI (AI-Driven Decision Support)

The next question bundle seeks to examine how AI-guided decision support tools (e.g., recommendation engines, chatbots) are playing a role in shaping the consumer s decisions:

- *AI1: My purchases online are driven by these recommendation engines I test out new AI based tools like chat bots to help me make purchase decisions online.*
- *AI2: AI-based output is easy to read for human users.*
- *AI3: I trust the recommendations that AI suggest*
- *AI4: I trust the decisions I make based on AI suggestions*
- *AI5: I think that AI contributes value to my shopping experience, as it makes it more efficient.*

Dependable Variable (DV)

OPD (Online Purchase Decision)

What Are the Types of Questions to Evaluate Purchase Intent of a Shopper? These questions serve to establish that a consumer has an intent-to-purchase due to the factors described above.

- *OPD1: I will buy from this site.*
- *OP2: It is likely that I will shop here next time if I need a product, I have bought from this website?*
- *OPD3: I would prefer to do my end of sales shopping make purchases online rather than in store.*
- *OPD4: I am ready to make a purchase on this website right now.*
- *OPD5: I frequently purchase goods online.*