Impact of Artificial Intelligence and Perceived Value on Online Purchase Intention: The case of North Cyprus

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Impact of Artificial Intelligence and Perceived Value on Online Purchase Intention: The case of North Cyprus

by

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A thesis submitted to the Institute of Graduate Studies in partial fulfillment of the requirements for the Degree of Master in Business Administration

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	FINAL INTERNATIONAL UNIVERSITY **INSTITUTE OF GRADUATE STUDIES**

APPROVAL

Title: Impact of Artificial Intelligence and Perceived Value on Online Purchase Intention: The case of North Cyprus

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ETHICAL DECLARATION

I, Rigersa Cara, hereby, declare that this thesis is my original work. I certify that I have followed all ethical standards while collecting and processing the data and the findings presented in this thesis paper are correct. All the sources used in this research thesis are cited accordingly.

Rigersa Cara

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ABSTRACT

Artificial intelligence (AI) technology has greatly impacted global businesses. Many studies are done on the effects of AI in different aspects such as business finances, AI effects on humans, trends.

This study explores key elements like accuracy, insight, and interactivity, perceived utility value, and hedonic value in order to examine how views of AI technology affect online purchase intentions. The study makes significant contributions to the existing literature by shedding light on the mediation effect of hedonic value in the relationship between AI technology and online purchase intention. Moreover, there is a gap in the literature review since there are not many studies and there is not enough contribution based on these factors. There are very few studies done in this classification of AI technology.

The quantitative method was chosen to collect primary data through using self-administered survey questionnaires to a sample consisting of the students studying in North Cyprus. The surveys were distributed via Google Forms, various social media platforms, and WhatsApp, with an added option for participants to access the survey through a QR code. Of those who took part, a total of 306 respondents successfully completed the surveys.

The findings indicate that accuracy, insight, interaction all have a positive correlation with utility value and hedonic value. The study also emphasizes the lack of a role utilitarian value plays as a mediator between purchase intention and AI technology. Utilitarian value does not display a mediating influence on consumer purchasing decisions, in contrast to hedonic value. These findings have important implications for companies and marketers looking to take use of AI technology by highlighting the subjective appeal and experience value of their products.

Keywords: AI technologies, online purchase intention, accuracy, interaction experience

ÖZ

Yapay zeka (AI) teknolojisi, küresel işletmeleri büyük ölçüde etkiledi. İş finansmanı, yapay zekanın insanlar üzerindeki etkileri, gelişen trendler gibi farklı açılardan yapay zekanın etkileri üzerine birçok çalışma yapılıyor. Ancak literatürde çok fazla çalışma olmaması ve bu faktörlere dayalı yeterli katkının olmaması nedeniyle bir boşluk bulunmaktadır. AI teknolojisinin doğruluk, içgörü ve etkileşim boyutları kullanılarak sınıflandırması ile yapılmış çok az çalışma vardır.

Bu çalışma, tüketicilerin çevrimiçi satın alma niyetlerini incelemek amacıyla yapay zeka teknolojisiyle ilgili algıların doğruluk, içgörü, etkileşim, algılanan fayda değeri ve hedonik değer gibi temel unsurların etkilerini araştırmaktadır. Çalışma, yapay zeka teknolojisi ile çevrimiçi satın alma niyeti arasındaki ilişkide algılanan değerin aracılık etkisine ışık tutarak mevcut literatüre önemli katkılar sağlamaktadır. Kuzey Kıbrıs'ta yüksek öğrenim gören öğrencilerden oluşan bir örneklemden anket yöntemi kullanılarak birincil nicel veri toplanmıştır. Anketler, Google Formlar aracılığıyla, çeşitli sosyal medya platformları ve WhatsApp üzerinden dağıtıldı ve katılımcıların anketi bir QR kodu aracılığıyla erişebilmesi için ek bir seçenek sunuldu. Katılanlardan toplam 306 katılımcı başarıyla anketleri tamamladı. Bulgular doğruluk, içgörü ve etkileşimin fayda değeri ve hedonik değer ile pozitif bir korelasyona sahip olduğunu göstermektedir. Çalışma ayrıca, faydacı değerin, hedonik değerin aksine yapay zeka teknolojisi ile satın alma niyetinin arasında aracı rolünün olmadığını bulmuştur.

Anahtar Kelimeler: AI teknolojileri, çevrimiçi satın alma niyeti, doğruluk, etkileşim deneyimi

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LIST OF ABBREVIATIONS

AC	Accuracy
AI	Artificial Intelligence
AICS	Artificial Intelligence Customer Service
AMOS	Analysis of Moment Structures
ANN	Artificial Neural Networks
AVE	Average Variance Extracted
CD	Cook's Distance
CFA	Confirmatory Factor Analysis
CPI	Consumer Purchase Intention
CR	Composite Reliability
DSSTNE	Deep Scalable Sparse Tensor Network Engine
FIU	Final International University
H	Homoscedastic
HMCCA	Human-Machine Collaboration Customer Service
HV	Hedonic Value
I	Independent
IBM SPSS	IBM Statistical Package for the Social Sciences
ILSVRC	ImageNet Large Scale Visual Identification Challenge
IS	Insight
IT	Interactivity

MCS	Manual Customer Services
MD	Mahalanobis Distance
ML	Machine Learning
MLE	Maximum Likelihood Estimation
N	Normal
NLP	Natural Language Processing
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
TRNC	Turkish Republic of Northern Cyprus
TRY	Turkish Lira
UV	Utility Value
VIF	Variance Inflation Factor

CHAPTER 1
INTRODUCTION

Artificial intelligence (AI) is among the most intense innovations that has transformed numerous sectors all over the world. AI is the development of computer systems capable of performing jobs and activities that need human intelligence (Russell & Norvig, 2016). According to Kaartemo and Helkkula (2018), Lu (2020) and Martnez Lopez and Casillas (2013), the Development of AI has significantly altered how marketing activities are implemented in terms of customer service, customer engagement, and sales management.

Sales of service oriented by Artificial Intelligence have increased 85 percent over the last five years, as reported in the World Robotics Report 2020. For instance, patients in the United Kingdom's National Health System are using chatbots to receive medical advice and for businesses on the internet such as Taobao, Tencent or J.D. use AICS extensively with clear financial benefits. The use of Artificial Intelligence, which is service oriented, can effectively reduce the costs of services and tackle a large number of recurring issues at any given moment while improving communication between users and businesses. According to Gao and Culbertson (2002), the challenges that AI faces in light of the rise and growing nature of information technology worldwide has characterized business- and non-business organizational development (Gao & Culberton, 2002).

Artificial Intelligence is the key element of the engineering field which allows machines and computers to make use of a variety of technological techniques and technologies enabling them to imitate or enhance human intelligence. With the use of huge amounts of data, Artificial Intelligence started to spread at an accelerating rate worldwide since the start of the 21st century. Marketing has evolved from one-way Web 1.0 marketing to interactive Web 2.0 marketing, then to precision marketing based on big data, and finally to smart marketing powered by AI technology. AI technology helps to improve interactions not just between consumers, goods, or services, as well as in interactive environments, and it can swiftly fulfill demands. AI Chatbots, content recommender systems, and consumer feature recognition have evolved into AI marketing agents. Amazon leads the retail migration of people, goods, and shops using artificial intelligence technology, and extends its artificial intelligence framework DSSTNE from dialogue, language understanding, and object recognition to the field of search and suggestion. This enhances the conversion rate of product sales and accomplishes precision marketing by making related and complementary product recommendations more tailored and real-time.

Many businesses and service providers are experimenting with AI to better understand their consumers' tastes and aspirations, with various degrees of success and accuracy. Despite increased AI acceptance and use of AI based recommendation bots, the knowledge of consumers' cognitive responses to these developing technologies remains restricted. Artificial intelligence At the ImageNet Large Scale Visual Identification Challenge (ILSVRC), an annual competition in which participants compete for the greatest picture recognition accuracy, deep learning improved dramatically from 2012 onward, and AI finally exceeded human accuracy in 2015.

Additionally, in order to maintain and develop accuracy, AI technologies and services that are easier for humans to use and run collaboratively have begun to emerge. Chatbots, for example, respond after a real conversation with a user. Machine - learning systems have frequently been of the "black box" variety, preventing people from knowing how a certain conclusion was generated. These technologies are challenging to use to vital decision-making affecting for instance human life.

There is an increasing need to understand how consumers will interact with AI domestic service robots, which are increasingly entering consumer homes, but without a conceptual model of the consumer preferences influencing the interaction roles such robots may play only within home. The interaction consists of the customer's actual usage of the system as well as the cognitive judgments that precede the user's activity. As indicated by the underlying theories of reasoned action and planned behavior, many theories describing user behavior define these cognitive processes as a chain of perceptions, attitudes, and intents (Ajzen 1991; Fishbein & Ajzen, 1975).

1.1 Problem Statement

There are just a few studies looking at the impact of AI technology on the online shopping environment, particularly the mechanism by which consumers' purchase intentions are influenced, and that take into account all of the AI technology application experiences in the background of online buying. It's not yet clear if perceived value may be an effective mediator between AI technology and consumer buy intent, or which mediator plays a greater role in online shopping platforms.

1.2 Purpose of the Study

The purpose of this thesis is to investigate the AI technology factors that have an influence on a consumer's decision to make a purchase and examine the effect of three different characteristics of an AI technology online shopping experience. The components of Artificial Intelligence such as: accuracy, insight and interaction have a great impact on the consumers' decision to purchase products or services based on perceived utility and hedonic perceived values. The formulation of a consumer's intention to make a purchase may be influenced by both the perceived utility value and the perceived hedonic value that can be achieved via the use of AI technology.

The study also aims to investigate whether consumers' intentions for buying are influenced by the Artificial Intelligence Technology of online shopping platforms with particular emphasis on evaluation of their perceptions of product hedonism and usefulness. In parallel, this research seeks to reveal the specific impacts which arise from using perceived utilitarian values and seeing hedonic value as a mediator.

1.3 Significance of the Study

The study aims to expand upon previous research, which has examined the relationship of AI technology and perceived value on online purchase intention, by applying the model to the specific context of Northern Cyprus and investigating the influence of both utilitarian and hedonic value on purchase intention. This contribution is important since the effects of the cultural differences and their effect on customer's perceived value of AI technology and the online purchase intention are essential to learn to provide better insights for higher education businesses. Moreover, the tested model will contribute into the literature since there are not many studies that used the AI classification adapted in this study as well as its impact on perceived value and online shopping intention.

1.4 Research Questions and Hypotheses

In order to understand better the impact of AI technology and perceived value on online purchase intention of students in TRNC the following research questions are formalized in a cohesive manner:

RQ: What are some of the factors of AI technology that influence online purchase intention of high education students in Northern Cyprus?

RQ1: How does accuracy of AI technology influence customers' perceived value?

RQ2: How does insight of AI technology influence customers' perceived value?

RQ3: How does interaction of AI technology influence customers' perceived value?

RQ4: How does customers' perceived value influence online purchase intention of high education students in Northern Cyprus?

RQ5: How does cultural differences influence customers' perceived value of AI technology?

RQ6: How do cultural differences influence online purchase intention of high education students in Northern Cyprus?

According to Davis's (1989) Technology Acceptance Model, consumers' attitudes and intentions to utilize a technology are significantly influenced by the perceived usefulness and simplicity of use. Users' perceptions of a technology's accuracy and dependability increase along with their view of its utility, which raises adoption and usage intentions. Although the TAM does not specifically address artificial intelligence (AI) technology, its ideas can be applied to AI systems where more accuracy can result in higher perceived utility value.

H1: The improvement of accuracy experience with AI technology leads to an increase in perceived utility value.

According to Mihaly Csikszentmihalyi's (1990) Flow theory, individuals enter a state of "flow" that is characterized by intense focus and enjoyment when they are participating in activities that are both challenging and appropriate for their skill level. A more seamless and engaging user experience, which increases the chance of feeling flow and increases perceived hedonic value, can be a result of improved accuracy in AI technology.

> H2: The improvement of accuracy experience with AI technology leads to an increase in perceived hedonic value.

Information foraging theory developed by Pirolli and Card (1999), users are driven to seek information in order to meet their cognitive demands. Users' informational objectives are satisfied when AI technology offers insightful and pertinent information, which raises the perceived utility value.

> H3: The improvement of insight experienced with AI technology leads to an increase in perceived utility value.

According to the emotional design framework (Norman, 2004), technology affects users' emotions based on their interactions with it. Users' emotional experiences and perceived hedonic value may be positively impacted by AI technology if it produces improved insights that surprise and excite them.

> H4: The improvement of insight experienced with AI technology leads to an increase in perceived hedonic value.

The potential of AI technology to customize interactions depending on unique tastes and demands, as stated by (Felfernig & Friedrich, 2018), can improve the overall interactive experience. By providing relevant and meaningful interactions, user-centric design that adapts the interaction to users' individual requirements can increase perceived utility value.

> H5: The improvement of interactive experience with AI technology leads to an increase in perceived utility value.

According to Bandura's Social Cognitive Theory, people learn through copying and observing others (1986). Users' perceptions of the hedonic worth of AI technology can be influenced, which in turn motivates them to interact with it more. Positive encounters with AI technology can be noticed through peers or online reviews.

H6: The improvement of interactive experience with AI technology leads to an increase in perceived hedonic value.

According to the Hedonic-Utilitarian Model, both hedonic (emotional and experiential) and utilitarian (functional and task-oriented) factors have an impact on how people perceive technology. AI technology can boost perceived hedonic value and, as a result, online purchase intention if it provides exciting and pleasurable interactions while simultaneously meeting practical objectives, such as making online purchasing more effective and convenient.

H7: Increased perceived hedonic value of AI leads to an increase in online purchase intention.

H7a: Hedonic value toward online purchase intention is a mediator between accuracy and online purchase intention of international students studying in TRNC.

H7b: Hedonic value toward online purchase intention is a mediator between insight and online purchase intention of international students studying in TRNC.

H7c: Hedonic value toward online purchase intention is a mediator between interaction and online purchase intention of international students studying in TRNC.

According to Ajzen and Fishbein's (1975), Theory of Reasoned Action (TRA) and Theory of Planned Behavior, a person's intents and behaviors are impacted by their attitudes, subjective norms, and perceived behavioral control. Users' propensity to make online purchases is expected to rise if they have favorable opinions toward AI technology in online shopping (perceived utility value), believe it to be socially acceptable (subjective norm), and feel comfortable utilizing it (perceived behavioral control).

H8: Increased perceived utility value of AI technology leads to an increase in online purchase intention.

H8a: Utility value toward online purchase intention is a mediator between accuracy and online purchase intention of international students studying in TRNC.

H8b: Utility value toward online purchase intention is a mediator between insight and online purchase intention of international students studying in TRNC.

H8c: Utility value toward online purchase intention is a mediator between interaction and online purchase intention of international students studying in TRNC

1.5 Assumptions

The following assumptions are made regarding this study:

1. The questions are fully understood by all respondents.

2. The respondents will provide honest expressions of their knowledge

3. All results provided are clear regarding the impact of AI technology and perceived value on online purchase intention.

1.6 Limitations

This study has some limitations and should be expanded upon in future research on AI technology and its impact on online purchase intention. Firstly, this study takes into consideration some of the factors of AI and perceived value of consumers' however, this research does not consider other internal factors that might affect the consumer behavior such as: perceived risk, consumer attitude, flow experience. Second, the survey's sample size was small and primarily made up of Final International University students. The results may not be representative of the entire population and may not accurately reflect the impact of AI and perceived value on the online purchase intention. It is also challenging to reach the elderly population and members of the working class because the majority of the population polled was made up of students between the ages of 18 and 27.

Future research on AI technology and its effects on online purchase intention should go beyond the constraints of this study. First off, while some aspects of AI and customer perceptions of value are taken into account in this study, other internal components that can have an impact on consumer behavior are not, such as perceived risk, consumer attitude, and flow experience. Second, only a small sample of Final International University students made up the survey's sample.

Time limitations throughout the data-collecting phase contributed to the study's very limited sample size and exclusive focus on students at Final International University. It would have taken more time and resources to conduct surveys and gather data from a larger demographic.

Elderly and working-class populations are excluded: Due to time restrictions in data collecting, the study was unable to reach a broader demographic, including seniors and people in the working class. The study's capacity to accurately reflect the whole internet consumer base is constrained by this exclusion.

The study was able to explore a portion of the intricate and constantly changing environment of AI technology's impact on online purchase intention due to time limitations. Future studies could cover more topics related to AI, such as its uses in chatbots, recommendation systems, and tailored marketing.

In conclusion, the time limitations imposed on this study prevented a thorough examination of several characteristics and limited the sample's capacity to represent the entire population. Understanding these limitations helps in guiding future research that can offer a more thorough and comprehensive understanding of the impact of AI technology on online purchase intention.

1.7 Key of terminology

Accuracy is a qualitative performance characteristic, expressing the closeness of agreement between a measurement result and the value of the measurand (Menditto et al., 2006).

Insight can be defined as the assessment of insight relies upon the purposeful use of information from a variety of sources, including multisource feedback (Brown et al., 2014).

Interactivity is defined as a psychological state experienced by a site-visitor during the interaction process (Wu et al.,2006).

Purchase intention is decision-making to buy a particular brand by consumer, (Shah et al., 2012; Morinez et al., 2007) define purchase intention as a situation where a consumer tends to buy a certain product in a certain condition.

Hedonic value is defined as that value a customer receives based on the subject experience of fun and playfulness (Babin et al., 1994).

Utilitarian value is defined as that value that a customer receives based on a task-related and rational consumption behavior (Babin et al., 1994).

CHAPTER 2
LITERATURE REVIEW

2.1 AI Technology

According to the World Robotics Report (2020), there has been a significant increase of 85 percent in sales of service-oriented Artificial Intelligence (AI) over the past five years. According to Tractica, the market for AI customer service (AICS) is expected to develop seven times faster than that of traditional manual customer service (MCS), with sales reaching $126 billion by 2025. The application of AI has expanded across various fields, from industrial production to customer service. Large-scale implementations of AICS, such as those used by Taobao, Tencent, and JD, have shown clear financial benefits. Users of the British National Health and Medical System are given medical advice by chatbots, and online businesses like Taobao, Tencent, and JD have adopted AICS extensively, which has obvious financial advantages. Service-oriented artificial intelligence has the potential to reduce service costs effectively, address a large number of persistent issues around-the-clock, and enhance customer interaction.

According to Barzilay et al. (2002), Baxter et al. (2001), Darwiche and Marquis (2002), Gao and Culberson (2002), Tennenholtz (2002), Wiewwiora (2003), the challenges that AI faces in light of the rise and growing nature of information technology worldwide, which has characterized business- and non-business organizational development.

The need for AI research is motivated by factor: to provide new entrants further into AI field with an understanding of the basic structure of the AI literature Brooks. (Gamberger & Lavrac, 2002), (Patel-Schneider & Sebastiani, 2003). Researchers from various disciplines are interested in learning about the work of others in their area and sharing what they have acquired through time (Rosati, 1999), Kaminka et al. (2002), Bod (2002), Acid and De Campos (2003), Walsh and Wellman (2003), Kambhampati (2000), and Barber (2000). New strategies and ideas can be developed as a result of sharing AI information, allowing for a better understanding of the topic.

To that goal, this paper has been produced for AI researchers so that they may continue to work on growing this field of expertise through freshly developed ideas. As a result, they would be able to push AI's knowledge frontier ahead. There are many researches done in many aspects of AI but this study will be focused on how AI technology is perceived and affects the consumer's buying intention. Researchers from various disciplines are interested in learning about the work of others in their area and sharing what they have acquired through time (Rosati, 1999), Kaminka et al. (2002), Bod (2002), Acid and De Campos (2003), Walsh and Wellman (2003), Kambhampati (2000), and Barber (2000). New strategies and ideas can be developed as a result of sharing AI information, allowing for a better understanding of the topic.

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Except for cost savings and 24/7 availability, service-oriented artificial intelligence improves the scalability of customer service operations. Scaling up to handle a growing customer base can be difficult for traditional manual customer service. Hiring and training new employees can be time-consuming and costly. AI-powered systems, on the other hand, can easily handle increased customer volumes without requiring significant additional resources. AI customer service's scalability enables businesses to effectively manage spikes in customer inquiries during peak periods, such as sales promotions or seasonal events, ensuring smooth and uninterrupted customer support. Also, service-oriented AI has the potential to personalize customer interactions and tailor recommendations to individual preferences and needs. AI systems can learn about customer behavior, purchase history, and preferences by analyzing massive amounts of customer data. This enables more targeted and personalized recommendations, improving the customer experience and making it more relevant and engaging. Personalization not only improves customer satisfaction, but also allows businesses to increase cross-selling and upselling opportunities, resulting in revenue growth.

Except for the financial and operational benefits, implementing AI customer service can lead to improved customer insights and feedback. AI-powered systems can collect and analyze customer data such as feedback, reviews, and social media interactions in order to generate valuable insights into customer preferences, pain points, and sentiment. This data can be used to improve products, optimize service offerings, and identify areas for growth. Businesses can make data-driven decisions to improve customer satisfaction and stay ahead of market trends by leveraging AI-generated customer insights.

It is important to note that, while AI customer service provides significant benefits, it is not intended to completely replace human interaction. Customer inquiries will always be complex and nuanced, requiring human empathy, problem-solving skills, and judgment. To provide the best possible customer experience, a balanced approach that combines AI technologies with human customer service agents is required. This hybrid model, also known as augmented intelligence, enables businesses to capitalize on the strengths of both AI systems and human agents, resulting in a more seamless and personalized customer service journey.

Finally, the growth and adoption of service-oriented AI in customer service reflect the industry's potential to revolutionize. AI-powered systems provide businesses with a competitive advantage in meeting customer expectations and driving growth through cost efficiency, scalability, personalization, and customer insights. Businesses can improve customer service, increase operational efficiency, and cultivate long-term customer loyalty by leveraging the power of AI. The role of AI in customer service is likely to expand further as technology advances and AI capabilities evolve, reshaping the way businesses interact with their customers.

2.2 Online Shopping

New human-machine collaboration customer service (HMCCS) modes have been used in online business services in recent years, and researchers have discovered that AI is good at dealing with repetitive mechanical problems, whereas manual work is better suited for dealing with personalized problems in the human-machine collaboration process. Some academics anticipate that human-AI involvement in marketing services will become the normal service strategy in the future. As a result, who can offer a better service experience to AICS, MCS, and HMCCS users? Do different types of online customer service have different effects on consumers' purchasing intentions? The classification of these types constitutes a major part of internet customer service. In the past, customer service had been classified by industry in studies. In the past few years, a large exploratory study on online classification of customer service has been conducted by academics in the area of marketing management and they are proposing various new approaches. In accordance with the various ways of communicating online customer service. According to Liu (2021) who states that different types of online customer service can be classified as text Customer Service, Voice Based Customer Service and Video Based Consumer Services, online shopping used to be primarily defined by straightforward transactions and a small selection of goods. Early internet retail platforms offered the most fundamental features, enabling customers to explore and buy things via static websites.

With the development of technology, online shopping gave rise to more complex e-commerce systems. Online customers' initial concerns about privacy and security were allayed by the development of secure payment gateways and encrypted transactions. This paved the way for people to accept online buying more widely.

The growth of mobile commerce (m-commerce) was another important change in internet buying. The growing use of smartphones and mobile applications has given customers access to internet shopping wherever they are and whenever they want. The reach of online retail was further increased by mobile-optimized websites and specialized shopping applications that offered a fluid and practical buying experience on portable devices.

Shopping on the internet has been transformed by the use of artificial intelligence (AI) technologies. To give tailored suggestions, targeted marketing, and real-time customer service, AI systems analyze enormous volumes of consumer data. Chatbots and virtual assistants powered by AI improve the entire shopping experience by offering quick support and efficiently resolving client concerns.

Online shopping has changed as a result of multichannel retailing. Nowadays, retailers provide a seamless experience across a variety of channels, including websites, mobile applications, and physical storefronts. Through this connection, shoppers may browse items online and buy them in-store or vice versa, resulting in a seamless and practical shopping experience.

Shopping online has grown rapidly in recent years, especially since the worldwide COVID-19 epidemic, which hastened the transition to e-commerce. The ease, wide range of products, low prices, and doorstep delivery of online shopping have won over customers.

Artificial intelligence (AI) and online shopping are intimately related, with AI significantly boosting the online buying experience. Numerous facets of online purchasing have been changed by AI technology, including tailored suggestions, customer service, inventory management, and fraud detection.

Personalized suggestions are a big area where AI has had a major influence. To create individualized product suggestions, AI algorithms go through a tremendous quantity of consumer data, including browsing history, purchasing trends, and demographic data. By offering pertinent and customized alternatives, these recommendations not only improve clients' browsing experiences but also raise the possibility that they will make a purchase.

Virtual assistants and chatbots driven by AI have also revolutionized customer service for online retailers. These advanced technologies are capable of offering immediate support, responding to consumer inquiries, and assisting customers with making purchases. AI chatbots are capable of handling a variety of client contacts, providing round-the-clock service, and speeding up response times. Artificial intelligence chatbots are able to comprehend and respond to client enquiries more as real people do by utilizing natural language processing and machine learning.

Another area in which AI has proven useful in online shopping is inventory management. To optimize inventory levels, AI systems can examine previous sales data, market trends, and other elements. By guaranteeing that customers can easily access popular items while reducing the expense of inventory storage, this aids businesses in avoiding stock outs or overstocking.

Online fraud detection and prevention are major issues, and AI is essential for spotting and thwarting fraudulent activity. Massive volumes of transactional data can be analyzed by AI systems to spot trends that might be signs of fraud. AI technologies aid in the protection of customers and businesses against fraud by instantly detecting questionable transactions.

Businesses may also analyze customer data using AI technology to learn more about consumer behavior, preferences, and market trends. Using this data can help you create more focused marketing efforts, enhance your pricing methods, and make better business decisions overall.

Personalized recommendations, improved customer service, improved inventory management, the detection of fraud, and data-driven decision-making are just a few of the ways AI has transformed online shopping. We can anticipate more innovations and improvements in the online buying experience as AI develops, which will ultimately increase customer satisfaction and fuel the expansion of e-commerce.

According to Gao (2019), online customer service can be grouped into three groups based on the elements of customer service: pre-sales customer service, in-sales customer service, and after-sales customer service. Thoms (1982) argued that customer service may be classified into human-supplied and device-provided services based on whether the service is delivered by a human or by technology.

2.3 Customer Insights

Researchers have found that effective integration between AI and human capabilities can lead to increased intelligence and improved decision-making. Collaborative efforts between humans and AI can significantly enhance work efficiency and quality. To extract valuable insights from data, advanced AI skills are necessary, primarily relying on machine learning algorithms (ML). In this regard, artificial neural networks (ANN) are particularly intriguing as they have the ability to reveal complex nonlinear relationships within large datasets using adaptable mathematical models (Miller and Brown, 2018). Moreover, studies have consistently demonstrated that when AI and humans are appropriately connected, it enables the attainment of higher intelligence and superior judgment. This human-AI collaboration has a profound impact on enhancing productivity and the overall quality of work. The utilization of ML-based AI skills is vital for data interpretation and generating novel insights. ANN, with their flexible mathematical models, prove to be especially compelling as they can effectively uncover intricate nonlinear correlations within extensive datasets (Miller and Brown, 2018). With the help of AI, hidden patterns, trends, and correlations in large, complicated datasets can be uncovered, revealing significant findings that could otherwise go overlooked. This makes it possible for businesses to comprehend customer behavior, market dynamics, and operational procedures better. Businesses can use these insights to inform data-driven decisions that result in better strategy, more efficient operations, and better resource management.

2.4 Interaction Experience

Technology acceptance, user happiness, trust, computer self-efficacy, personalization, and privacy are some of the study themes in this field. Zhang and Li (2004), examined human-computer interaction research in the field of information systems. They discovered that the most prominent research themes were users' cognitive assessments and behavior, attitudes, and performance. Aside from these user-related aspects, other elements impacting human-computer interaction include task, context, and system features Zhang and Li (2004). Moreover, the researchers provide a framework of themes in human computer interaction IS study based on these findings.

According to this concept, interaction occurs between a system and a user attempting to complete a certain task inside a specific environment. The interaction is shaped by the qualities of the user, system, task, and situation. The interaction consists of the user's actual usage of the system as well as the cognitive judgments that precede the user's behavior. As indicated by the underlying theories of reasoned action and planned behavior, many IS theories describing user behavior define these cognitive processes as a chain of perceptions, attitudes, and intents (Ajzen 1991; Fishbein and Ajzen, 1975). In turn, use behavior might influence attitudes and intentions regarding the system for instance the continuance intention. The researchers put these cognitive processes, as well as use behavior, into the heart of the framework for the purposes of our literature evaluation. The interaction experience between consumers and internet platforms has been altered by AI technology. AI-powered virtual assistants have replaced traditional human customer support reps due to breakthroughs in natural language processing and machine learning. These virtual assistants can interpret and reply to user enquiries, providing a communication method that is similar to human contact. Their uses go beyond simple customer care, as they help businesses with consumer marketing and sales activities, as well as collecting vital data on client behaviors and preferences.

The incorporation of AI virtual assistants into online buying has grown increasingly common. Amazon, Jindong, and Alibaba have pioneered the development of smart speakers such as Echo, Dingdong, and Tmall Genie, which serve as portals to an enhanced shopping experience. By providing thorough product information, recommendations, and comparisons, these virtual assistants enable consumers to make complex buying decisions. Users can easily explore through product catalogs, inquire about inventory availability, track orders, handle invoicing, and even assist refunds by using voice-based interactions. AI virtual assistants act as smart shopping companions, providing individualized guidance and expediting the purchasing experience.

AI technology enables engaging experiences that go beyond simple transactional interactions. Virtual assistants create a more engaging and conversational environment for customers through voice-based interactions and natural language understanding.

These AI-powered solutions improve the overall shopping experience by providing personalized recommendations and personalized ideas based on individual preferences. Consumers can converse with virtual assistants in real time, expressing their preferences, asking advice, and obtaining pertinent information. This personalized and interactive approach not only assists consumers in making educated selections, but it also promotes a sense of trust and satisfaction, affecting their buy intentions.

The incorporation of AI technology and interactive experiences in online shopping highlights the transformative impact it has on consumer behavior and engagement. Businesses can foster deeper client relationships, provide more tailored and efficient service, and ultimately promote online purchase intents by exploiting the capabilities of AI virtual assistants. The seamless integration of AI technology into the purchasing experience not only improves the convenience and accessibility of online platforms, but it also improves consumers' overall perceived value, ultimately leading to higher engagement and buy intentions.

Furthermore, the interactive experience made possible by artificial intelligence in purchasing goods online goes beyond transactional factors. Platforms can now offer customized product recommendations based on individual interests and browsing history by integrating AI-powered chatbots and virtual assistants (Ajzen 1991; Fishbein and Ajzen, 1975). AI algorithms can efficiently anticipate and meet the unique wants and wishes of consumers by evaluating massive volumes of data, including prior purchases, customer evaluations, and demographic information. This customized approach enhances the online purchasing experience by making it more tailored and relevant to each individual consumer.

AI technology, in addition to personalization, improves the interactive experience by delivering real-time assistance and direction along the consumer journey. For example, virtual assistants might provide proactive decision-making support by answering frequent concerns or questions that arise while browsing products or comparing possibilities. This rapid access to information and guidance eliminates the need for customers to explore complex websites or wait for human support, expediting the purchasing process and reducing potential inconveniences.

Moreover, interactive experiences driven by AI contribute to the perception of correctness and dependability in online shopping. AI-enabled virtual assistants can quickly scan enormous databases and deliver accurate, up-to-date information on product availability, pricing, and specification. This precision instills trust in consumers, who rely on AI-powered systems to give exact and reliable information, resulting in improved trust in the online shopping platform and impacting their buy intentions.

The engaging experience made possible by artificial intelligence (AI) in online purchasing extends to post-purchase interactions as well. Personalized follow-up communication, such as order confirmations, delivery updates, and customer feedback requests, can be provided by AI-powered systems. This continual interaction with customers not only improves the entire shopping experience, but it also fosters long-term customer loyalty and repeat buy intentions.

To summarize, the incorporation of artificial intelligence in online shopping websites has transformed the interaction between consumers and businesses. AI-powered virtual assistants and chatbots improve the overall perceived value of online purchasing through personalization, real-time support, accuracy, and post-buy involvement, resulting in higher consumer happiness and purchase intentions. Businesses can not only increase revenue but also strengthen client connections and gain a competitive advantage in the ever-changing digital market by harnessing the possibilities of AI technology.

2.5 Accuracy

In another research it was argued that there are three components of AI related to accuracy. Machine learning is an Artificial Intelligence approach or subset that employs algorithms to evaluate and infer patterns in data, allowing it to learn and adapt without explicit programming. Natural Discourse Processing (NLP) is a subset of AI that refers to the automated ability to accurately and precisely analyze and comprehend human discourse. Sentiment analysis is the act of recognizing and categorizing views expressed in text in order to form an opinion about a certain problem.

Mated capacity to interpret and comprehend human language with accuracy and precision. Consumer perceived value refers to the entire assessment of perceived differences that customers spend and acquire during the purchase process. Businesses must collect insights from all customer encounters and transform them into a reference knowledge base to properly understand and optimize customer-perceived value. Businesses may use conversational artificial intelligence (AI) to not only improve their client interactions, such as in sales or customer service, but also to gain a competitive edge, enhancing their reputation and market share.

The incorporation of AI technologies into online purchasing platforms has dramatically improved customer accuracy. Intelligent recognition and search functions have altered the way consumers navigate and find products by leveraging big data analytics and advanced AI algorithms. AI systems can quickly screen through enormous product catalogs and provide users with highly relevant and tailored recommendations due to their capacity to evaluate vast volumes of data. This not only saves consumers time, but also ensures that their search results are tailored to their unique interests and needs. Continuous improvements in image recognition and speech recognition technology have increased the accuracy of AI-powered search engines. Image recognition error rates have substantially decreased over the years, allowing AI systems to recognize and categorize products with surprising precision. Furthermore, significant advances in speech recognition have enabled AI systems to accurately transcribe and understand user voice instructions, making the search experience more intuitive and efficient.

Leading online shopping platforms' adoption of intelligent recognition and search features demonstrates their dedication to providing consumers with accurate and personalized experiences. Platforms like Taobao, Jindong, and Pinduo, for example, have effectively used AI technology to achieve text, image, and voice recognition, allowing consumers to discover products using a variety of input methods.

This multi-modal strategy improves search results accuracy since customers may express their preferences in the most comfortable way, whether by typing, voice input, or image uploads. In addition, constant breakthroughs in artificial intelligence, along with an ever-increasing volume of data, contribute to the continuous improvement of intelligent recognition and search algorithms. The accuracy of search results will improve as AI systems continue to learn and adapt to customer behavior and preferences, giving users with a more personalized and precise buying experience.

The increased precision provided by artificial intelligence in online shopping platforms has important ramifications for both customers and enterprises. Consumers gain from the capacity to locate desired products quickly and correctly, minimizing the time and effort required to find suitable solutions. AI systems' tailored and relevant recommendations increase consumer happiness and confidence in their purchasing decisions. Businesses, on the other hand, can use the accuracy experience to improve inventory management, optimize product offers, and conduct customized marketing efforts.

The greater accuracy provided by artificial intelligence in online shopping platforms has important ramifications for both customers and enterprises. Businesses may improve consumer engagement, generate sales, and develop long-term customer loyalty by providing accurate and personalized product recommendations. Businesses can adjust their marketing efforts to target certain client segments by employing AI algorithms to learn consumer preferences and purchasing behavior. AI-powered systems can analyze massive volumes of data to detect patterns and trends, allowing businesses to give targeted promotional offers and personalized suggestions to specific clients. Personalization not only improves the consumer experience, but it also raises the likelihood of conversion and repeat purchases. Moreover, the accuracy of AI technology allows firms to optimize their inventory management and supply chain processes. Businesses can ensure the availability of popular products, minimize stockouts, and improve overall customer happiness by properly anticipating demand based on consumer preferences and market trends. AI-powered forecasting models can provide accurate demand estimates by analyzing past sales data, external factors such as seasonality and trends, and customer insights. This allows organizations to optimize their inventory planning and procurement procedures. This not only helps to meet consumer demand quickly, but it also lowers inventory holding costs and improves operating efficiency.

Long-term client loyalty is also fostered by the capacity to give accurate and personalized experiences. Customers are more likely to establish confidence and loyalty towards an online shopping platform or brand when they constantly obtain relevant product recommendations and experience seamless and speedy purchasing processes. Businesses may establish themselves as dependable and customer-centric entities in the highly competitive internet market by continuously fulfilling and even exceeding client expectations. Customers that are satisfied and loyal are more likely to become brand champions, promoting the platform through favorable word-of-mouth referrals, boosting consumer engagement and driving organic growth.

In result, the accuracy experience offered by artificial intelligence in shopping sites enables businesses to improve consumer engagement, generate sales, and develop long-term customer loyalty. Businesses can adjust their marketing efforts and provide a seamless shopping experience by employing AI algorithms to deliver personalized product recommendations, enhancing consumer happiness and conversion rates. AI-powered inventory management and demand forecasting also help with operational efficiency and customer happiness. Customer loyalty is fostered by the capacity to consistently deliver accurate and tailored experiences, with delighted consumers becoming brand advocates and contributing to organic growth.

2.6 Customer-Perceived Value

One of the most important parts of retail difference is the belief and desire of customers, as well as their expectations following a purchase and during usage of the acquired goods. In retail market firms, the production and transmission of value to consumers is becoming an element of their marketing strategy (Rintamaki et al., 2006; Turel et al., 2010). Customer-perceived value is determined in its most basic form by subtracting total customer cost from total customer value. Empirical research has shown that the perceived value of an online store's image in an online shopping environment may influence both conscious and spontaneous purchasing behavior. Consumer perceived value refers to the overall assessment of the perceived benefits that consumers receive in exchange for their shopping efforts. When studying consumer behavior, a multidimensional survey of perceived value can provide a more detailed understanding of how different consumption scenarios impact consumers' desires compared to a one-dimensional approach. The perception of product attributes, cost perception, convenience perception, perception of interactive and comparative experiences, perception of brand value, and perception of consumer lifetime value are some examples of perceived value research dimensions. Additionally, utilitarian value, hedonic value, social value, and cognitive value have all been classified by academics as types of consumer perceived value.

The Technology Acceptance Model (TAM), put forth by (Davis, 1989), treats perceived utility and ease of use as independent variables in the context of technological systems (Yin & Qiu, 2021). It implies that users' attitudes toward using technology, which in turn affect their behavior, are influenced by their opinions of the system's utility (how well it enhances work performance) and usability (how convenient it is to use). Yang and Lin studied the hedonic value, social value, and cognitive value components of the perceived value dimension of online social platforms and their mediation roles in the use of social platforms by consumers. In order to demonstrate their major influence on customers' intention to choose online buying channels, Chu Tanming split perceived value into three dimensions: perceived utilitarian value, perceived hedonic value, and perceived social value. To assess whether customers would adopt internet banking, Sang Jon Ahn split consumer perception into perceived convenience value, perceived emotional value, and perceived use value (Yin & Qiu, 2021).

Gusti N.M.W.A came to the conclusion that perceived hedonism and utilitarianism significantly affect consumers' intentions to make more online purchases (Yin & Qiu, 2021). The term "perceived utilitarian value" relates to how consumers view the advantages and utility of utilizing a good or service. It includes elements like effectiveness, productivity, and capacity for problem-solving. The consumer's view of the emotional and experiential enjoyment connected to the good or service, on the other hand, is known as perceived hedonism. It takes into account elements like sensory enjoyment, novelty, and aesthetic appeal (Yin & Qiu, 2021).

Consumers' perceived utilitarian value is connected to the useful and practical advantages that a behavior or product provides (Yin & Qiu, 2021). It includes aspects like convenience of use, effectiveness in reaching goals, and time and money savings when buying. The perception of lower time and shopping costs, the impression of streamlined procedures, and the perceived ease of locating and buying things are all examples of perceived utilitarian value in the context of online shopping. Enhancing perceived utilitarian value in online shopping has been made possible in a major way by AI technology. AI algorithms may continuously self-learn, iterate, and provide useful features like tailored analysis, suggestions, and real-time adoption of visual stimuli by utilizing large volumes of consumer behavior data, including browsing histories and customer attributes. Therefore, Customers assess the extent to which AI technology improves their efficiency, convenience, and effectiveness in performing tasks related to shopping by using their perceived utility value, which reflects their assessment of the practical benefits derived from using AI-enabled platforms (Yin & Qiu, 2021). The capacity to find desired things quickly, at a reasonable price, and with ease are all examples of perceived utility value. When consumers view AI technology as having high utility value, they think it improves their whole purchasing experience by offering pertinent and reliable information, individualized recommendations, and simplified procedures.

AI-enabled technologies' efficiency and simplicity expedite the shopping experience, making it more fun and convenient for customers. Virtual shopping assistants powered by AI, for example, may help customers find the perfect products, provide in-depth information, and facilitate simple transactions. Consumer confidence and happiness are boosted by such features, which ultimately results in a rise in purchase intentions. Additionally, the capacity of AI algorithms to analyze enormous amounts of data enables the development of customized and relevant marketing plans. With the use of AI technology, personalized marketing and product recommendations may be made based on consumer preferences, browsing history, and purchase trends. With this individualized approach, consumers are more likely to perceive value and make online transactions.

In conclusion, customers' perceived utility value of AI technology influences their intention to make online purchases in a positive way. Increased trust, satisfaction, and eventually higher buy intentions result from consumers' good perceptions of the online purchasing experience, which are influenced by the convenience, effectiveness, and tailored experiences provided by AI-enabled systems.

2.7 The Utilitarian and Hedonic Value

Hedonism and its effects on customer intention have been the subject of several scientific studies in marketing literature over the last half-century. Hedonism as a manifestation of value in the theory of consumer behavior has not been well studied at the current level of theoretical and empirical study.

The concept of perceived utilitarian value captures the practical and functional benefits associated with a specific behavior or product. It includes a variety of features such as cost savings on shopping and time, as well as ease of use. Consumers frequently seek online shopping platforms with efficient and time-saving features that allow them to quickly find desired products, compare prices, and complete transactions. AI technology contributes significantly to the perceived utilitarian value of online shopping.

E-commerce platforms can use AI to optimize search results, provide personalized recommendations, and streamline the overall shopping experience by leveraging advanced algorithms and data analysis. These AI-powered features increase the perceived value of convenience and efficiency by saving consumers time and effort.

In contrast, perceived hedonic value focuses on the emotional and experiential aspects of a behavior or product. Pleasure, relaxation, arousal, curiosity, surprise, and the mental engagement and interest experienced throughout the interactive process are all included. Online shopping platforms have recognized the importance of providing consumers with engaging and enjoyable experiences.

They can use AI technology to create visually appealing interfaces, interactive product demonstrations, and personalized recommendations based on individual preferences and interests. These platforms can create a dynamic and immersive shopping environment that evokes positive emotions, fosters a sense of exploration, and improves overall satisfaction by leveraging AI-driven algorithms and advanced data analytics.

Since their access to vast amounts of consumer behavior data, the marketing aspects of online shopping platforms have emerged as early adopters of AI technology. These platforms have amassed vast amounts of data, including browsing histories and consumer characteristics. AI technology can continuously self-learn, iterate algorithms, and provide practical value to consumers through analysis, personalized recommendations, and visually stimulating experiences by leveraging this data. The incorporation of artificial intelligence (AI) technology into online shopping platforms enables more accurate product suggestions, efficient search results, and real-time updates, thereby improving the perceived utility value and hedonic value of the overall online shopping experience. The perceived value of AI technology in online shopping grows as consumers perceive the convenience, efficiency, and enjoyable aspects of AI-powered features.

The goal of hedonic shopping is to attain a desired outcome, providing pleasure and contentment without necessarily resulting in a purchase of a certain goods or service. To put it another way, the hedonic side of shopping is frequently expressed through the enjoyment and new experiences that are obtained when shopping (Wertenbroch & Dhar, 2000; Arnold & Reynolds, 2003; Kim, 2006; Cardoso & Pinto, 2010; Ballantine et al., 2010). Numerous studies have shown that a product's functional features have an impact on consumers' intents of purchasing it, whereas utilitarian value refers to the usefulness, comfort, and affordability that consumers perceive during the process of purchasing it. When customers focus primarily on the tangible benefits of the product itself, utilitarian value becomes a significant factor that guides their buying decisions based on their individual requirements throughout the online shopping process. The utilitarian value provided by technological convenience and improved shopping efficiency can increase customer happiness, increase consumption desire, and stimulate re-consumption.

CHAPTER 3

METHOD AND PROCEDURES

In line with the bulk of the research in the literature review, quantitative data gathering methods including online surveys were used in the study to assess the impact of AI and perceived value on online purchase intention of the respondents. The research methodology is thoroughly described in detail in this section.

3.1 Research Design and Proposed Model

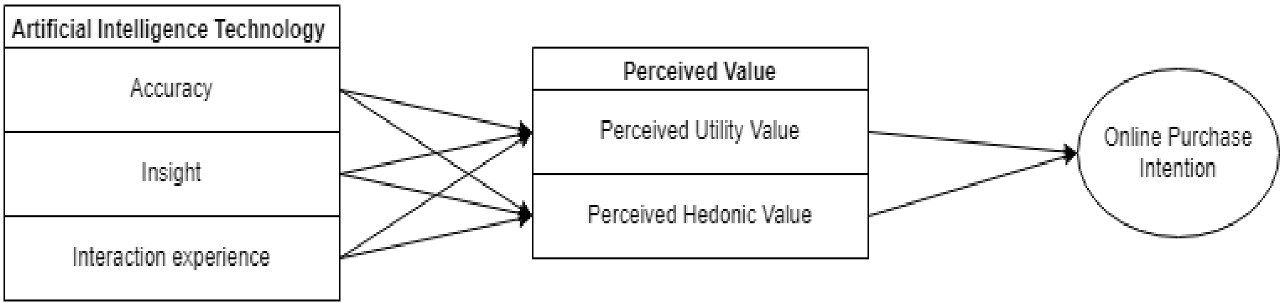
Considering the purpose and context of this research, the quantitative research method was adopted in this study. The data was used to determine if the study's deductively constructed thesis was supported by the empirical findings. Structured self-administered questionnaires were used to create online surveys to gather primary data. The cross-sectional data collection took place between April 2023 and May 2023. Online surveys were used to obtain data from the targeted demographic sample.

As shown in Figure 1, the study model consisted of 3 AI variables: Accuracy, Interaction Experience and Interaction, perceived utilitarian and hedonic value variables and online purchase intention. In order to measure each variable, 5-point Likert scales, ranging from 1-strongly disagree to 5-strongly agree, were adapted from the literature to construct a questionnaire (Appendix A). In total, 6 variables and 23 items were examined to retain results from individuals regarding impact of AI and perceived value while they shop online as well as the mediation effect of perceived value between Artificial intelligence dimensions and online shopping intention.

The questionnaire starts with asking the participant their consent to be a participant of the study following questions regarding their intention and the later part of the questionnaire consists of scale items and demographic questions of the participants such as age, gender, marital status, monthly budget, nationality, and if they shop online, also the platforms they use.

Figure 1

Proposed Conceptual Model



3.2 Population and Sampling

Convenience sampling approach was used in this study due to practical considerations and the accessibility of participants. Convenience sampling enables participants to be recruited from the chosen university, Final International University (FIU), depending on their availability and convenience. Given limitations on time, resources, and access to the target demographic, this strategy was probably more practical and effective to this study.

There are 103.110 students enrolled in higher education across the TRNC, per the data provided by the TRNC Ministry of National Education and Culture (2022). Saunders et al. (2019) recommended using a minimum sample size of 383 to reduce the possibility of non-response bias in situations where the targeted audience is 100000 or more, with a confidence interval of 95% and a 5% margin of error. Accordingly, this study initially aimed to collect at least 383 student participants from one university, namely Final International University (FIU).

According to the information gathered from FIU, in April 2023, there are a total of 3,400 active students in the university and 1937 of them are international students that study in English Preparatory School and different programs for which English is the teaching medium. Out of 1937 international students, 306 students in total took part in the study and answered the questionnaire.

3.3 Instruments and Procedures of Data Collection

The major data for this investigation was collected via a self-administered online survey with validated scale items taken from other studies. The study scales have been adapted to better reflect the participant's perceived value from AI technology while they shop online and to better fit the study's specific context. The item codes, original question as well as the sources of the scales are all listed in Table 1. All the scales were adapted from Qiu and Yin (2021).

The survey measured attitudes and opinions using a five-point Likert scale, which ranged from "strongly disagree" to "strongly agree." Likert scales give participants a scale to rate their level of agreement or disagreement and are frequently employed in social science research. Likert scales depend on variables like sample characteristics and question wording for their validity and reliability. It is clear that Likert scales are reliable and valid measuring tools based on their high levels of internal consistency, test-retest reliability, and construct validity.

Table 1

Constructs and Scale Items

Variable Name	Code	Measurement Items
Accuracy (AC)	AC1	When I shop online, AI technology can help me accurately retrieve the goods I want by inputting words.
	AC2	When I shop online, AI technology can help me accurately retrieve the goods I want by inputting pictures.
	AC3	When I shop online, AI technology can help me accurately retrieve the goods I want by inputting voice.

Insight (IS)	IS1	When I shop online, AI technology can recommend what I want based on my browsing habits
	IS2	When I shop online, AI technology can provide a (personalized) user shopping interface in line with my preferences according to my information (browsing habits, registration information, shopping history).
	IS3	When I shop online, the “read and see”, “guess what you like”, and “recommend for you” sections on the platform can provide the goods I may buy
Interactivity (IT)	IT1	When I shop online, the AI virtual customer service assistant can answer my questions.
	IT2	When I shop online, the AI virtual customer service assistant can answer my questions in time.
	IT3	When I shop online, the answers of the AI virtual customer service assistant are closely related to my questions.
	UV1	With the support of AI technology, online shopping can save me more time and cost.
	UV2	With the support of AI technology, online shopping can save my shopping from costing more.
	UV3	Shopping on a platform supported by AI technology improves my shopping efficiency.

Utility Value (UV)	UV4	AI technology can provide me with choice, let me feel more practical.
	UV5	With the support of AI technology, I think shopping is more convenient
Hedonic Value (HV)	HV1	With the support of AI technology, online shopping makes me feel very happy.
	HV2	With the support of AI technology, online shopping makes me feel very relaxed
	HV3	With the support of AI marketing technology, online shopping can arouse my shopping desire
	HV4	With the support of AI technology, it can bring me a sense of surprise and curiosity
Hedonic Value (HV)	HV5	I am willing to browse the products or services recommended by the platform many times when Shopping on an online platform that is supported by AI technology
	CPI1	Shopping on an online platform that is supported by AI technology
	CPI2	I am willing to buy the goods or services recommended by the platform when shopping on an online platform that is supported by AI technology.

Consumer Purchase Intention (CPI)	CPI3	I am likely to buy the goods or services recommended by the platform when shopping on an online platform that is supported by AI technology.
	CPI4	I am likely to buy unplanned goods or services when shopping on an online platform that is supported by AI technology.

CHAPTER 4

DATA ANALYSIS RESULTS

A comprehensive data analysis, including reliability and validity analysis, correlation analysis, confirmatory factor analysis (CFA), and structural equation modeling (SEM) route analysis, is presented in this section of the thesis. Both IBM SPSS V20 and IBM SPSS Amos v24 were used for the analyses.

4.1 Preliminary Data Analysis

According to Tabachnick and Fidell (2013), it is essential to guarantee the accuracy of the results in any quantitative investigation. The data collection in this study underwent rigorous data cleaning and validation in order to guarantee the accuracy of the analysis.

Data accuracy, missing data, outliers, multicollinearity, linearity, homoscedasticity, and normality were all evaluated during this process. Self-administered online surveys that used a questionnaire with categorical, numerical, and continuous data were used to collect the data for this study. Using the convenience sampling technique, the sample was selected. The online surveys were disseminated to a sample of more than 400 university students now attending Final International University in TRNC using Google Forms, social media, and WhatsApp. Also, the survey was converted into a QR code in order to reach out to the participants. 306 respondents completed the surveys which makes the completion rate of 76.5%.

Before being entered into the system, the survey responses have been verified for completeness to make sure no information was missing. 10 out of 306 participants were eliminated because any missing data were taken out of the data set. The Google Forms platform enabled the output data to be retrieved in Excel format, which was then transferred to IBM SPSS Statistics software for analysis.

Two popular and precise metrics are Cook's Distance (CD) and Mahalanobis Distance (MD) to check for any "change in regression coefficients when a case is detected" (Tabachnick & Fidell 2013, p. 75). After erasing each observation one at a time, Cook's Distance determines the variations in regression coefficients (Cook, 1977). According to Mahalanobis (1936), the Mahalanobis distance is a metric for comparing the similarity of two points in a multivariate space that takes data covariance into account. None of the participants had MD values less than 0.001 and CD values larger than 1.00, according to CD and MD values. No participants had to be excluded because they were outliers. Regression residuals are assumed to be normal (N), homoscedastic (H), and serially independent (I) in traditional regression analysis (Alsoufi et al., 2020). Incorrect interpretive implications may be drawn by the researcher when the normalcy assumption is not met. According to the normality test, all variables and their linear combinations have a normally distributed distribution (Alsoufi et al., 2020).

According to West, Finch, and Curran (1995), two key metrics are utilized to evaluate the normality of any data set: skewness and kurtosis. The symmetry of the distribution is shown by Skewness values and its elevation is indicated by Kurtosis, according toHair et al. (2014). The skewness and kurtosis values for a normal distribution should be zero. Any value outside of the range of -1 to + 1 denotes a fully or partially skewed distribution (Hair et al., 2014). In Table 2, skewness values (max. 0.502 and min. 0.177) and kurtosis values (max. 0.56 and min. -0.440). As the data set was reviewed, it showed traits typical of an expected normal distribution. As a result, the distribution can be categorized as normal, allowing the use of several statistical tools designed for analyzing normally distributed data.

Table 2

Descriptive Statistics

	Sum	Mean		Std. Deviation	Skewness		Kurtosis	
N=296	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
AC	2729.00	9.2196	0.15570	2.67868	0.353	0.142	-0.425	.282
IS	2690.00	9.0878	0.16906	2.90862	0.502	0.142	-0.440	.282
IT	2807.00	94831	0.15764	2.71213	0.277	0.142	-0.157	.282
UV	4626.00	15.6284	0.25547	4.39534	0.372	0.142	0.56	.282
HV	4774.00	16.1284	0.23754	4.08682	0.177	0.142	0.512	.282
CPI	3781.00	12.7736	0.20140	3.46500	0.178	0.142	0.045	.282

Linearity indicates that a straight line represents the connection between two parameters. In SPSS software, it could be depicted as a Scatter/Dot graph. Figure 2 indicates that IT and UT and IS exhibit near perfect linearity, as do IS and IT and UT exhibit linear correlations with other constructions as well, but not as linear as it is with the previous constructs.

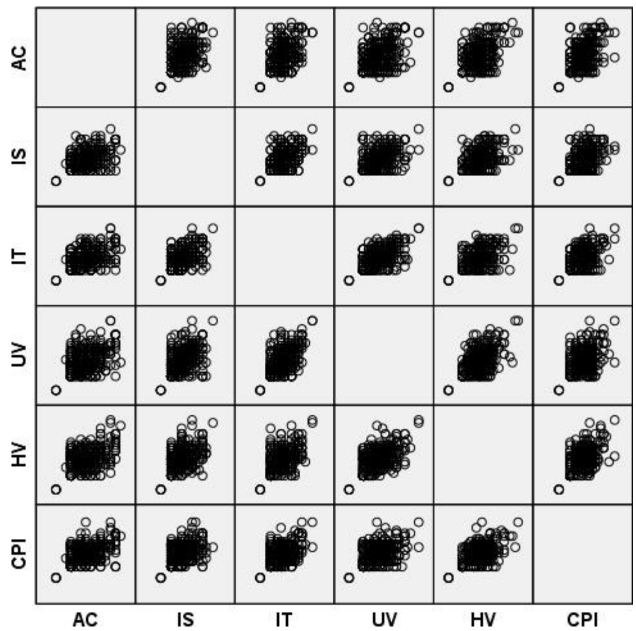
According to Hair et al. (2014, p. 217), homogeneity is the stability of the residuals over a range of independent variable values. The concept of homogeneity of variance claims that scores for a continuous component exhibit identical variability across all levels of another factor when analyzing ungrouped data.

It is expected that the variability will remain constant for both variables in grouped data where one variable is discrete and the other is continuous (Tabachnick & Fidell, 2013). It is possible to run homoscedasticity tests using statistical and visual techniques.

The assumption that the data collection is normally distributed is made when the connection between variables is thought to be homoscedastic. Contrarily, heteroscedasticity happens when the data do not adhere to the homoscedasticity criteria.

Figure 2

Scatter Plot for Linearity



Multicollinearity, according to Hair et al. (2014), is defined as the extent to which one analysis parameter may be influenced by another analysis variable. Variance Inflation Factor (VIF) and Tolerance values are used to determine collinearity by using linear regression. In their study, Hair et al. (2019) indicated that the tolerance value should be greater than 0.10 and the minimum value of VIF should be less than 10.0. Table 3's collinearity analysis reveals that both the tolerance and VIF values are within the permitted bounds. As a result, the data set's collinearity is not a concern.

Table 3

Collinearity Statistics

Variables	Tolerance	VIF
AC	.643	1.554
IS	.625	1.600
IT	.564	1.772
UT	.517	1.933
HV	.558	1.791

Dependent Variable: CPI

4.2 Sample Demographics

During the online data collection phase, 180 individuals clicked on the questionnaire links and 223 printed paper-based questionnaires were collected. However, some participants did not complete their questionnaires, resulting in the elimination of cases with missing or incomplete data and outliers. A total of 306 responses were collected during the online data collecting phase and 296 responses in total were used for the study's subsequent analysis. Based on their responses, the respondents' demographics were examined (Table 4).

It is crucial to compare the sample to the population to assess the sample's representativeness because the study's objective was to survey a population of people who were enrolled in higher education in TRNC.

Table 4

Sample Demographics

Gender	Frequency	Percent
Male	158	53.4
Female	134	45.3

Age	Frequency	Percent
15 thru 22	171	57.8
23 thru 27	108	36.6
28 thru 32	11	3.8
33 thru Highest	6	1.7

Marital status	Frequency	Percent
Complicated Relationship	1	0.3
Couple	1	0.3
Divorced	2	0.6
Engaged	1	0.3
Living with partner	12	3.9

Married	15	4.9
Secret	1	0.3
Separated	1	0.3
Single	254	82.2
Widowed	3	1.0
With Family	1	0.3

Do you shop online	**Frequency**	**Percent**
Participants who do not shop online	97	32.8
Participants who shop online	195	65.9

Monthly Budget	**Frequency**	**Percent**
Less than 1000 TRY	96	27.8
1000 TRY – 3000 TRY	16	5.1

3000 TRY – 10000 TRY	15	13.3
10000 TRY and above	23	6.93

Nationality	**Frequency**	**Percent**
Africa (Burundian, Cameroonian, Congolese, Ethiopian, Ivorian, Libyan, Malian, Moroccan, Nigerian, Somalian, Sudanese)	174	59.1

4.3 Summary of Results

The reliability and validity analysis, confirmatory factor analysis, and structural equation modelling analysis are provided in the next section of this study to test the hypotheses.

4.3.1 Reliability and Validity

For the validity and reliability of the research data, the SPSS and SPSS Amos programs are used. When describing and communicating the rigor of research techniques and the veracity of study findings, the terms' reliability and validity are adopted (Johnson and Long, 2000). Reliability is the degree to which a parameter is measured represents its "true" value (Long & Johnson, 2000). Simply put, objects with high dependability will produce consistent results when the same queries are posed in different settings.

Internal consistency is one of the most often utilized criteria of dependability, claim Hair et al. (2019; 2014). The internal consistency of study scales can be assessed using the item-total correlation and the inter-item correlation procedures.

The value of the item-total correlation and the inter-item correlation both need to be greater than 0.50 and 0.30, respectively, for the scale to be considered acceptable. Table 5 demonstrates that all variables' inter-item and item-total correlation values satisfy the internal consistency requirement. Second, internal consistency can be evaluated using the dependability standard known as Cronbach's alpha. Cronbach's alpha values, which are considered satisfactory for values larger than 0.60, can be used to test the internal reliability of scales. (Robinson et al., 1991; Hair et al., 2014).

The reliability analysis was carried out to evaluate the internal consistency of the study's scales. The scales' internal consistency ranged from moderate to good overall. The Cronbach's alpha for the Accuracy (AC) scale was 0.675, indicating moderate reliability. Cronbach's alpha values of 0.612 for the Insight (IS) and Interactivity (IT) Cronbach's alpha value is 0.630, respectively, also indicating moderate reliability.

With a Cronbach's alpha of 0.748, the Utility Value (UV) scale indicated strong internal consistency, while the Hedonic Value (HV) scale displayed good dependability with a Cronbach's alpha of 0.695. With a Cronbach's alpha of 0.707, the Online Purchase Intention (CPI) scale demonstrated strong internal consistency.

The variable Utility Value (UV) has the greatest Cronbach's alpha value of 0.748 based on the results which are supplied, indicating good internal consistency and high reliability. This indicates that the Utility Value scale's items are closely related to one another and provide accurate measurements of the target construct.

Table 5

Reliability Analysis

Variables	Items	No. of Items	Cronbach's Alpha	Inter-item Correlations (lowest-highest)	Corrected Item-Total Correlations (lowest-highest)
Accuracy	AC1	3	0.675	0.396-0.433	0.472-0.501
	AC2				
	AC3				
Insight	IS1	3	0.612	0.302-0.388	0.388-0.454
	IS2				
	IS3				
	IT1				
Interactivity		3	0.630	0.299-0.364	0.412-0.487
	IT2				
	IT3				

Utility Value	UV1	5	0.748	0.290-0.410	0.473-0.541
	UV2				
	UV3				
	UV4				
	UV5				
Hedonic Value	HV1	5	0.695	0.203-0.507	0.379-0.528
	HV2				
	HV3				
	HV4				
	HV5				
Purchase Intention	CPI1	4	0.707	0.334-0.478	0.448-0.536
	CPI2				
	CPI3				
	CPI4				

The congruence between the planned emphasis of the analysis and the actual measures gathered is at the multifaceted idea of validity. It allows for the evaluation of how precisely the data obtained represents the actual subject of the study. Data validity, according to Ghauri and Gronhaug (2005), reflects how much of the desired subject matter is covered. Expanding on this idea, Hair et al. (2019) states that validity includes how closely a measure corresponds to the value or measurement it is intended to represent.

Diagnostic assessments heavily rely on reliability metrics like Average Variance Extracted (AVE) and Composite Reliability (CR). In order to understand the convergence of items that represent the underlying idea, AVE estimates the average percentage of variance explained among the construct's components (Hair et al., 2014).

According to Tepe and Demir (2012), the alpha coefficient assumes equal factor loadings and error variances while the CR coefficient assumes unequal factor loadings and error variances. These measurements are essential in determining a scale's convergent validity and are frequently evaluated in tandem.

Utilizing several methodologies, such as discriminant validity, face validity, and convergent validity, is part of the validity assessment process. These three forms of validity are investigated in the current study. Face validity entails gathering measurement scales from the literature and having them reviewed by a professional before using them in the study (Hair et al., 2019). It includes the researchers' subjective assessment of the instrument's presentation and importance, ensuring that the items included are pertinent, sensible, unambiguous, and clear (Oluwatayo, 2012). The poll questions are taken from reliable sources and put through a thorough evaluation by academics and experts to determine their validity on their face.

The construct validity and reliability analysis provided significant new information on the study's variables.

Significant information about the variables covered by the test was revealed by the reliability and validity study of the entire sample. Utility Value demonstrated accurate assessment (CR = 0.747), whereas Consumer Purchase Intention showed favorable inner consistency (CR = 0.711).

However, both constructs (AVE = 0.38 and AVE = 0.372, respectively) indicated that there was space for improvement in convergent validity. Hedonic Value and Accuracy demonstrated admirable reliability (CR = 0.697 and CR = 0.568, respectively), but they also suggested that more appropriate convergent validity was required (AVE = 0.0316 and 0.309, respectively). Although Insight and Interactivity demonstrated flawless reliability (CR = 0.614 and CR = 0.561, respectively), convergent validity has to be improved (AVE = 0.0347 and AVE = 0.299).

These results underline how important it is to take construct reliability and convergent validity into account when ensuring accurate measurement and interpretation of the study's variables. In brief, for all variables, the construct dependability (CR values) is often adequate. The AVE values for Consumer Purchase Intention, Utility Value, Hedonic Value, Accuracy, and Insight, however, may still leave ample opportunity for improvement.

Table 6

Construct Reliability and Validity Summary

	CR	AVE	MSV	MaxR(H)	CPI	UV	HV	AC	IS	IT
CPI	0.711	0.381	0.618	0.713	**0.617**					
UV	0.747	0.372	0.817	0.747	0.646***	**0.61**				
HV	0.697	0.316	0.665	0.7	0.786***	0.816***	**0.562**			
AC	0.568	0.309	0.647	0.583	0.764***	0.750***	0.781***	**0.556**		
IS	0.614	0.347	0.738	0.617	0.619***	0.704***	0.717***	0.805***	**0.589**	
IT	0.561	0.299	0.817	0.563	0.742***	0.904***	0.811***	0.803***	0.859***	**0.547**

4.3.2 Correlation Analysis

A statistical method for examining the connections between variables is correlation analysis. The major variables in this study were accuracy (AC), insight (IS), interactivity (IT), utility value (UV), hedonic value (HV), and consumer purchase intention (CPI). Correlation analysis was used to examine the relationships between these variables. Investigating the degree and direction of the correlations between these variables was the goal of the correlation study.

The findings of the correlation analysis showed that there were significant correlations between the study's variables. With regard to insight, interaction, utility value, hedonic value, and consumer purchase intention, accuracy showed a moderate significance. The correlation coefficients, which ranged from 0.424 to 0.582, showed that these factors were significantly associated. Similar positive and moderate associations were seen between Consumer Purchase Intention and Insight, Interactivity, Utility Value, and Hedonic Value.

These results show the possible impact of Accuracy, Insight, Interactivity, Utility Value, and Hedonic Value on Consumer Purchase Intention by indicating that there are connections between the variables. The significant associations help to better understand consumer behavior and decision-making processes by offering insightful information about how these constructs interact.

These results can help inform marketing tactics targeted at raising customer happiness and engagement by providing a deeper understanding of the variables impacting consumers' purchase intentions.

Table 7

Inter-Construct Correlation

	AC	IS	IT	UV	HV	CPI
AC	1					
IS	0.482**	1				
IT	0.454**	0.511**	1			
UV	0.478**	0.480**	0.582**	1		
HV	0.492**	0.472**	0.508**	0.593**	1	
CPI	0.481**	0.424**	0.472**	0.473**	0.550**	1

**. Correlation is significant at the 0.01 level (2-tailed).

4.3.3 Confirmatory Factor Analysis (CFA)

A crucial component of this study is the measurement of Goodness of Fit Indices, which enables an assessment of how well the suggested statistical model fits the collected data. Researchers can learn more about the overall quality and suitability of the model's representation of the underlying relationships between variables by evaluating several fit indices. The model's Goodness of Fit Indices, which were obtained, showed encouraging results. The model and observed data difference is measured by the CMIN/DF ratio, which produced a value of 1.778, indicating an excellent fit within the advised range of 1 to 3.

The Comparative Fit Index (CFI) also showed a value of 0.904, which is below the target level of 0.95 but still denotes a respectable fit. The Standardized Root Mean Square Residual (SRMR), with a value of 0.077 and below the cutoff of 0.08, showed a good match.

Additionally, the Root Mean Square Error of Approximation (RMSEA) score of 0.051 indicates a very good fit as it is lower than the advised threshold of 0.06. Last but not least, the P Close value of 0.385, which was higher than the 0.05 cutoff, demonstrated an excellent fit. Overall, these results show that the suggested model has a good fit to the measured data.

Figure 3

Confirmatory Factor Analysis (CFA)

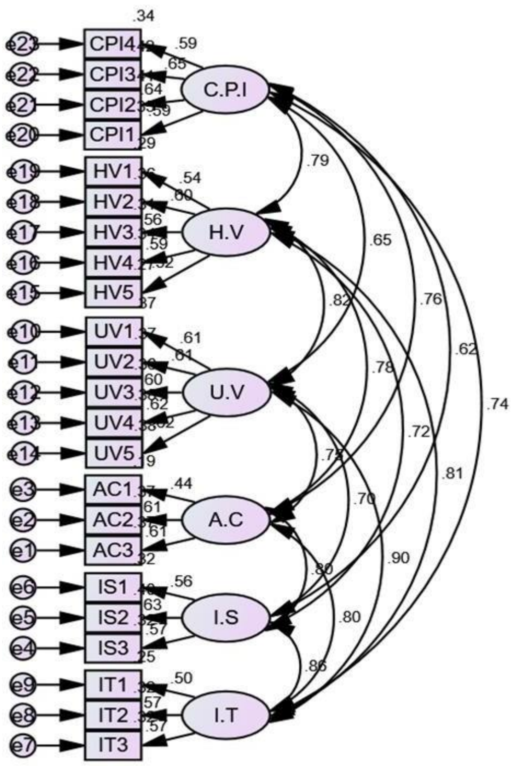


Table 8

Goodness of Fit Indices

Measure	Estimate	Threshold	Interpretation
CMIN	382.331	--	--
DF	215	--	--
CMIN/DF	1.778	Between 1 and 3	Excellent
CFI	0.904	>0.95	Acceptable
SRMR	0.077	<0.08	Acceptable
RMSEA	0.051	<0.06	Excellent
PClose	0.385	>0.05	Excellent

(Gaskin & Lim, 2016).

4.3.4 Structural Equation Modeling (SEM) – Path Analysis

Structural Equation Modeling (SEM), also known as covariance structure analysis or latent variable analysis, is a subset of confirmatory factor analysis (CFA) (Hair et al., 2019). According to Hair et al. (2019), it is a powerful multivariate technique that enables researchers to simultaneously explore a variety of dependent interactions within variables. Researchers can evaluate the usefulness of each scale item, look at reliability, and investigate pre-established correlations using SEM (Hair et al., 2014).

SEM provides for the discovery of experimental errors during model testing, going beyond simply relying on the data to understand the nature of the relationship between elements (Byrne, 1998).

SEM offers a confirmatory method to measure correlations by combining exploratory factor analysis (EFA) with multiple regression (Ullman & Bentler, 2012). Based on theory and previous findings, it enables researchers to characterize intricate interactions between observable and latent variables (Schreiber et al., 2006).

Using maximum likelihood techniques, the model's parameters can be inferred from the covariance matrix of the observed data (Ullman & Bentler, 2012).

Latent variables, which are constructs evaluated indirectly through several measurable variables or indicators, can be incorporated into SEM, which is one of its primary advantages (Hair et al., 2019). Researchers can capture underlying dimensions that might not be readily apparent using these latent variables, which can be both exogenous and endogenous elements (Hair et al., 2019).

By examining the covariance matrix indicated by the model and contrasting it with the estimated parameters and the observed matrix, SEM is used to evaluate the strength of fit of the hypothesized model (Hair et al., 2019).

In conclusion, SEM is a potent statistical methodology that fuses CFA and route analysis. It enables researchers to study intricate interrelationships, look at the correlations between variables, and include latent structures. Researchers can validate theoretical models, spot experimental mistakes, and comprehend the underlying mechanisms underlying their data better by using SEM.

According to Baron and Kenny (1986), endogenous constructs are categorized as dependent variables, whereas exogenous constructs are classified as independent variables. Accuracy (AC), Insight (IS), and Interactivity (IT) are therefore thought of as external constructs, as seen in Table 9. Utility Value (UV) and Hedonic Value (HV), on the other hand, are thought of as endogenous constructs.

Table 9

Exogenous and Endogenous Constructs

Exogenous constructs	Endogenous Constructs
Accuracy	Perceived Utility Value
Insight	Hedonic Value
Interactivity	Purchase Intention

To assess the recommended model fit and test the assumptions, a covariance-based path analysis was performed using the IBM SPSS AMOS v21 software and the Maximum Likelihood Estimation (MLE) method. Exogenous variables are connected by correlation curves in the measurement model, which is shown in Figure 4, whereas relationship variables are connected by one-way arrows. The analysis in AMOS v21 enabled a thorough investigation of the connections between variables and gave information about the underlying structural pathways.

The results shown in Table 10 show that the suggested model exhibits a satisfactory match as indicated by the model fit measures.

The CMIN/DF ratio of 1.773 is excellent and falls within the range of 1 to 3. Additionally, a great match is indicated by the fact that the SRMR value of 0.079 is lower than the cutoff of 0.08. A strong match is further supported by the fact that the RMSEA value of 0.051 is below the advised cutoff point of 0.06. Last but not least, an outstanding match is indicated by the PClose value of 0.397, which is higher than the significance level of 0.05.

It's important to keep in mind that although the CFI value of 0.902 is just a little bit below the cutoff of 0.95, it still remains within the allowed range. As a result, the model shows overall good fit to the data. Overall, the model fit measurements show that the suggested model fits the data well, supporting the accuracy and dependability of the connections under investigation. These findings support the hypothesis under investigation and deepen our comprehension of the underlying constructs.

Figure 4

Structural Equation Modeling-Path Analysis

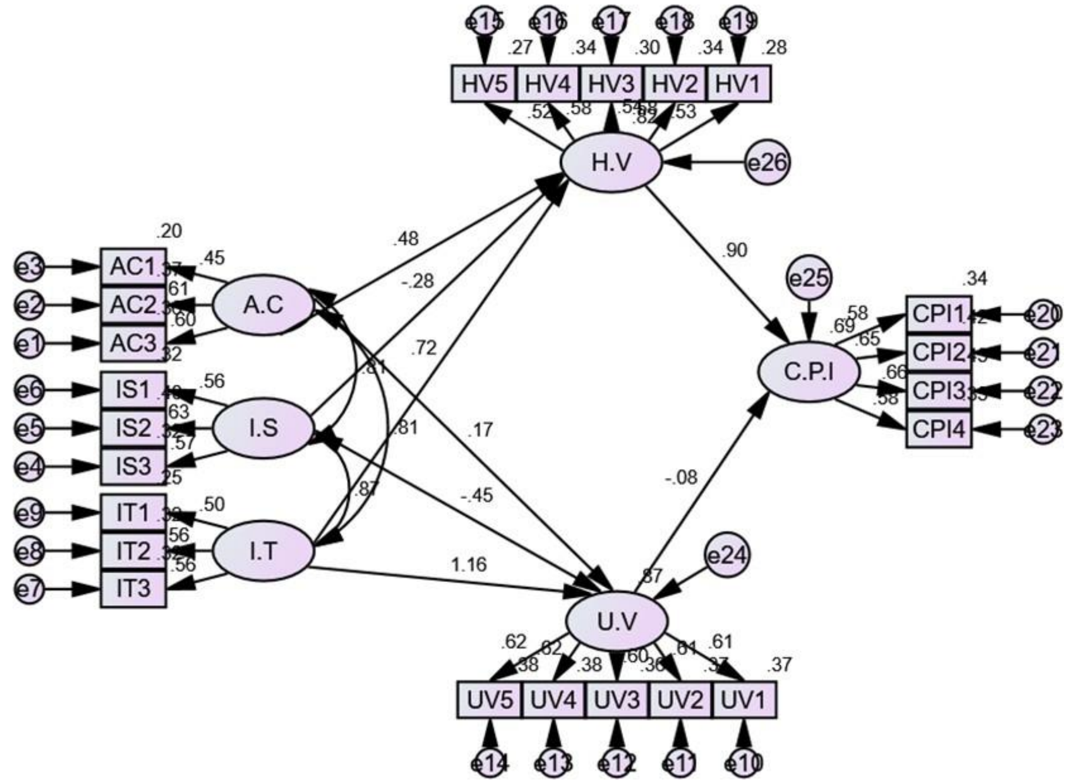


Table 10

Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	388.299	-	-
DF	219	-	-
CMIN/DF	1.773	Between 1 and 3	Excellent
CFI	0.902	>0.95	Acceptable
SRMR	0.079	<0.08	Acceptable
RMSEA	0.051	<0.06	Acceptable
PClose	0.397	>0.05	Excellent

(Gaskin & Lim, 2016).

4.3.5 Hypothesis Testing

The study's developed hypotheses were assessed using SEM analysis. The postulated hypotheses (p) are supported by standard estimates (B), standard error (S.E), critical ratio (C.R), and significance level. Overall, Table 11 demonstrates that 7 of the 8 hypotheses are supported, whereas 1 of the hypotheses is not. H1 to H7. The p-values larger than 0.05 do not support the hypothesis H8. The findings of the hypothesis tests are summarized in table 11 below.

Table 11

Hypothesis Testing

Description	B	S.E	C.R.	P	Outcome
There is a positive relationship between accuracy and perceived utility value.	0.307	0.070	4.356	***	**Supported**
There is a positive relationship between accuracy and hedonic value.	0.352	0.072	4.874	***	**Supported**
There is a positive relationship between insight and perceived utility value.	0.284	0.081	3.522	***	**Supported**
There is a positive relationship between insight and hedonic value.	0.250	0.066	3.756	***	**Supported**
There is a positive relationship between interactivity and perceived utility value.	0.690	0.122	5.646	***	**Supported**
There is a positive relationship between interactivity and hedonic value.	0.450	0.092	4.903	***	**Supported**
There is a positive relationship between hedonic value and consumer purchase intention.	1.094	0.280	3.903	***	**Supported**
There is no significant relationship between perceived utility value and consumer purchase intention.	-0.130	0.168	-0.774	0.439	**Not Supported**

4.3.6 Mediation Analysis

The present study used IBM SPSS Amos (Analysis of a moment structures) v24 software to carry out the mediation analysis in order to investigate the relationship between the independent variables (i.e., accuracy, insight, interaction,) and purchase intention as the dependent variable, with hedonic and utilitarian value acting as the mediator.

Table 12

Mediation Effect Analysis

Relationship	Direct effect	Indirect effect	Outcome
H7a: Hedonic value toward online purchase intention is a mediator between accuracy and online purchase intention of international students studying in TRNC. AC>HV>CPI	0.266(0.108) ns	0.310(0.001) ***	**Full mediation**
H7b: Hedonic value toward online purchase intention is a mediator between insight and online purchase intention of international students studying in TRNC. IS>HV>CPI	0.082(0.565) ns	0.227(0.002) ***	**Full mediation**
H7c: Hedonic value toward online purchase intention is a mediator between interaction and online purchase intention of international students studying in TRNC. IT>HV>CPI	0.229(0.217) ns	0.364(0.001) ***	**Full mediation**
H8a: Utility value toward online purchase intention is a mediator between accuracy and online purchase intention of international students studying in TRNC.	0.462(0.002) **	-1789(0.148) ns	**Not significant**

AC>UV>CPI			
H8b: Utility value toward online purchase intention is a mediator between insight and online purchase intention of international students studying in TRNC. IS>UV>CPI	0.254(0.128) ns	-1.420(0.142) ns	**Not significant**
H8c: Utility value toward online purchase intention is a mediator between interaction and online purchase intention of international students studying in TRNC. IT>UV>CPI	0.628(0.024) *	-3.978(0.136) ns	**Not significant**

*=p<.05; **=p<.01; ***=p<.001; ns= "not significant"

CHAPTER 5
CONCLUSION

5.1 Conclusion and Discussions

This thesis aimed to understand the impact of Artificial Intelligence and perceived value on online purchase intentions of higher education students in North Cyprus.

Therefore, several significant conclusions have been drawn after a thorough survey and data analysis. The findings demonstrated that customer perceived value is significantly influenced by accuracy, insight, and interaction with AI technologies.

Customers' perceived hedonic value was increased through improved accuracy and insight, interactive experiences. Customers may value the ability of AI technology to precisely identify and recommend goods or services based on their tastes and needs, as this demonstrates. Additionally, the interactive nature of AI platforms enables tailored and interesting experiences, enhancing overall customer satisfaction and perceived value.

Additionally, it was found that customers' perceived value had a considerable impact on their decision to make an online purchase. According to the study, the greater perceived hedonic value of AI technology enhanced the tendency of people to make online purchases. This result underlines how crucial it is to give clients useful and enjoyable experiences using AI-powered platforms. Businesses can improve consumers' intention to make online purchases and increase sales by efficiently fulfilling customers' requirements and preferences.

According to the study's findings, marketers and businesses should prioritize improving the accuracy, insight, and interactivity of AI technology on their online platforms. Businesses can improve their consumers' perceived value and raise the possibility that they will make online purchases by continuously enhancing the accuracy of product recommendations, offering insightful information, and enabling engaging interactions.

The study also underlines the need of comprehending and adapting customers' utility and hedonic perceptions of value since from the findings the hedonic value significantly influences purchase intentions. Additionally, in order to comprehend the underlying mechanisms influencing consumer behavior, the mediating impacts of perceived utility value and hedonic value were studied.

Our study revealed that perceived utilitarian value had no statistically significant effect on customers' intention to buy. This fascinating finding emphasizes the complexity of customer decision-making in the context of AI-driven interactions and motivates us to further investigate the various variables that influence online purchasing behavior. These findings highlight the need to study deeper into the wide range of factors that affect how consumers behave and what they decide to buy in the digital market as the landscape of AI and e-commerce continues to change

Furthermore, according to the descriptive statistics, the factors accuracy (AC), insight (IS), interactivity (IT), and hedonic value (HV) all had a significant effect on consumer purchase intention (CPI). The internal consistency and reliability of these variables ranged from moderate to good, indicating that they can be used as reliable measurements. The durability of the measuring scales utilized in the study was further supported by the construct reliability and validity analyses. The scales have an effective high level of reliability, with UV having the highest Cronbach's alpha score of 0.748. However, there is potential for improvement with regard to the convergent validity of some conceptions.

Significant correlations between the variables were found by correlation analysis, proving their interdependence. With regard to insight, interaction, utility value, hedonic value, and customer purchase intention, accuracy revealed positive and moderate relationships. The remaining independent factors showed similar associations, showing their potential impact on customer behavior. The proposed model obtained support from the structural equation modeling (SEM) study, demonstrating a strong fit to the data. The majority of the hypotheses were confirmed by the SEM results, with perceived utility value and hedonic value acting as mediators between consumer purchase intention and experience with AI technology.

Overall, the results emphasize the significance of AI marketing technology in online shopping markets. The perceived value, and purchase intention of consumers are highly influenced by accuracy, insight, and interactive components. These results have marketing implications, highlighting the need to emphasize accurate information, offer insightful experiences, and improve interactive elements that promote pleasant consumer experiences and influence purchasing behavior.

In conclusion, this study contributes to the literature review by offering insights into how AI technology affects consumer behavior and purchase intention. The results highlight the importance of accuracy, insight, and interactive elements in raising consumers' perceptions of value. The relationship between AI technology and consumer purchase intention has been shown to be mediated by perceived hedonic value, respectively.

5.2 Implications and Recommendations

For academics and professionals who work in the fields of marketing and consumer behavior, the study's conclusions have a number of implications. The study first highlights how crucial it is to improve AI marketing technologies in order to raise consumer perceptions of value and intention to purchase. To ensure precise suggestions and enjoyable user experiences, the accuracy, intelligence, and interactive characteristics of AI algorithms should be given priority. This may be accomplished by continuing to invest in data analytics, AI technology, and user interface design.

Therefore, in order to address the limitations found in this study, future research and development efforts should concentrate on enhancing AI technology. To improve the retrieval experience for users, one area of study may be enhancing the precision of AI algorithms in multiple areas, such as picture identification and speech recognition. To continuously enhance and update the AI models, this may entail improving the algorithms, utilizing cutting-edge machine learning techniques, and taking user feedback into account.

Future research on the influence of AI and perceived value on online shopping should be conducted in big cities like Istanbul, Paris, Rome, Barcelona, New York, Tokyo since online shopping in these big cities is more popular than North Cyprus and should compare AI implementation strategies, conduct regional consumer surveys, examine user experience, consider AI ethics, and evaluate the long-term impact. Retailers should be advised to use AI to improve perceived value, client contentment, and general shopping experiences.

Future studies should also look into ways to improve the insight and interactive skills of AI technologies. This can entail creating more complex algorithms that offer more in-depth understandings of consumer preferences, habits, and trends. Marketers can customize their offers and communication methods to deliver more interesting and individualized experiences by developing an improved understanding of consumer wants and preferences.

Moreover, future studies should also look into how AI technology affects consumer perception and trust. Understanding how consumers view and regard AI-driven marketing is crucial as the use of AI in marketing grows. Studies might examine elements like transparency, explain ability, and the perception of algorithmic fairness that affect consumer trust in AI technology. Additionally, investigating potential ethical challenges with AI-driven marketing, such as algorithmic bias, privacy, and data security, might offer insights on how to resolve these problems and increase customer confidence in these programs.

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APPENDIX

APPENDIX A: Survey Questionnaire

Dear Participant,

I am Rigersa Cara, a Master student of Business Administration program at Final International University and this research will be conducted by me under the supervision of Assist. Prof. Dr. Kevser Taşel Jurkoviç. This research project aims to understand better the impact of Artificial Intelligence and perceived value on online purchase intention. This survey is intended for people 18 years or older and the estimated number of participants will be approximately 400 people. The survey will be available between March 2023 and April 2023. I am inviting you to participate in a research study. Your decision to participate in this study is completely voluntary. If you decide to not participate in this study, it will not affect you in anyway. You are expected to participate in this survey study only once. You will be required to fill an online survey questionnaire. Moreover, this survey is anonymous. No personal identifying information or IP addresses will be collected. Also, no information is required to identify you and you cannot be identified by the answers you supply. The data collected from you will be kept safely in an encrypted file on a computer and will be used for academic purposes only. None of the steps in the survey can cause personal discomfort. Withdrawing from this survey will not affect the relationship you have, if any, with the researcher. If you withdraw from the study before data collection is completed, your data will be dismissed.

I appreciate your participation in this survey and thank you in advance. Please feel free to ask any questions that you may have about the research; I will be happy to explain anything in greater detail. You may contact me through the following email address: rigersa.cara@final.edu.tr

By proceeding to the questions, you will give your consent regarding participation in this study. Do you want to proceed to the survey?
*

Yes

No

By proceeding to the questions, you will give your consent regarding participation in this study. Do you want to proceed to the survey?

*

Yes

No

Artificial Intelligence (AI) is the simulation of human intelligence in machines that are programmed to think and learn like humans.

To what extent do you agree with the following statement regarding Accuracy. (Accuracy in Artificial Intelligence (AI) refers to the ability of a model or algorithm to correctly identify or predict the correct output or class, based on a set of input data. It is a measure of how well the model or algorithm is able to correctly classify or predict the outcome)

*

When I shop online, AI technology can help me accurately retrieve the goods I want by inputting words.

Strongly disa

Disagree

Neutral

Agree

Strongly agre

When I shop online, AI technology can help me accurately retrieve the goods I want by inputting pictures.

Strongly disa

Disagree

Neutral

Agree

Strongly agre

When I shop online, AI technology can help me accurately retrieve the goods I want by inputting voice.

Strongly disa

Disagree

Neutral

Agree

Strongly agre

To what extent do you agree with the following statement regarding Insight of AI. (Insight in Artificial Intelligence (AI) refers to the ability of an AI system to identify patterns, relationships, or hidden information within data, and to make predictions or decisions based on that knowledge.)

*

When I shop online, AI technology can recommend what I want based on my browsing habits.

Strongly disa
Disagree
Neutral
Agree
Strongly agre

When I shop online, AI technology can provide a (personalized) user shopping interface in line with my preferences according to my information (browsing habits, registration information, shopping history).

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

When I shop online, the “read and see”, “guess what you like”, and “recommend for you” sections on the platform can provide the goods I may buy.

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

To what extent do you agree with the following statement regarding Interaction of AI

Interaction in Artificial Intelligence (AI) refers to the way in which humans and AI systems interact and communicate with each other.

*

When I shop online, the AI virtual customer service assistant can answer my questions.

Strongly disa
Disagree
Neutral
Agree
Strongly agre

When I shop online, the AI virtual customer service assistant can answer my questions in time.

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

When I shop online, the answers of the AI virtual customer service assistant are closely related to my questions.

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

To what extent do you agree with the following statement regarding Utility Value of AI in online shopping.

The utility value of Artificial Intelligence (AI) refers to the benefit or usefulness that a particular AI system provides.

*

With the support of AI technology, online shopping can save me more time and cost.

Strongly disa
Disagree
Neutral
Agree
Strongly agre

With the support of AI technology, online shopping can save my shopping from costing more.

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

Shopping on an online platform supported by AI technology improves my shopping efficiency.

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

AI technology can provide me with choices and it makes me feel more practical.

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

With the support of AI technology, I think online shopping is more convenient.

*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

To what extent do you agree with the following statement regarding Hedonic Value of AI in online shopping

Hedonic value in Artificial Intelligence (AI) refers to the pleasure or enjoyment that people derive from interacting with AI systems.

*

With the support of AI technology, online shopping makes me feel very happy.

Strongly disa
Disagree
Neutral
Agree
Strongly agre

With the support of AI technology, online shopping makes me feel very happy.

*

Strongly disa
Disagree
Neutral

Agree
Strongly agre

With the support of AI technology, online shopping makes me feel very relaxed
*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

With the support of AI technology, online shopping can arouse my shopping desire
*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

With the support of AI technology, it can bring me a sense of surprise and curiosity.
*

Strongly disa
Disagree
Neutral
Agree
Strongly agre

To what extent do you agree with the following statement regarding a Consumer's Purchase Intention on an online shopping platform using AI technology

(Consumer online purchase intention related to Artificial Intelligence (AI) refers to the likelihood that a consumer will buy a product or service that uses AI technology.)
*

I am willing to browse the products or services recommended by the platform many times when shopping on an online platform that is supported by AI technology

Strongly disa
Disagree
Neutral
Agree
Strongly agre

I am willing to buy the goods or services recommended by the platform when shopping on an online platform that is supported by AI technology.
*

Strongly disa
Disagree
Neutral

Agree

Strongly agre

I am likely to buy the goods or services recommended by the platform when shopping on an online platform that is supported by AI technology.
*

Strongly disa

Disagree

Neutral

Agree

Strongly agre

I am likely to buy unplanned goods or services when shopping on an online platform that is supported by AI technology.
*

Strongly disa

Disagree

Neutral

Agree

Strongly agre

Do you shop online?
*

Yes

No

Do you shop on social media platforms?
*

Yes

No

Where do you shop online?
*

Tablet

PC

Mobile phon

Other…

Do you use any online shopping platform that use AI (making you reccomandations)
*

Yes

No

How frequently do you shop online?
*

Short answer text

Gender
*

Male

Female

Marital Status
*

Single

Married

Divorced

Seperated

Living with p

Widowed

Other…

Age
*

Short answer text

Nationality
*

Short answer text

Occupation
*

Short answer text

Monthly household income

Short answer text

APPENDIX B: Ethics Committee Approval Document

İÇ YAZIŞMA / INTER OFFICE MEMORANDUM

Gönderilen/To: Rigersa Cara

Tarih/Date: 17/03/2023

Gönderen/From: Prof. Dr. Hüseyin YARATAN
Rector

Ref/Sayı: 100/050/REK.001

Konu/Subject: About ethical approval

In line with the decision taken at the Ethics Committee meeting on March 10th, 2023, it was decided that your study was ethically and scientifically appropriate.

Distribution: Chair of the Ethics Commitee

Ethics Committee Decision:

Decision no / Karar Sayısı: 2023/007/01
Rigersa Cara's application to the Ethics Committee titled "IMPACT OF ARTIFICIAL INTELLIGENCE AND PERCEIVED VALUE ON ONLINE PURCHASE INTENTION: THE CASE OF NORTH CYPRUS", a proposed study to be carried out under the supervision of Asst. Prof. Dr Kevser Taşel Jarkoviç was discussed. With the justification, purpose, approach and methods stated in the application, the proposed research was found ethically and scientifically appropriate.

SK/HY