THE ROLE OF MACHINE LEARNING CHATBOT IN INFLUENCING CONSUMER PURCHASE INTENTION IN FASHION INDUSTRY

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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THE ROLE OF MACHINE LEARNING CHATBOT IN INFLUENCING CONSUMER PURCHASE INTENTION IN FASHION INDUSTRY

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Report submitted in fulfilment of the requirement for the degree of Bachelor of Technology Management (High Technology Marketing) With Honours

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DECLARATION

I declare that this thesis research project of title “The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry” is the result of my own research except the citied in the references. The research project has not been for any degree and is not concurrently submitted in candidature of any other degree.

Signature :…… …………

Name : Thean Kah Keat

Date :…20/ 1/ 2024………………

APPROVAL

I hereby declare that I have read this thesis research and in my opinion this thesis is sufficient in terms of scope and quality for the award of Bachelor of Technology Management and High Technology Marketing with Honours

Signature : ………………

Supervisor : Dr Atirah Binti Sufian

Date : 20/1/2024……………

Signature : … ……………..

Panel : Dr Nor Azah Binti Abdul Aziz

Date : 20/ 1/ 2024…………………………..

DEDICATIONS

I wholeheartedly dedicate my final year project, titled "The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry," to my loving parents, my esteemed supervisor Dr, Atirah Binti Sufian, and my beloved university. To my dear parents, your unwavering love, support, and sacrifices have been the foundation of my academic journey. Your constant encouragement and belief in my abilities have inspired me to pursue excellence. This research project is a testament to your endless encouragement and the values you instilled in me. I am forever grateful for your unconditional love and unwavering belief in my potential. To my respected supervisor, Dr. Atirah Binti Sufian, your guidance and expertise have been instrumental in shaping this research project. Your dedication to mentoring and your passion for knowledge have ignited my enthusiasm for research. Your invaluable feedback, patience, and unwavering support have propelled me forward, allowing me to grow both academically and personally. I am profoundly grateful for the knowledge and skills I have acquired under your guidance. To my esteemed university, University Teknikal Malaysia Melaka, my esteemed faculty, Faculty of Technology Management and Technopreneurship (FPTT) I extend my heartfelt appreciation for providing me with a conducive learning environment. The resources, opportunities, and platform you have provided have been instrumental in shaping my academic journey. The interdisciplinary approach to education, the vibrant academic community, and the exposure to diverse perspectives have broadened my horizons and enriched my research experience. This research project is a culmination of the collective support, encouragement, and guidance from my parents, supervisor, and university. It is dedicated to all those who have played a significant role in my academic growth and success.

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ABSTRACT

With the rapid advancements in artificial intelligence and machine learning, chatbots have become increasingly prevalent in online shopping experiences. These chatbots offer personalized assistance and information, enhancing the decision-making process for consumers. The study focuses on identifying the key factors that shape consumers' purchase intention when interacting with machine learning chatbots in the fashion industry's e-commerce platforms. The study uses quantitative methods to explore how machine learning chatbots impact consumers' buying decisions in fashion e-commerce. Surveys are employed to collect numerical data on consumer behavior, preferences, and perceptions. The findings of this research contribute to the existing knowledge by providing a deeper understanding of how machine learning chatbots impact consumer behavior in the context of fashion e-commerce. The study has practical implications for businesses in designing effective chatbot interactions and personalized recommendations to improve customer engagement, conversion rates, and overall satisfaction. By optimizing the design and functionality of machine learning chatbots, fashion e-commerce platforms can enhance the user experience and drive higher purchase intentions. A total of 384 responses were obtained through questionnaire. The findings reveal that system quality emerges as the primary influencer, followed by substantial effects from perceived usefulness, perceived ease of use, and information quality. The findings underscore the pivotal role of user-friendly experiences, reliable systems, and quality information in shaping consumer behaviors and intentions in the fashion industry's e-commerce facilitated by machine learning chatbots.

Keywords: Machine learning chatbot, Ecommerce, Fashion industry, Consumer purchase intention

ABSTRAK

Dengan kemajuan pesat dalam kecerdasan buatan dan pembelajaran mesin, chatbot semakin meluas dalam pengalaman membeli dalam talian. Chatbot ini menawarkan bantuan dan maklumat yang dipersonalisasi, meningkatkan proses pembuatan keputusan bagi pengguna. Kajian ini memberi tumpuan kepada mengenal pasti faktor-faktor utama yang membentuk niat pembelian pengguna ketika berinteraksi dengan chatbot pembelajaran mesin dalam platform e-dagang industri fesyen. Kajian menggunakan kaedah kuantitatif untuk meneroka cara chatbot pembelajaran mesin memberi kesan kepada keputusan pembelian pengguna dalam e-dagang fesyen. Tinjauan digunakan untuk mengumpul data berangka tentang tingkah laku, pilihan dan persepsi pengguna. Hasil kajian ini menyumbang kepada pengetahuan sedia ada dengan menyediakan pemahaman yang lebih mendalam mengenai bagaimana chatbot pembelajaran mesin mempengaruhi tingkah laku pengguna dalam konteks e-dagang fesyen. Kajian ini mempunyai implikasi praktikal bagi perniagaan dalam merancang interaksi chatbot yang berkesan dan cadangan yang dipersonalisasi untuk meningkatkan penglibatan pelanggan, kadar penukaran, dan kepuasan keseluruhan. Dengan mengoptimumkan reka bentuk dan fungsi chatbot pembelajaran mesin, platform e-dagang fesyen dapat meningkatkan pengalaman pengguna dan meningkatkan niat pembelian yang lebih tinggi. Sebanyak 384 jawapan telah diperolehi melalui soal selidik. Penemuan mendedahkan bahawa kualiti sistem muncul sebagai pengaruh utama, diikuti oleh kesan yang besar daripada dirasakan kegunaan, persepsi kemudahan penggunaan dan kualiti maklumat. Penemuan ini menekankan peranan penting pengalaman mesra pengguna, sistem yang boleh dipercayai dan maklumat berkualiti dalam membentuk tingkah laku dan niat pengguna dalam e-dagang industri fesyen yang difasilitasi oleh chatbot pembelajaran mesin.

Kata kunci: Chatbot pembelajaran mesin, E-dagang, Industri fesyen, Niat pembelian pengguna.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The research begins with a chapter discussing the study's background in relation to The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry. This is followed by the formulation of a problem statement, research questions, and research objectives, as well as a discussion of the research's scope, and significance of the study.

1.2 Background of study

Rapid advancements in science and technology continually introduce new discoveries and inventions, with artificial intelligence (AI) emerging as a leading force in driving societal progress (Mariani et al., 2022). In the modern era, AI holds immense potential for revolutionizing various industries, including the fashion industry. Extensive research has shown that the integration of AI, particularly machine learning, has the ability to streamline consumer decision-making processes by reducing search costs, saving time, offering diverse options, and providing an autonomous delivery system independent of selling entities (Huang & Rust, 2021).

Fashion industry has experienced significant transformations driven by technological advancements and evolving consumer preferences. Machine learning techniques have gained traction within the industry, enabling businesses to analyse vast datasets and extract valuable insights into consumer behavior. These insights are used to customize marketing communications, understand consumer preferences, and forecast trends (Brei, 2020). Additionally, AI technologies, such as human-like chatbots, natural language processing, and deep learning, are utilized to predict upcoming trends by analyzing extensive data from social media platforms, search engines, and e-commerce websites.

Malaysia's apparel industry has demonstrated expertise and resilience since the 1970s, serving renowned global brands like Nike, Gucci, Calvin Klein, Alain Delon, H&M, Burberry and Uniqlo which contributing substantially to the national economy. According to Statista (2023), Malaysian fashion industry is projected to experience growth, with an expected revenue of 13.2 billion ringgit in 2023 and a compound annual growth rate (CAGR) of 12.25% between 2023 and 2027. Retail sales of clothing and accessories in Malaysia are anticipated to reach 53 billion ringgit (approximately US$12.4 billion) by 2022 (Euromonitor). These statistics indicate the industry's potential for expansion and its substantial contribution to the global fashion market. Despite the challenges posed by the COVID-19 pandemic, the industry has adapted by embracing digital transformation and innovative methodologies, particularly in fashion retail and e-commerce (Farhana et al., 2022). There is considerable consumer demand for categories such as casual wear, sunglasses, and costume jewellery, highlighting market opportunities within the fashion industry. Malaysia's apparel sector has also gained recognition for its ability to cater to global brands while bolstering the country's export earnings.

Chatbots, powered by automated algorithmic technologies such as natural language processing, machine learning, and artificial intelligence, have become popular tools within the realm of e-commerce. They contribute significantly to brand awareness and mitigate the influence of familiarity bias on consumer purchase intention. Research indicates that chatbots play a substantial role in enhancing brand recognition by engaging users in interactive dialogues (Presti et al., 2021). Personalized chatbot messages have been found to increase purchase intention by providing convenient and tailored information that instills a sense of product comprehension and convenience (Li & Wang, 2023a). Customer satisfaction, a critical metric in online shopping, is positively influenced by chatbot interactions, which in turn shape favorable online shopping intentions and foster enduring customer relationships (Lo Presti et al., 2021). A chatbot is a software application that uses artificial intelligence or machine learning principles to simulate intelligent human-to-human conversations. Using spoken or written text as input, users converse or interact with the chatbot through a conversational interface. Chatbots enable sellers on e-commerce websites to connect with a wider audience and boost sales through direct user interaction (Shafi et al., 2020).

Machine learning chatbots utilize advanced algorithms and AI techniques to process user queries, offer relevant responses, and facilitate various tasks in the fashion industry online shopping experience (Alboqami & Alboqami, 2023). By leveraging natural language processing capabilities, chatbots enhance customer engagement, streamline the shopping process, and influence consumer purchase intention. The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry has gained significant attention, as they have the potential to shape factors such as perceived ease of use, perceived usefulness, information quality, and customer satisfaction (Li & Wang, 2023b). Through personalized assistance, chatbots shape consumers' perceptions, attitudes, and ultimately their intention to make purchases.

1.3 Problem statement

Fashion sector, encompassing clothing, footwear, bags, accessories, and more, significantly contributes to e-commerce revenue (Dionysios et al., 2016). Therefore, ensuring an optimal user experience in fashion product discovery is crucial. In this context, the visual attractiveness of products plays a vital role in driving purchase decisions (Fadillah et al., 2023) . Incorporating visual attributes into the primary mechanisms of product discovery, specifically "Search" and "Recommendations," is essential in addressing the unique challenges posed by the fashion industry. Conventional e-commerce search engines predominantly rely on text-based queries and metadata, which may not effectively capture the nuances of fashion products (Ellwood & Rettie, 2010).

Research indicates that 46% of people prefer interacting with a human rather than a chatbot, even if the latter could save them time (Jovic, 2020) . While chatbots offer advantages like 24/7 availability and prompt responses (Tran et al., 2021), not everyone perceives the benefits of interacting with chatbots over other channels. Dissatisfaction arises from the perception that chatbots provide inadequate answers (41% of respondents) or are generally unhelpful (37% of respondents). Moreover, when questions become too complex, 60% of respondents would abandon using a chatbot, and 41% would give up if directed to an frequently asked question (Garcia, 2019).

A comprehensive study by the Baymard Institute (2021), which examined 60 of the highest-grossing e-commerce sites, revealed several key findings. Notably, 61% of the sites required users to search using the exact product terms employed by the site, resulting in irrelevant search results when alternative terms were used. For example, if a website uses the term "hair dryer," a search for "hair blower" might not yield relevant products. Likewise, 46% of sites do not support topical search queries such as "spring jacket" or "office chair." Additionally, 46% of the sites did not support topical search queries, and a staggering 70% of the search engines on the top 50 e-commerce sites failed to provide relevant results for product type synonyms, hindering effective information retrieval. Limitations of text-based search in e-commerce stores stem from the vocabulary gap, where users describe products differently than the store categorizes them, leading to lost conversions and suboptimal consumer journeys (Jangra & Jangra, 2022).. Moreover, e-commerce store managers often struggle to anticipate the correct search terms, particularly for complex products with associated terms.

Rise of chatbots in the e-commerce domain necessitates a comprehensive understanding of human interaction dynamics, with a focus on linguistic aspects. Chatbots strive to improve their proficiency in interpreting human language, generating coherent responses, and addressing challenges associated with computer-mediated communication (Hill et al., 2015). Additionally, it has been acknowledged that consumer purchase decisions are influenced by robot anthropomorphism and that users' trust and enjoyment of human voice-based communication are affected by humanoid robots. Humanoid robots have the potential to be helpful tools that improve customer experiences (M. C. Han, 2021). To overcome limitations in traditional customer service chatbots, leveraging in-page product descriptions and user-generated content from e-commerce sites has been found to be a practical and cost-effective approach for answering repetitive questions, freeing human support staff to focus on higher-value tasks (Cui et al., 2017). However, interaction designs for conversational commerce through chatbots still require further improvement (Pricilla et al., 2018). Given the gaps in current literature, this research aims to investigate The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry. The study aims to deepen the understanding of the determinants that influence consumers' decision-making processes.

1.4 Research Questions

Research questions proposed in this study are as below:

1. What are the factors of machine learning chatbot in influencing consumer purchase intention in fashion industry?

2. What is the relationship between factors of machine learning chatbots and consumer purchase intention in fashion industry?

3. Which machine learning chatbots' factors has the most significant influence on consumer purchase intention in fashion industry?

1.5 Research Objectives

Research objectives developed in this study are as follow:

1. To identify the factors of machine learning chatbot in influencing consumer purchase intention in fashion industry.

2. To determine the relationship between factors of machine learning chatbot and consumer purchase intention in fashion industry.

3. To determine the most significant machine learning chatbots' factors in influencing consumer purchase intention in fashion industry.

1.6 Scope of Research

This research focusses mainly on identifying the role of machine learning chatbot in influencing consumer purchase intention in fashion industry. Questionnaire is distributed through Google Form to those who individuals engaging with fashion industry e-commerce or those specifically hashtagged certain brands on social media platforms consider as a actual fans and have experience in this area (Arief, 2023).

1.7 Significant of study

Study on the "The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry" is significant in terms of both theoretical and practical contributions. Theoretically, it advances understanding of consumer behavior by investigating the influence of machine learning chatbots on purchase intention in the fashion industry e-commerce context. It expands existing theories related to purchase intention and enhances our knowledge of how technology-driven interactions shape consumer behavior.

Practically, the study has important implications for marketing and customer relationship management (CRM) strategies. The findings can guide businesses in designing effective chatbot interactions and personalized recommendations to enhance customer engagement and conversion rates. Moreover, the research provides insights for optimizing chatbot design and functionality, improving the user experience and customer satisfaction in fashion e-commerce platforms.

1.8 Organization Research

In the study conducted by Johnson et al. (2023), the main objective is to explore the factors that influence consumer purchase intention when interacting with machine learning chatbots in the fashion industry's e-commerce sector. The researchers aim to investigate the impact of factors such as perceived ease of use, perceived usefulness, and information quality on consumers' intentions to make purchases through chatbot interactions. Furthermore, it is important for fashion e-commerce businesses to develop innovative systems that align with consumer preferences and expectations. By continuously improving the capabilities and performance of machine learning chatbots, businesses can enhance the overall customer experience and increase purchase intention.

Building upon previous research on consumer behavior and emerging technologies, this study aims to contribute to the existing body of knowledge by examining the factors that influence consumer purchase intention of machine learning chatbots in the fashion industry's e-commerce sector. The findings will provide valuable insights for fashion e-commerce businesses to enhance their chatbot strategies, improve customer engagement, and ultimately drive conversion rates and customer satisfaction.

1.9 Conclusion

This chapter provided an introduction to the research on the factors influencing consumer purchase intention of machine learning chatbots in fashion industry e-commerce. It highlighted the significance of AI and machine learning in revolutionizing the fashion industry and discussed the challenges in fashion product discovery and chatbot interactions. The study's significance lies in advancing our understanding of consumer behavior, providing insights for marketing strategies, and improving the user experience in fashion e-commerce platforms.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In prior research, significant efforts have been devoted to identifying the optimal set of variables that elucidate and forecast acceptability, a construct conventionally assessed through behavioral intentions, attitudes, or usage measures. This endeavour has resulted in the development and refinement of numerous models, building upon earlier works and culminating in the emergence of technology acceptance models during the 1970s (Al-Tarawneh, 2019). These models aim to comprehend the process by which users adopt and utilize a given technology. When individuals encounter a novel technology, various factors come into play, influencing their decisions regarding its timing and manner of usage (Fishbein & Ajzen, 1975). In addition to well-established frameworks such as the Unified Theory of Technology Acceptance and Use (UTAUT), Diffusion of Innovation Theory (DOI), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT), other theoretical perspectives, including Expectation Confirmation Theory (ECT), contribute to the understanding of technology acceptance. Grasping the factors that influence technology acceptance holds paramount importance in the design and implementation of successful novel technologies. These theoretical frameworks offer valuable insights into users' perceptions of technology and serve as guiding principles for the development and deployment of innovative technologies. By comprehending users' needs, beliefs, and expectations, technology designers can effectively create technologies that are more likely to be embraced by the intended user base.

Davis (1986) formulated the Technology Acceptance Model (TAM), an adaptation of the Theory of Rational Action (TRA) designed specifically to model user adoption of information systems. The TAM aims to furnish a comprehensive account of the factors governing computer acceptability, capable of elucidating user behavior across diverse end-user computing technologies and user communities. It is founded on principles that are both economically and theoretically sound. Prior research has identified a restricted set of cognitive and affective variables that are associated with computer acceptance, thereby paving the way for the development of TAM. TAM utilizes TRA as its theoretical foundation to model the relationship between these variables. In particular, TAM is predicated on two beliefs, Perceived Utility (PU) and Perceived Ease of Use (PEOU), as the fundamental tenets of computer acceptance (Davis, 1989).

Information Systems Success Model (ISSM), which was developed by DeLone and McLean in 1992, is a comprehensive multivariate framework that is used to assess the success of information systems (IS). The model is based on communication research and is grounded in the conceptualization of IS validity. The ISSM model comprises six key dimensions: system quality, information quality, service quality, utilization rate, user satisfaction, and net income. The model explains that the achievement of an information system is dependent on the quality of the system itself, the caliber of information and services it delivers, the degree of its utilization, the satisfaction experienced by its users, and the net benefits it generates. Numerous studies have utilized the ISSM model to evaluate the effectiveness of information systems in different sectors, such as healthcare, education, and e-commerce. In one particular study, the success of an integrated health records system in Iran was scrutinized based on the Clinical Information System Success Model (CISSM) using the ISSM model (Bitaraf et al., 2022).

The evaluation of information systems (IS) and their quality is a fundamental aspect of research in this domain. The IS success model serves as a crucial criterion for assessing the success and comprehending the quality of such systems. The primary dimensions for analyzing and evaluating IS quality encompass information quality, system quality, and quality of services rendered. Initially, DeLone and McLean emphasized quality and system quality variables; however, the advent of e-commerce and mobile application platforms necessitated the inclusion of service quality as a critical factor. Consequently, in 2003, DeLone and McLean revised their IS model to incorporate service quality. The IS success model developed by DeLone and McLean has gained significant attention in research examining the success of information systems. It has also been applied and refined to evaluate website effectiveness.

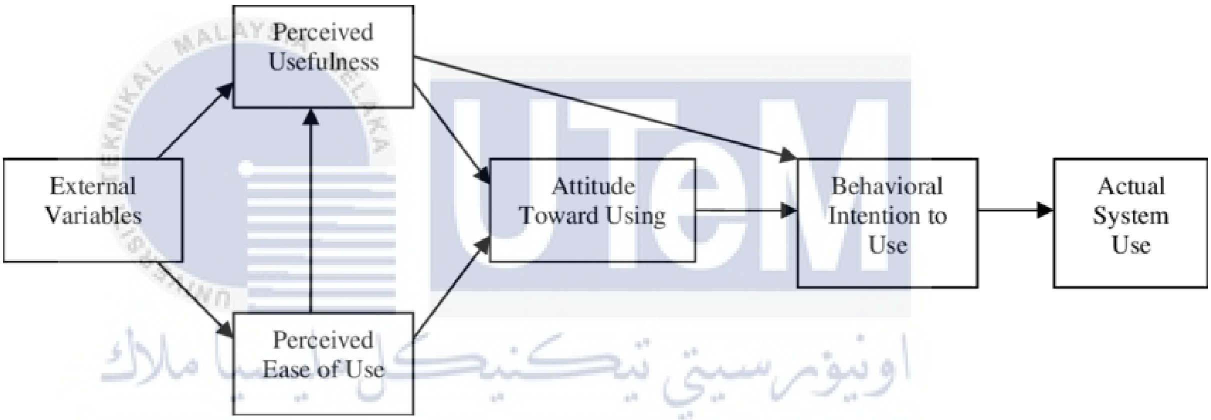

Figure 2.1: Framework of Technology Acceptance Model (TAM)

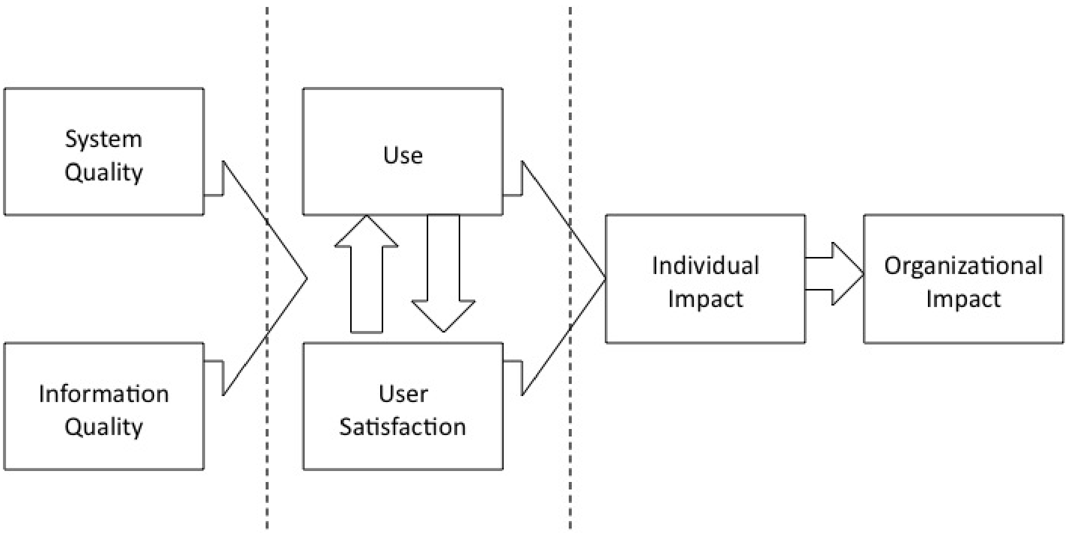

Figure 2.2: Information System Success Model (1992)

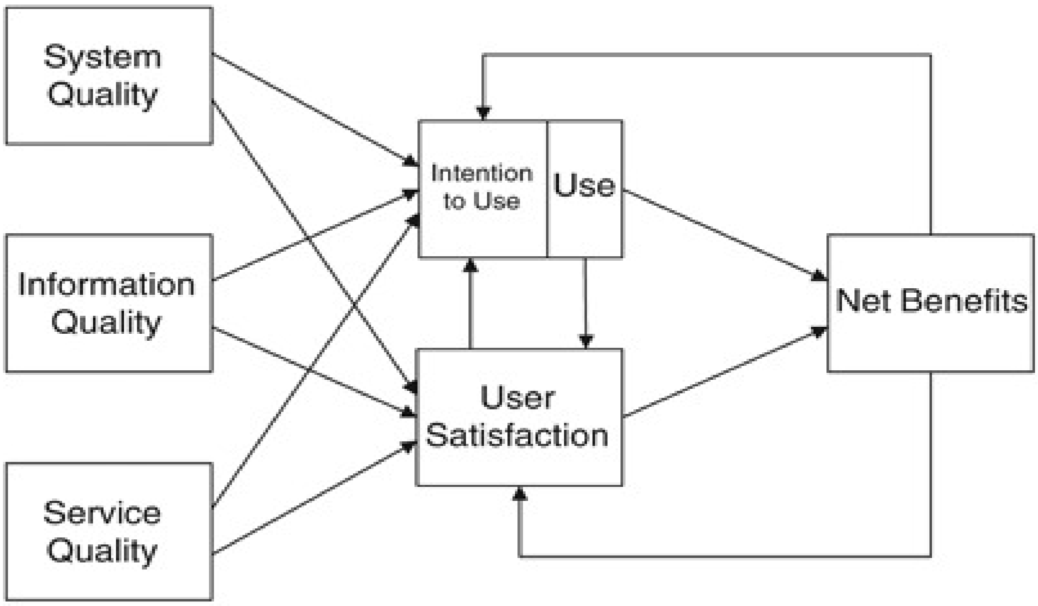

Figure 2.3: Information System Success Model (2003)

2.2 Proposed Conceptual Framework

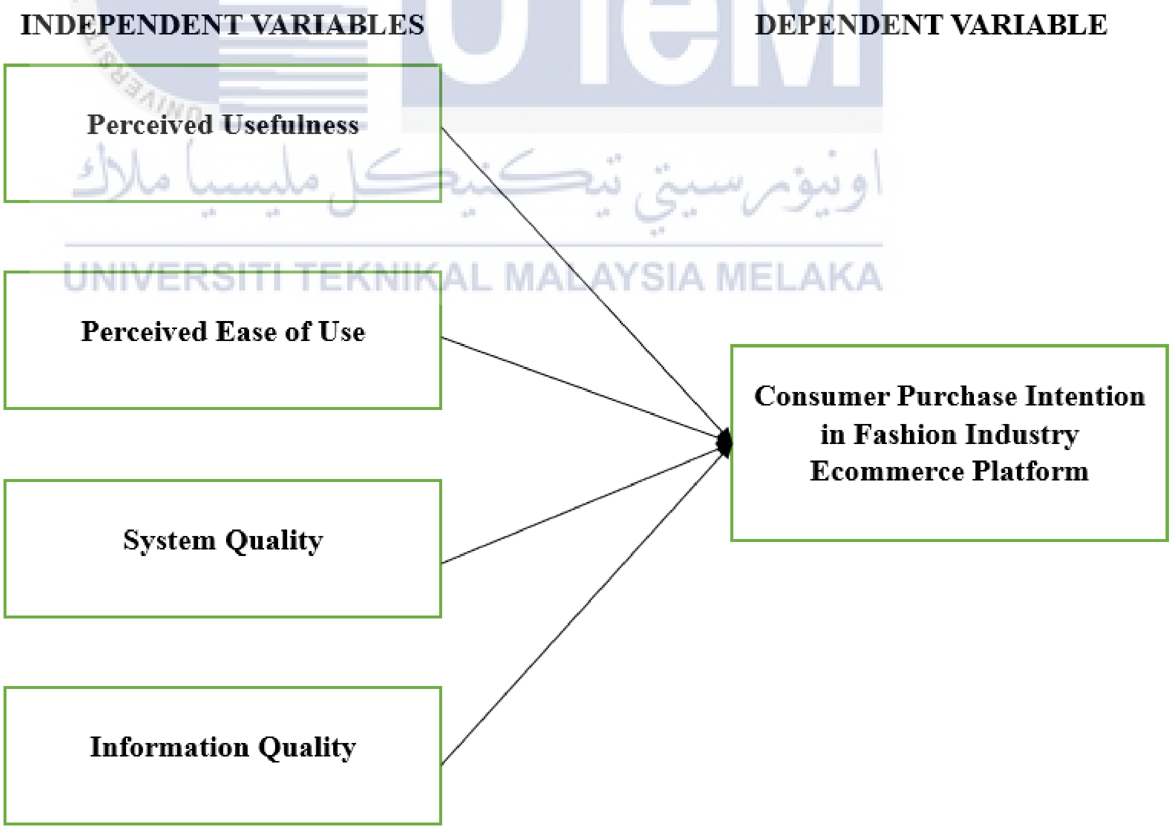

Figure 2.4: Proposed Conceptual Framework

2.3 Perceived Usefulness

According to Technology Acceptance Model (TAM), perceived usefulness is a key variable explaining various mechanisms related to technology adoption. The concept of perceived usefulness was first proposed by (Davis, 1989), who stated that "people tend to use or not use an application to the extent that they believe it will help them do their jobs better". Perceived usefulness has to do with the utility of technology in day-to-day interactions.An individual adopts a new technology only if he or she believes it will significantly improve their quality of life. As a result, customers may not accept applications that are difficult to use.

According to a study by Cheon (2019), innovative services such as AI services form positive attitudes by inducing perceived usefulness, and Han et al. (2015) found that in systems that apply new technologies such as simple payment services, the perceived usefulness increases as consumers perceive that they are more efficient than less effort when using a particular technology. Perceived usefulness also has a significant impact on consumer satisfaction and intention, with the perceived usefulness of mobile fashion shopping having a defining effect on consumer attitudes leading to purchase intent (Kim et al., 2015) and a positive effect on the trust and satisfaction of mobile website users (Amin et al., 2014) . Therefore, in this study, the perceived usefulness was defined to the extent that consumers believe that using the fashion chatbot product recommendation service will be useful because it is easy and convenient, and when the user perceives that the quality of the chatbot product recommendation service system is useful, user's purchase intention expected to have a positive effect. Research shows that artificial intelligence (AI)-enabled technologies, such as machine learning chatbots, play a crucial role. These technologies use artificial intelligence algorithms to provide consumers with personalized and customized choices, helping them understand their purchasing preferences more effectively (Nguyen, 2020) . By leveraging perceived usefulness, AI chatbots can provide automated assistance and enhance the overall consumer experience as consumers use services or purchase products.

Author	Definition	Theme
Cheon (2019)	Innovative services such as AI services form positive attitudes by inducing perceived usefulness.	Perceived Usefulness
Han et al. (2015)	In systems that apply new technologies such as simple payment services, the perceived usefulness increases as consumers perceive that they are more efficient than less effort when using a particular technology.	Perceived Usefulness
Kim et al. (2015)	Perceived usefulness also has a significant impact on consumer satisfaction and intention, with the perceived usefulness of mobile fashion shopping having a defining effect on consumer attitudes leading to purchase intent.	Perceived Usefulness
Amin et al. (2014)	Perceived usefulness has a positive effect on the trust and satisfaction of mobile website users.	Perceived Usefulness

Author	Definition	Theme
Nguyen (2020)	Technologies use artificial intelligence algorithms to provide consumers with personalized and customized choices, helping them understand their purchasing preferences more effectively.	Artificial Intelligence

Table 2.1: Perceived Usefulness Defined

2.4 Perceived Ease of Use

A wide range of factors, including product offerings, entertainment, customer service functionality, site navigation, and site design, affect the success of e-commerce. Customers are more likely to trust and believe in a website that offers current, relevant information (Islam et al., 2019). The degree to which a person believes that utilising a specific system is simple is known as perceived ease of use. According to earlier research by Amin (2007) and Al-Somali, Gholami, & Clegg (2009), perceived usefulness is positively impacted by perceived ease of use. The degree to which an individual believes that utilising a specific system or technology to carry out a task will be simpler or require less effort is known as perceived ease of use (Lu, Yu, & Yao, 2014). Perceived usefulness (USE) and perceived ease of use (EoU) are two specific behaviours that influence the intention to use an information system, which TAM defines as a behavioural intention (BI) construct. Perceived ease of use has been identified as a key construct for analysing and evaluating user acceptance of a specific technology, drawing on the literature on information technology (IT). Perceived ease of use is a key motivator for consumers' intention to use technology (Revels et al., 2010).

In the view of machine learning chatbots and consumer purchase intention, the perceived ease of use becomes more important. When consumers interact with chatbots, their perception of how easy it is to use the chatbot system influences their acceptance and willingness to engage with it. If consumers perceive the chatbot as user-friendly, intuitive, and requiring minimal effort to obtain information or assistance, they are more likely to engage with the chatbot and utilize its capabilities in their decision-making process. Machine learning chatbots, powered by advanced algorithms and natural language processing, aim to provide seamless and convenient user experiences. A high level of perceived ease of use ensures that consumers can easily navigate the chatbot interface, understand how to interact with it, and obtain the desired information or support without encountering significant obstacles or complexities.

Author	Definition	Theme
Islam et al. (2019)	Providing updated and relevant information on the website helps build trust and credibility with consumers.	Perceived Ease of Use
Amin (2007)	Perceived ease of use positively affects perceived usefulness.	Perceived Ease of Use
Lu, Yu, & Yao (2014)	Perceived ease of use refers to the degree to which a person perceives that using a particular system or technology to perform a task will be easier or require little effort.	Perceived Ease of Use
Revels et al. (2010)	An important motivational factor for consumers' technology usage intention is perceived ease of use	Perceived Ease of Use

Table 2.2: Perceived Ease of Use Defined

2.5 System Quality

System quality is recognized as a determining component that contributes to the overall success of an information system. System quality refers to the technical aspects and characteristics of the system, including its reliability, functionality, performance, usability, and security (Azmi, 2020). It focuses on the effectiveness and efficiency of the system in delivering the intended functionalities and meeting user requirements. System quality plays a significant role in determining user satisfaction and the overall success of an information system. When the system exhibits high-quality attributes, such as reliability and usability, users are more likely to perceive the system as valuable and trustworthy, leading to increased user satisfaction. Furthermore, system quality influences user perceptions of the system's usefulness, ease of use, and overall performance, which in turn impacts their intention to continue using the system. A study conducted in Jordan proposed a service quality model for mobile learning in university environments based on the Information System Success Model(Nassar, 2020).

In the view of machine learning chatbots and consumer purchase intention, system quality plays a symbolic role. For chatbots to effectively assist consumers in making purchasing decisions, the underlying information system must possess high system quality. This means that the chatbot system should be reliable, responsive, and capable of providing accurate and relevant information to users. The system should also be user-friendly, ensuring a seamless and intuitive interaction experience for consumers. Machine learning chatbots rely on sophisticated algorithms and artificial intelligence techniques to understand user queries, provide personalized recommendations, and simulate natural language conversations. A high-quality system is essential to ensure the chatbot functions properly, delivers accurate responses, and meets consumer expectations. It also contributes to building trust and confidence in the chatbot's capabilities, which can positively influence consumer purchase intention.(Adeyemi & Issa, 2020).

A study investigated the impact of chatbot system quality on consumers' trust and purchase intention in the e-commerce context. They specifically investigated how a well-performing chatbot system, characterized by accurate responses and personalized recommendations, influenced consumer perceptions of trust and subsequent purchase intention (Nicolescu & Tudorache, 2022). The researchers conducted surveys among participants who had interacted with an e-commerce chatbot. They found that a well-performing chatbot system, characterized by accurate responses and personalized recommendations, positively influenced consumer trust, which in turn enhanced purchase intention. The accuracy of responses provided by the chatbot was a key factor contributing to consumer trust. When the chatbot consistently provided accurate and helpful information, consumers felt confident in its capabilities and were more inclined to trust its recommendations. Nicolescu and Tudorache (2022) emphasizes the importance of chatbot system quality in building consumer trust and influencing purchase intention. It provides valuable insights for businesses in the fashion industry and other e-commerce sectors, highlighting the need to prioritize system quality to maximize the potential of chatbots in driving consumer engagement and sales.

Author	**Definition**	**Theme**
Azmi (2020)	System quality is recognized as a determining component that contributes to the overall success of an information system. System quality refers to the technical aspects and characteristics of the system, including its reliability, functionality, performance, usability, and security.	System Quality

Author	Definition	Theme
Nassar, (2020)	A study conducted in Jordan proposed a service quality model for mobile learning in university environments based on the Information System Success Model.	
Adeyemi & Issa (2020)	A high-quality system is essential to ensure the chatbot functions properly, delivers accurate responses, and meets consumer expectations. It also contributes to building trust and confidence in the chatbot's capabilities, which can positively influence consumer purchase intention.	System Quality, Consumer Purchase Intention
Nicolescu & Tudorache, (2022)	A study investigated the impact of chatbot system quality on consumers' trust and purchase intention in the e-commerce context. They specifically investigated how a well-performing chatbot system, characterized by accurate responses and personalized recommendations, influenced consumer perceptions of trust and	System Quality

	subsequent purchase intention.	

Table 2.3: System Quality Defined

2.6 Information Quality

Information quality refers to the characteristics of information within the system, including its accuracy, completeness, relevance, timeliness, and usefulness. It focuses on the extent to which the information provided by the system meets the needs and expectations of its users. When the information presented by the system is accurate, complete, and relevant, users perceive it as reliable and trustworthy, leading to increased satisfaction with the system. Furthermore, high-quality information enhances users' ability to make informed decisions, solve problems, and perform tasks effectively and efficiently. Moreover, information quality influences user perceptions of the system's usefulness and its impact on their work. When users perceive the information provided by the system as valuable and relevant to their tasks, they are more likely to view the system as useful and beneficial in achieving their goals. Study analyzed the factors affecting consumer online purchase intention in Indonesia and found that quality of service and quality of information had a positive impact on online purchase intentions (Prabawa et al., 2022).

In the realm of e-commerce and online shopping, information quality is vital for delivering accurate and relevant product information to consumers. Machine learning chatbots can play a vital role in enhancing information quality by leveraging their ability to understand user preferences, analyze vast amounts of data, and generate tailored recommendations (Kulkarni et al., 2019). By considering factors such as past purchase history, browsing behavior, and demographic information, machine learning chatbots can provide highly personalized product recommendations that align with the specific needs and preferences of individual consumers (Qian et al., 2021). By ensuring high information quality through machine learning chatbots, e-commerce platforms can improve customer satisfaction, increase sales conversions, and foster long-term customer loyalty. Additionally, machine learning algorithms can continuously learn from user interactions and feedback, allowing the chatbots to further enhance their recommendation capabilities and provide even more accurate and personalized information over time (Caldarini et al., 2022).

Author	Definition	Theme
Kulkarni et al. (2019)	Machine learning chatbots can play a vital role in enhancing information quality by leveraging their ability to understand user preferences, analyze vast amounts of data, and generate tailored recommendations	Information Quality
Qian et al. (2021)	Machine learning chatbots can provide highly personalized product recommendations that align with the specific needs and preferences of individual consumers	Information Quality
Caldarini et al. (2022)	Machine learning algorithms can continuously learn from user interactions and feedback, allowing the chatbots to further enhance their recommendation capabilities and provide even more accurate and personalized information over time.	Information Quality

Author	**Definition**	**Theme**
Prabawa et al. (2022)	Study analyzed the factors affecting consumer online purchase intention in Indonesia and found that quality of service and quality of information had a positive impact on online purchase intentions	Information Quality

Table 2.4: Information Quality Defined

2.7 Consumer Purchase Intention

Purchase intention refers to the consumer's willingness to pay for a specific product or service and their attitude towards the buying process. In today's digital age, online platforms have become the primary mode of purchasing for many consumers. However, the online marketplace presents challenges due to the vast amount of information, product choices, and store alternatives available. This complexity makes it difficult for buyers to evaluate all available options and make informed decisions. Consequently, both academic and industry researchers have dedicated significant efforts to studying consumer behavior and purchase intention in order to better understand and cater to consumer needs (Liao et al., 2021). Before making a purchase decision, shoppers often turn to online sources to gather product information, compare alternatives, and review feedback from other customers. The abundance of information and choices can be overwhelming, making it crucial to provide consumers with assistance in navigating through the options. This is where artificial intelligence (AI) can play a significant role. AI, with its advanced technologies like machine learning and data analysis, can efficiently process large amounts of data and generate personalized recommendations for consumers. By using intelligent algorithms, AI systems can consider various factors such as consumer preferences, past purchase history, and product reviews to identify the most suitable alternatives from the available pool of options.

AI has become increasingly prevalent in organizations, aiming to provide consumers with customized and optimal options. Through the application of innovative and creative technologies, AI enables consumers to gain a clear understanding of their purchase preferences (Reinartz et al., 2019). By automating the assistance provided to customers throughout their service experiences, artificial intelligence contributes to enhancing decision-making processes related to purchase intention. Moreover, studies have indicated that the integration of artificial intelligence into online platforms instills a sense of confidence in customers, thereby reducing perceived risks associated with purchase decisions. According to Yoo et al. (2010), artificial intelligence is a technology that is easy to use and helps consumers make decisions about what products or services to buy. Since artificial intelligence provides a wealth of pertinent and well-organized information to support consumers' purchase-related activities, consumers are becoming more and more attracted to the capabilities and potential of this technology (Sohn & Kwon, 2020).levant in addressing consumer needs.

Machine learning technologies such as chatbots have become invaluable tools for analyzing and predicting consumer purchase intentions. Chatbots equipped with natural language processing capabilities can interact with consumers, understand their queries, and provide personalized recommendations based on their preferences and purchase history. By leveraging machine learning algorithms, chatbots can efficiently analyze large volumes of data, including customer reviews, feedback, and browsing behavior, to identify patterns and trends that influence consumers' purchase intentions.

Author	**Definition**	**Theme**
Liao et al. (2021)	Academic and industry researchers have dedicated significant efforts to studying consumer behavior and purchase intention in order to better understand and cater to consumer needs.	Consumer Purchase Intention
Reinartz et al. (2019)	AI enables consumers to gain a clear understanding of their purchase preferences.	Consumer Behavior

Author	**Definition**	**Theme**
Yoo et al. (2010)	Artificial intelligence is a technology that is easy to use and helps customers when they are choosing what goods or services to buy.	Artificial Intelligence, Consumer Behavior
Sohn & Kwon (2020)	Consumers are increasingly drawn to the capabilities and potential of artificial intelligence, as it offers a vast amount of relevant and well-structured information, supporting their purchase-related activities.	Consumer Behavior

Table 2.5: Consumer Purchase Intention Defined

2.8 The Link between Perceived Usefulness and Consumer Purchase Intention

Numerous studies have consistently shown a strong positive relationship between perceived usefulness and consumer purchase intention. Perceived usefulness, as highlighted by Davis (1989), is a crucial factor that influences individuals' attitudes and intentions towards technology usage, and this concept can also be extended to consumer purchase decisions. When consumers perceive a product or service as useful, they tend to develop a favorable attitude towards it and express a higher intention to make a purchase. Perceived usefulness acts as a cognitive cue that influences consumers' evaluation of the product and its potential value in fulfilling their desired outcomes. For instance, a recent study investigated the impact of perceived usefulness on purchase intention, either directly or indirectly through perceived customer value. It's interesting to note that the study discovered that while perceived ease of use, cost savings, and time savings do not directly affect purchase intention, perceived usefulness does (Qing & Jin, 2022). On the other hand, a different study on e-commerce discovered that user behaviour and purchase decisions are positively influenced by perceived usefulness, ease of use, and trust (Budyastuti et al., 2019). These studies indicate the importance of perceived usefulness in influencing consumer behaviour and attitudes towards goods and services, even though they may not specifically address the relationship between perceived usefulness and purchase intention.

In online fashion purchasing, consumer behavior and technology adoption theories emphasize the importance of perceived usefulness in influencing consumers' purchase intentions. Perceived usefulness specifically refers to consumers' beliefs regarding the advantages and enhanced shopping experience associated with using chatbots during online purchases. Chatbots in the fashion industry offer several benefits to engage consumers effectively. Personalized product suggestions based on consumer preferences, style, and purchase history are one such advantage (Whang et al., 2022). This personalized approach assists consumers in finding suitable fashion items while streamlining their decision-making process. Additionally, chatbots can provide real-time assistance by promptly answering queries and offering immediate feedback, thereby reducing consumer uncertainty and enhancing customer satisfaction. By facilitating expedited customer service such as returns and exchanges, chatbots contribute to a seamless online shopping experience. Consequently, consumers perceive chatbots as valuable tools that augment their online purchasing experience and provide value-added services. Thus, the perceived usefulness of chatbots plays a significant role in shaping consumer purchase intention in the fashion industry's online shopping domain.

H0: There is no significant relationship between perceived usefulness of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between perceived usefulness of machine learning chatbot and consumer purchase intention.

2.9 The Link between Perceived Ease of Use and Consumer Purchase Intention

Perceived ease of use technology refers to an individual's belief regarding the level of effortlessness associated with using a particular system. If a person perceives a system as easy to use, they are more likely to utilize it, whereas if they perceive it as difficult, they are less inclined to engage with it (Zaremohzzabieh et al., 2015).. Within the context of online shopping in the fashion industry, consumer behavior and technology adoption theories emphasize the significance of perceived ease of use in shaping consumer purchase intention (Davis, 1989). Perceived ease of use, in this context, pertains to how consumers perceive the use of chatbots during online purchasing experiences as being simple, intuitive, and user-friendly. In fashion industry, where consumers prioritize convenience and efficiency, user-friendly chatbots can greatly enhance the online shopping experience. A well-designed chatbot interface with clear navigation and intuitive functionality facilitates the browsing and selection of fashion items. For instance, the Chat-to-Design system allows users to design apparel through a two-step process: dialogue-based coarse-grained selection and interactive fine-grained editing, resulting in an immersive user experience (Zhuang et al., 2022). By simplifying complex processes and providing clear instructions, chatbots reduce cognitive load and make the online shopping journey more enjoyable and efficient for consumers. Moreover, a user-friendly chatbot interface can offer helpful prompts, suggestions, and recommendations, further enhancing ease of use and the decision-making process.

A study aimed to investigate the relationship between the theory of planned behavior (TPB) and the technology acceptance model (TAM) elements and consumer purchase intention, with a focus on the mediating role of consumer purchase intention in the relationship between TPB and TAM elements and online shopping behavior. The study also explored the moderating effects of trust and commitment on the relationship between consumer purchase intention and online shopping behavior. Data were collected from students and lecturers at recognized universities in Punjab, Pakistan, and analyzed using the partial least squares structural equation modeling (PLS-SEM) technique. The findings of this research shed light on the factors influencing consumer purchase intention in the context of online shopping. The study revealed that perceived usefulness, perceived ease of use, attitude, subjective norms, and perceived behavioral control had a positive and significant influence on consumer purchase intention (Rehman et al., 2019)

When consumers perceive chatbots as easy to use, it not only alleviates frustration but also boosts their confidence in making successful fashion purchases. Chatbots serve as valuable assets to customer service by addressing repetitive inquiries without human involvement, thereby reducing purchase time and interaction volume (Carter & Knol, 2019). In the apparel retail sector, chatbots have proven invaluable in enhancing customer satisfaction, especially during the COVID-19 pandemic, as online shopping increased and in-store interactions became limited. Chatbots have emerged as crucial communication channels between retailers and customers, providing real-time assistance and promptly addressing customer inquiries. They supply essential information regarding product availability, sizes, shipping, and return policies. By delivering accurate and timely responses, chatbots ensure that customers are well-informed, thereby boosting overall satisfaction (Solis-Quispe et al., 2021).

H0: There is no significant relationship between perceived ease of use of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between perceived ease of use of machine learning chatbot and consumer purchase intention.

2.10 The Link between System Quality and Consumer Purchase Intention

A research study conducted by Krishnadas and Renganathan in 2019 investigated the impact of website quality on consumer behavior in the online retail industry. The findings of this study indicated that the usability aspect of system quality significantly influences consumers' intentions to make purchases. Usability refers to the ease of use and user-friendliness of a website, encompassing features such as intuitive navigation, well-organized information display, efficient product search capabilities, and overall convenience of the online shopping experience. The research highlighted that when consumers perceive an online retail site as useful, they are more likely to develop positive intentions to make a purchase.

A user-friendly interface and simplified navigation not only enhance user satisfaction but also boost consumers' confidence in finding and selecting the right fashion items. This, in turn, positively influences their intention to engage in purchasing activities. The study emphasizes the importance of optimizing the usability aspects of system quality in online retail platforms to effectively shape consumer purchasing behavior. The findings underscore the significance of usability within the Information System Success Model (ISSM) as a critical dimension in influencing consumer purchase intention in the context of fashion online shopping.

Additionally, (L. Han, 2023) looked into how African consumers' intentions to buy in cross-border e-commerce (CBEC) are affected by the quality of the information, the system, and the services they receive. The study investigates the roles of perceived value and trust while highlighting the importance of CBEC platform quality using the ISS model. The results show that consumers' perceived intention to buy is positively impacted by the quality of the information, system, and services. Remarkably, perceived value is more strongly influenced by service quality than by information and system quality. The study highlights how important it is for consumers' purchase intentions on the CBEC platform to take into account perceived value and trust, with perceived value having a direct impact on purchase intentions and trust acting as a mediator in this relationship. A moderating effect of consumers' acculturation levels is also taken into account in the research, suggesting that acculturation can alter the way that CBEC platform information and system quality affect perceived value. This emphasises how crucial it is to comprehend how system quality and customer purchase intention relate to each other when it comes to online shopping.

H0: There is no significant relationship between system quality of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between system quality of machine learning chatbot and consumer purchase intention.

2.11 The Link between Information Quality and Consumer Purchase Intention

The provision of high-quality information by chatbots has a notable impact on consumer behavior, particularly in relation to their willingness to make purchases. When chatbots consistently deliver accurate and reliable information, consumers develop a higher level of trust and reliability in these virtual assistants. This trust is crucial as it assures customers that the information provided by the chatbot is up-to-date, accurate, and trustworthy. Consequently, consumers feel confident in their ability to make well-informed purchasing decisions. Chatbots play a vital role in providing consumers with accurate product information, including specifications, sizes, colors, and availability. This enables consumers to make informed decisions based on their preferences and requirements. The availability of accurate and thorough information reduces uncertainty and minimizes the likelihood of unsatisfactory purchases (Sree et al., 2023).

The research conducted by Kim, Lee, and Kim (2004) explored the relationship between individuals' intention to use the internet for product information search and their intention to use the internet for making purchases (Kim et al., 2004). The study revealed that the act of seeking information online positively predicts the intention to make a purchase. The authors emphasized the significance of product information availability on websites and the ease of accessing such information, as they contribute to an increased likelihood of actual purchase. Building upon this line of inquiry, Chiu, Hsieh, and Kao (2005) proposed that the quality of information provided is directly associated with customers' behavioral intention.

Moreover, the accurate and relevant information offered by chatbots empowers consumers by saving their time and effort in searching for desired fashion items. By minimizing the need for manual search and comparison, chatbots streamline the shopping process, making it more efficient and convenient for consumers. This enhanced user experience leads to higher levels of engagement, as consumers actively interact with chatbots, posing questions, seeking recommendations, and receiving personalized suggestions based on their preferences. The perception of reliable and helpful information provision by chatbots significantly influences consumers' trust, satisfaction, and reliance on these virtual assistants within their fashion online shopping experience.

H0: There is no significant relationship between information quality of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between information quality of machine learning chatbot and consumer purchase intention.

2.12 Summary of Hypothesis

The relationship between perceived usefulness and consumer purchase intention has been consistently supported by numerous studies. Perceived usefulness, as described by Davis (1989), is a critical factor that influences individuals' attitudes and intentions towards technology usage and extends to consumer purchase decisions. When consumers perceive a product or service as useful, they develop a favorable attitude and express a higher intention to make a purchase. Perceived usefulness acts as a cognitive cue, influencing consumers' evaluation of the product and its potential value in fulfilling their desired outcomes. Although some studies have shown that perceived usefulness may not have a direct effect on purchase intention, others highlight its significance in shaping consumer behavior and attitudes towards products and services. In the context of online fashion purchasing, perceived usefulness plays a significant role in influencing consumer purchase intention by providing enhanced shopping experiences, personalized product suggestions, and value-added services through chatbot interactions.

Similarly, the link between perceived ease of use and consumer purchase intention is supported by consumer behavior and technology adoption theories.

Perceived ease of use refers to individuals' belief in the level of effortlessness associated with using a particular system. In online fashion shopping, consumers prioritize convenience and efficiency, and user-friendly chatbots can greatly enhance their experience. Well-designed chatbot interfaces with clear navigation and intuitive functionality simplify the browsing and selection of fashion items, reducing cognitive load and making the online shopping journey more enjoyable and efficient. Furthermore, user-friendly chatbots offer helpful prompts, suggestions, and recommendations, boosting ease of use and the decision-making process. Positive consumer perceptions of chatbot ease of use contribute to increased confidence in making successful fashion purchases and serve as valuable assets in customer service, reducing purchase time and improving overall satisfaction.

System quality, specifically website usability, has been found to significantly influence consumer purchase intention in online retail contexts. Usability encompasses features such as intuitive navigation, well-organized information display, and efficient product search capabilities. When consumers perceive an online retail site as useful and user-friendly, they develop positive intentions to make a purchase. User-friendly interfaces and simplified navigation in the fashion industry enhance user satisfaction and confidence in finding and selecting the right fashion items, positively influencing consumer purchase intention. The usability aspect of system quality, as highlighted by research, underscores the importance of optimizing usability within online retail platforms to effectively shape consumer purchasing behavior.

The provision of high-quality information by chatbots also plays a significant role in shaping consumer purchase intention. When chatbots consistently deliver accurate and reliable information, consumers develop trust and reliability in these virtual assistants, enabling them to make well-informed purchasing decisions. Chatbots provide accurate product information, reducing uncertainty and minimizing the likelihood of unsatisfactory purchases. Additionally, the availability of accurate and relevant information saves consumers time and effort in searching for desired fashion items, streamlining the shopping process and enhancing the overall experience. The perception of reliable and helpful information provision by chatbots significantly influences consumers' trust, satisfaction, and reliance on these virtual assistants, thereby impacting their purchase intention.

In summary, perceived usefulness, perceived ease of use, system quality, and information quality are all positively linked to consumer purchase intention in the context of online fashion shopping. These factors influence consumer behavior, attitudes, and decision-making processes, shaping their intentions to make purchases. Acknowledging and optimizing these factors can contribute to a more satisfying and successful online shopping experience for consumers in the fashion industry.

2.13 Conclusion

This literature review delved into the factors influencing consumer purchase intention of machine learning chatbots in the fashion industry e-commerce, with a specific focus on perceived ease of use, perceived usefulness, system quality, and information quality. The analysis of existing research revealed several important insights. Firstly, perceived ease of use was found to be a crucial determinant of consumer purchase intention. Consumers preferred chatbots that were user-friendly, intuitive, and required minimal effort to interact with, as it enhanced their overall shopping experience. Secondly, perceived usefulness emerged as a significant factor influencing purchase intention. Consumers valued chatbots that provided relevant and personalized recommendations, streamlined the decision-making process, and offered timely assistance. Moreover, system quality played a pivotal role in shaping consumer purchase intention. Consumers favored chatbots that exhibited high reliability, responsiveness, and functionality, as it instilled confidence in their capabilities. Lastly, information quality was identified as a key determinant of purchase intention. Consumers sought accurate, comprehensive, and trustworthy information from chatbots, as it significantly influenced their purchasing decisions. Understanding and optimizing these factors is crucial for businesses operating in the fashion industry e-commerce, as it enables them to develop machine learning chatbots that effectively engage consumers and drive purchase behavior.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter will expound on the research methodology utilized in this study, with greater detail. It shall provide a precise account of the approach taken in conducting research to attain the research objectives. Research methodology pertains to the systematic and scientific methods utilized to explore new facts or analyse existing information to advance knowledge. It is the art of comprehending how to systematically procure solutions to research quandaries. Research methodology encompasses the specific methods utilized to conduct research and it differs depending on the nature of the inquiry (Sahithi, 2021).

3.2 Research Design

Research design provides a structured framework for conducting the study and gathering relevant data to address the research objectives. It encompasses the planning and organization of various elements, such as research questions, variables, data collection methods, and data analysis techniques. A well-designed research study ensures the reliability, validity, and generalizability of the findings. In the field of research methodology, different research designs are available, each suited for different types of research questions and objectives.

Explanatory research design aims to investigate causal relationships between variables and understand the underlying mechanisms or reasons behind certain phenomena. It seeks to explain the relationships between variables by establishing cause-and-effect relationships through rigorous data analysis. In an explanatory research design, the researcher typically starts with a theory or a hypothesis and tests it using empirical data. This type of research design is suitable when the researcher wants to identify the impact or influence of one or more variables on another variable and explain why such relationships exist. On the other hand, exploratory research design aims to explore new phenomena, generate new insights, or gain a better understanding of a research topic. It is often used in situations where little is known about the topic, and the researcher seeks to gather preliminary data and explore various factors and relationships without specific hypotheses. Exploratory research design involves methods such as interviews, focus groups, and observational studies to collect qualitative or quantitative data. Descriptive research design, on the other hand, focuses on describing and documenting characteristics, behaviors, or phenomena in a systematic and detailed manner. It involves collecting data to provide an accurate and comprehensive picture of a specific research topic or population. Descriptive research design is often used to answer questions related to "what," "who," "when," and "where."

Employing a descriptive research design in the study on The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry would allow the researcher to gather comprehensive and detailed information about the prevalence, characteristics, and consumer perceptions of chatbot usage in the fashion sector. This information can serve as a foundation for further analysis and hypothesis development, helping to shape future research and strategies aimed at optimizing the integration and effectiveness of chatbots in the fashion industry. In addition to the descriptive design, a causal research design will be implemented to establish cause-and-effect relationships between the identified factors and consumer purchase intention. This design will involve manipulating independent variables and observing their impact on the dependent variable. For example, different factors such as chatbot responsiveness, trustworthiness, and personalization can be manipulated to examine their effects on consumer purchase intention. To ensure internal validity, control groups may be utilized, and random assignment of participants to different conditions will be conducted. Statistical analysis, such as regression analysis, will be employed to determine the causal relationships between the variables.

3.3 Methodological Choice

Research methodology refers to the actual "how" of research. More specifically, it is about how a researcher systematically designs a study to ensure valid and reliable results that address the research purpose, objectives, and research question. It deals with specific techniques used to collect, assemble and evaluate data during research.

Quantitative research involves the systematic collection and analysis of numerical data to understand and explain a research phenomenon. It focuses on quantifying variables, measuring relationships, and generating statistical models to make generalizations and draw conclusions. This research approach employs structured data collection instruments, such as surveys or experiments, and utilizes statistical methods for data analysis. Quantitative research aims to provide objective and measurable evidence, allowing for the testing of hypotheses and the identification of patterns and trends within a large sample. Qualitative research, on the other hand, is concerned with understanding and interpreting phenomena through the exploration of meanings, experiences, and perspectives. It involves the collection of non-numerical data, such as interviews, observations, or textual analysis, and relies on qualitative analysis techniques to identify themes, patterns, and insights. Qualitative research aims to provide a rich and nuanced understanding of the research topic, delving into the complexities and subjective aspects that quantitative methods may not capture. A mixed methodological choice combines both quantitative and qualitative approaches within a single study. This approach recognizes the value of integrating different types of data to gain a more comprehensive understanding of the research problem. It involves collecting both numerical and non-numerical data and employing both statistical analysis and qualitative analysis techniques. Mixed methods research allows for triangulation, where findings from different data sources are compared and validated, providing a more robust and multi-faceted understanding of the research topic.

In the study on The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry, a quantitative research design would provide valuable insights into the relationship between variables and allow for statistical analysis to draw meaningful conclusions. By using a quantitative research design, the researcher can employ surveys or experiments to collect data from a large sample of participants. The design enables the measurement of variables such as consumer purchase intention, perceived usefulness, perceived ease of use, system quality, and information quality using standardized scales. Statistical techniques such as correlation analysis, regression analysis, or structural equation modeling can be applied to examine the associations and effects between these variables (Sekaran & Bougie, 2005).

This research design offers several advantages. Firstly, it allows for generalizability as findings can be applied to a larger population of online fashion shoppers. Secondly, it provides a structured and systematic approach to data collection and analysis, ensuring rigor and reliability. Finally, the use of statistical techniques facilitates objective interpretation of the data and enables the identification of significant relationships and patterns.

3.4 Research Philosophies

A research philosophy is the view of how data about a phenomenon should be collected, analysed, and applied. It deals with the source, nature, and development of knowledge (Lewis. P,2019) This research would involve considering the nature of the approach for the project and testing the reality quotient followed by validity, reliability and generality.

Under this study, a quantitative approach will be utilized, in accordance with the positivist research philosophy. Positivism, as a research philosophy, highlights objectivity, the usage of quantitative data, and the establishment of causal relationships. It is premised on the notion that an objective reality exists, which can be observed and assessed through empirical evidence. Through the application of a positivist perspective, researchers aim to discover generalizable patterns and trends through the collection of numerical data and its subsequent statistical analysis (Creswell, J. W. 2014).

3.5 Research Approaches

Deductive research approaches involve the testing of specific hypotheses derived from existing theories or frameworks. In the study on The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry, a deductive research approach would be suitable for examining the relationships between variables based on established theories and previous research. By adopting a deductive research approach, the researcher starts with a theoretical framework or a set of hypotheses about the influence of machine learning chatbots on consumer purchase intention. The research design involves collecting data that can be analyzed to either support or refute these hypotheses. This approach enables the researcher to draw conclusions based on logical deductions from the collected data (Creswell & Creswell, 2018)

In this study, the researcher may formulate hypotheses based on existing theories related to technology acceptance, consumer behavior, and online shopping. For example, it could be hypothesized that a higher perceived usefulness of machine learning chatbots leads to increased consumer purchase intention in the fashion industry online shopping. The research design would then involve collecting data on perceived usefulness and consumer purchase intention and analyzing it to test the hypothesis.

3.6 Data Collection

Data collection is the process of accumulating and measuring information on variables of interest in a predetermined and systematic manner, allowing one to answer stated research questions, test hypotheses, and evaluate results. It can be utilised to answer research inquiries, make prudent business decisions, and enhance products and services. Collecting data was an integral part of the investigation into the effect of machine learning chatbots on consumer online purchasing intentions in the fashion industry. It entails the systematic gathering of pertinent information and data to resolve research objectives and provide answers to research questions. Combining primary and secondary data sources can be used to compile information for this study. Primary data refers to information collected specifically for research purposes, whereas secondary data refers to data already collected for a different purpose.

3.6.1 Primary Data

Primary data refers to the data that is collected first-hand by the researcher specifically for the purpose of the research study. Primary data collection involves gathering new and original information directly from the target population. To collect primary data, various methods can be employed, such as surveys, interviews, observations, or experiments. In the case of this research, primary data can be collected through various methods to capture consumer perceptions, attitudes, and purchase intentions towards machine learning chatbots. One effective method is to conduct a survey or questionnaire with a representative sample of online fashion shoppers. The survey tool can be designed to collect quantitative data by incorporating Likert scales or multiple-choice questions related to The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry. Researcher can design a questionnaire that includes questions about consumer perceptions of machine learning chatbots, purchase intentions, and other relevant variables. By administering the survey to a representative sample of fashion industry online shoppers, the researcher can collect primary data that specifically relates to the research objectives (Bryman, A. 2016).

3.6.2 Secondary data

Secondary data refers to the data that has been previously collected by someone else for a different purpose but can be utilized by researchers in their own investigations. It is a valuable resource in the field of research as it allows researchers to analyze existing data and draw meaningful insights without the need for primary data collection. Secondary data can be obtained from various sources, including government agencies, research institutions, academic publications, and online databases. Secondary data can be a valuable source of information for researchers. It can save time and resources compared to collecting primary data. Secondary data can also provide a broader perspective on a research topic by providing access to large datasets and historical data. The secondary analysis of existing data has become an increasingly popular method of enhancing the overall efficiency of the health research enterprise. Researchers often assess many more variables than those strictly needed to answer their original hypotheses, and these data can be used for additional research purposes. Secondary data analysis can be a powerful tool for the resourceful researcher, but it is often ignored as a methodological tool (Saunders, 2017).

In this research, secondary data plays a valuable role in providing additional insights and context to support the analysis and interpretation of the primary data. Secondary data can be collected from industry reports, academic journals, research papers, and publicly available datasets. These sources can provide valuable information on consumer behavior, market trends, and technological advancements, supporting the research objectives and enriching the findings.

3.7 Research Strategy

In the context of scientific research, a research strategy refers to the overall plan or approach adopted to investigate a particular phenomenon or problem. It guides the researcher's actions, methods, and procedures to ensure the study's objectives are met effectively and efficiently. For instance, in quantitative research, strategies such as experimental design, survey research, or correlational analysis may be employed to gather numerical data and establish causal relationships. On the other hand, qualitative research strategies, including ethnography, grounded theory, or case study analysis, aim to explore and understand complex phenomena in their natural settings.

Data collection from a standardised and structured sample of participants is often achieved through the use of survey research strategies or questionnaires. The purpose of this study is to create a well-crafted questionnaire that will gather pertinent data on consumers' opinions, attitudes, and plans to buy regarding machine learning chatbots. The survey will consist of a number of carefully crafted questions designed to extract information about the variables affecting customers' intent to purchase from a machine learning chatbot in the fashion e-commerce sector. Additionally, a five-point Likert scale will be used for analysis of the data gathered from the questionnaire. With the help of the widely used Likert scale, participants can indicate on a five-point scale, from strongly disagree to strongly agree, how much they agree or disagree with a series of statements. With the use of a scale like this, researchers can analyse participant responses and spot trends and patterns in consumer perceptions and purchase intentions through an organised and quantitative methodology. Researchers can systematically collect and analyse quantitative data related to The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry by using a five-point Likert scale for data analysis and a questionnaire or survey research strategy. This method provides useful insights into the relationship between chatbot interactions and participant responses by enabling the measurement and comparison of responses.

3.8 Questionnaire Design

A well-designed questionnaire ensures the effective and reliable measurement of variables, facilitates data collection, and contributes to the overall validity of the study. The design of a questionnaire involves careful consideration of various factors, including question structure, response options, question wording, and overall questionnaire layout. Questionnaire begins with clear and concise instructions, providing participants with a clear understanding of the study's purpose and how they should respond to the questions. It is important to include an introduction section that offers background information about the research and emphasizes the confidentiality and anonymity of the participants' responses. Additionally, collecting demographic information such as age, gender, and occupation allows for demographic analysis and potential subgroup comparisons.

Structured and focused questions are integral to the questionnaire design. Closed-ended questions, such as multiple-choice or Likert scale questions, are effective in gathering quantitative data related to consumer perceptions, attitudes, and purchase intention concerning machine learning chatbots. Open-ended questions can also be included to allow participants to provide more detailed qualitative responses, offering additional insights into their experiences and perspectives. To ensure a logical flow, the questions should be organized in a manner that groups related topics together. This allows participants to better understand the context and make informed decisions when responding.

First section of the questionnaire, Section A, is dedicated to collecting demographic information from the respondents. Questions related to gender, age, education level, and experience of using fashion online shopping chatbots are included. This section aims to obtain general demographic background information, which can later be analysed to identify any potential demographic influences on consumer purchase intention.

Second section, Section B, focuses on the independent variables of the research. This section explores the factors that may influence consumer purchase intention in relation to machine learning chatbots. The variables include perceived ease of use, perceived usefulness, system quality, and information quality. Each variable is assessed through 4 to 5 questions, allowing for a comprehensive understanding of the respondents' perceptions and attitudes towards these variables. Through the analysis of this section, the factor that holds the greatest influence on consumer purchase intention can be determined.

Third section, Section C, centres around the dependent variable, which is consumer purchase intention. This section assesses the respondents' intentions to make a purchase in the context of fashion industry online shopping. The questions in this section are designed to capture the respondents' attitudes, motivations, and likelihood of making a purchase influenced by machine learning chatbots.

By structuring the questionnaire into these three sections, the research aims to gather comprehensive data on the demographic background of the respondents, the key independent variables influencing consumer purchase intention, and the actual consumer purchase intention itself. This questionnaire design allows for a systematic and focused examination of the research objectives. To investigate the relationships between the independent and dependent variables, the data gathered from each section will be analysed using the proper statistical methods. This analysis can provide insightful information about the variables influencing machine learning chatbot purchase intention in the fashion e-commerce.

3.9 Sampling Design

Sampling design refers to the method used to select a subset of individuals or items from a larger population for the purpose of data collection. In this regard, there are two fundamental types of sampling techniques, namely probability or random sampling and nonprobability or non-random sampling. Probability sampling ensures that every unit or element in the general population has an equal chance of being included in the sample, while nonprobability sampling does not guarantee this. Although researchers tend to favor probability samples, nonprobability samples also have some advantage (Jawale & Baba, 2012).

3.9.1 Population and Sampling Frame

In scientific research, the population refers to the entire group of individuals, objects, or events that the researcher is interested in studying and making inferences about. It represents the larger target group that the researcher aims to draw conclusions or generalize findings to. The population would encompass all online shoppers in the fashion industry who engage in online shopping activities and have the potential to interact with machine learning chatbots. This population includes individuals from various demographics, such as different age groups, genders, educational backgrounds, and geographical locations, who engage in online fashion shopping. While sampling frame is a list or source that serves as a practical guide for selecting the sample from the larger population. Sample is a subset of the population that is selected for study. The process of selecting a sample population from the target population is called sampling. It provides a clear and defined source of potential participants from which the researcher can draw their sample. It should include a comprehensive and up-to-date list of individuals who are part of the target population, specifically those who engage in online fashion shopping and have the potential to interact with machine learning chatbots.

In this present study, the population would encompass all Malaysian consumers who engage in online shopping for fashion products and have the potential to interact with machine learning chatbots. On the other hand, the sampling frame could include databases of online fashion retailers in Malaysia, social media platforms, or other online platforms that facilitate fashion e-commerce. The selection of an appropriate sampling frame is crucial as it ensures that the sample is representative of the population and increases the external validity of the study's findings. It is important to establish a clear and well-defined sampling frame to ensure that the sample adequately reflects the characteristics and diversity of the target population.

3.9.2 Sampling Strategy

A sampling strategy refers to the approach used to select a sample from a population. The objective of a sampling strategy is to ensure that the selected sample allows you to generalize your findings to the entire population you're targeting. To develop a sampling strategy for a research study, researchers should define their target population, select a sampling frame, determine the appropriate sampling technique, determine the sample size, and execute the sampling plan.

Probability sampling and non-probability sampling are two frequently employed sampling techniques. Choosing participants from a population in a way that assigns each person a known, positive chance of being included in the sample is known as probability sampling. It is possible to draw statistical conclusions about the population using this method. Simple random sampling, stratified random sampling, and cluster sampling are a few types of probability sampling techniques. The results are more broadly applicable when researchers use a probability sampling strategy to guarantee that every member of the target population has an equal chance of being chosen. Conversely, non-probability sampling involves the subjective selection of participants without any assurance of equal or known chances of selection. When probability sampling is not practicable or feasible, non-probability sampling techniques are frequently used. Convenience sampling, in which participants are chosen according to their availability, and purposeful sampling, in which participants are chosen according to particular attributes pertinent to the study, are two examples. It is crucial to keep in mind, though, that non-probability sampling might introduce bias and restrict how broadly the results can be applied.

Sampling strategy used in this study is convenience sampling. This non-probability sampling technique was chosen for its practicality and applicability in the research objectives. Convenience sampling involves selecting participants based on the researcher's accessibility and availability, rather than through randomization. By selecting convenience sampling, the study aims to efficiently collect data from an easily accessible population, which includes online shoppers and individuals actively engaged in fashion-related activities. However, it is important to acknowledge that convenience sampling may pose limitations in terms of representativeness, as the sample may not fully reflect the broader population of e-commerce consumers in the fashion industry. Convenience sampling, however, allows cost-effective and timely data collection, enabling initial exploration of a research topic and laying the groundwork for further investigation.

3.9.3 Sample size

Size of a sample is a crucial aspect to consider in research, as it has a direct impact on the dependability and applicability of the findings. The selection of a suitable sample size entails choosing an appropriate number of participants from the target population, while considering practical limitations, in order to obtain significant outcomes. The appropriate sample size depends on both non-statistical and statistical considerations. Non-statistical considerations include availability of resources, manpower, budget, ethics, and sampling frame. Statistical considerations include the desired level of precision (sampling error), variability, and confidence level (Omair, 2014).

Based on population estimates provided by the Department of Statistics Malaysia, the population of Malaysia in 2021 is approximately 32.6 million, while in 2022, it was estimated to be around 32.7 million.

Table 1: Population and annual population growth rate, Malaysia, 2010-2021

Year	Number ('000)			Annual Population Growth Rate (%)		
	Total	Citizens	Non Citizens	Total	Citizens	Non Citizens
2010	28,588.6	26,264.1	2,324.5	1.8	1.6	4.0
2011	29,062.0	26,616.9	2,445.1	1.6	1.3	5.1
2012	29,510.0	26,961.7	2,548.3	1.5	1.3	4.1
2013	30,213.7	27,325.6	2,888.0	2.4	1.3	12.5
2014	30,708.5	27,696.2	3,012.3	1.6	1.3	4.2
2015	31,186.1	28,060.0	3,126.1	1.5	1.3	3.0
2016	31,633.5	28,403.5	3,230.0	1.4	1.2	3.3
2017	32,022.6	28,735.1	3,287.5	1.2	1.2	1.8
2018	32,382.3	29,059.6	3,322.7	1.1	1.1	1.1
2019	32,523.0	29,382.7	3,140.4	0.4	1.1	(5.6)
2020	32,584.0	29,677.4	2,906.6	0.2	1.0	(7.7)
2021[e]	32,655.4	29,962.3	2,693.1	0.2	1.0	(7.6)

[e] *Estimates*

Figure 3.1: Population in Malaysia from 2010 to 2021 (Estimates)

In order to determine an appropriate sample size for the research on The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry in Malaysia, a sample size calculation was performed using the guidelines outlined by Morgan (1970). Morgan's table provides recommendations for determining the necessary sample size based on the population size. Using this table, it was determined that a sample size of 384 respondents would be required to complete the research. Researchers decide to observe individuals engaging with fashion industry e-commerce or those specifically hashtagged certain brands on social media platforms. Individuals who interacted with fashion industry ecommerce social media platform selected as a sample because they are actual fans and have experience in this area (Arief, 2023)

N	S	N	S	N	S
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.—*N* is population size. *S* is sample size.

Source: Krejcie & Morgan, 1970

Figure 3.2: Sample Size for Different Size of Given Population

3.10 Pilot Test

A pilot study is an important step in research that is often recommended to address various issues such as the validity and reliability of the instrument to be used in the study. A pilot study is conducted on a smaller scale to test the logistic aspects of the execution of the study, which will avoid making mistakes in larger studies.

Pilot testing would involve administering the questionnaire or survey, which includes questions related to The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry, to a small subset of participants who are similar to your target population. The main objectives of the pilot test are to assess the clarity and comprehensibility of the questionnaire, identify any ambiguities or confusing items, and gauge the appropriateness and relevance of the questions. During the pilot test, participants' feedback and responses are collected and analyzed to detect any potential problems with the questionnaire, such as unclear instructions, biased wording, or missing response options. This feedback is invaluable in refining and improving the questionnaire to enhance its validity and reliability. Pilot testing also allows researchers to assess the feasibility and practicality of the data collection process. It helps identify any logistical challenges, time constraints, or technical issues that may arise during the actual data collection phase. By addressing these concerns early on, researchers can make necessary adjustments to ensure smooth and efficient data collection in the main study. The insights gained from the pilot test provide valuable feedback and enable researchers to refine their research instruments and procedures before embarking on the full-scale data collection. By conducting a pilot test, researcher can enhance the validity and reliability of study by fine-tuning the questionnaire and addressing any potential issues, ultimately improving the quality of research findings.

3.11 Time Horizon

Time horizon refers to the timeframe over which a research study is conducted and the duration for which data is collected (Thornhill, A. 2019) . It is an important variable in defining the study's scope and depth and symbolises the temporal component of the research design. The time horizon, or the precise duration of data collection and analysis, is one of the factors influencing consumer purchase intention of machine learning chatbots in fashion e-commerce. The time horizon that is selected should be in line with the goals of the research and the phenomenon that is being studied. Depending on the goals of the study and the characteristics of the phenomenon being examined, the time horizon may change. It may be cross-sectional, in which case information is gathered all at once to give a quick overview of the relevant variables and relationships.

Considering the dynamic nature of the fashion industry and online shopping behaviors, a longitudinal time horizon may be beneficial in capturing changes in consumer purchase intention and the factor of machine learning chatbots over time. However, the choice of time horizon should also consider practical constraints, such as available resources and the duration required to collect and analyze the data effectively. By carefully selecting an appropriate time horizon, researchers can ensure that the data collected is relevant, representative, and aligns with the research objectives. This decision contributes to the overall validity and reliability of the research findings and enables a comprehensive understanding of The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry.

3.12 Data Analysis

Data analysis is an important aspect of research that involves examining, interpreting, and making sense of the collected data to derive meaningful insights and draw valid conclusions (Bryman & Bell, 2019). It is a process used by researchers to reduce data to a story and interpret it to derive insights. The data analysis process helps reduce a large chunk of data into smaller fragments, which makes sense. Researchers rely heavily on data as they have a story to tell or research problems to solve.

The data analysis process typically begins with organizing and preparing the collected data for analysis. This involves data cleaning, where inconsistencies, missing values, and outliers are addressed to ensure the accuracy and quality of the data. Once the data is cleaned, it can be coded and entered into statistical software for further analysis. In this study, the data analysis would involve analyzing the responses obtained from the questionnaire or survey.

SPSS (Statistical Package for the Social Sciences) is a widely used software program for data analysis in social sciences research. SPSS (Statistical Package for the Social Sciences) is a collection of software products that enables academics, researchers, and organizations to study and mine data related to the social sciences. SPSS can run various statistical tests and models on data obtained from surveys, market research, data mining. SPSS is a statistical package for social science research that is widely used for quantitative data analysis. It is a combined package of software that can be used for survey research, market analysis, and more. SPSS is designed to handle large amounts of variables within a short period of time by using different technical commands to produce a set of suitable outputs. The benefits of the package include its relative ease of use, its familiarity to many statistical consultants, and its practicality. Researchers can use SPSS to properly analyze the activities and views of people in an analytical method.

SPSS offers a user-friendly interface that allows researchers to input, manage, and analyze their data efficiently. The software provides a wide range of statistical procedures, including descriptive statistics, inferential statistics, correlation analysis, regression analysis, and factor analysis, among others. These procedures enable researchers to examine relationships, test hypotheses, and explore patterns within their data. To conduct SPSS data analysis, the first step involves entering the collected data into the software. This can be done by creating variables and assigning appropriate labels and values. Once the data is entered, SPSS provides a range of options for data manipulation, such as recoding variables, creating new variables, and merging datasets if necessary. After data preparation, researchers can proceed with the desired analyses using SPSS. Descriptive statistics can be used to summarize the characteristics of variables and provide an overview of the data. Inferential statistics, such as t-tests or analysis of variance (ANOVA), can be employed to test hypotheses and examine differences between groups (Pallant, 2020).

Using SPSS for data analysis in research provides a powerful and comprehensive approach to understand The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry. The software's features and statistical procedures enable researchers to gain meaningful insights from their data and draw valid conclusions. In this study, descriptive and inferential analyzes were used and the reliability and validity of the data were assessed.

3.12.1 Descriptive Analysis

Descriptive analysis is a type of observational study design that allows researchers to study and describe the distribution of one or more variables without regard to any causal or other hypotheses. It is a method used for providing descriptive knowledge and understanding of the phenomenon under study. Descriptive analysis is often used in qualitative data analysis, which is a method of analyzing data that involves identifying patterns, themes, and categories in the data. SPSS is a statistical package that can be used for descriptive analysis, among other types of statistical analysis (Aggarwal & Ranganathan, 2019).

By conducting descriptive analysis, researcher will be able to provide a comprehensive overview of the key variables and their distributions in your research. This analysis allows for a better understanding of consumer perceptions and attitudes towards machine learning chatbots and their impact on purchase intentions in the fashion industry online shopping. The insights derived from descriptive analysis contribute to the overall understanding of the research topic and inform subsequent inferential analyses and interpretations.

3.12.2 Inferential Analysis

Inferential analysis is a statistical method used to make inferences about a population based on a sample of data. It involves using probability theory to draw conclusions about the population from the sample data. Inferential analysis is often used in hypothesis testing, where a researcher tests a hypothesis about a population based on sample data. SPSS is a statistical package that can be used for inferential analysis, among other types of statistical analysis (Gogoi, 2020).

By conducting inferential analysis, researcher can draw meaningful conclusions about the wider population based on sample data. These conclusions provide insights into The Role of Machine Learning Chatbot in influencing Consumer Purchase Intention in Fashion Industry. Inferential analysis adds depth and rigor to research, allowing researcher to make valid inferences and contribute to the existing knowledge in the field.

3.12.2.1 Regression Analysis

A statistical technique for examining the relationship between a dependent variable and one or more independent variables is regression analysis. Regression analysis is one of the many statistical analyses that can be performed with the statistical package SPSS. In order to model the future relationship between these two types of variables, this makes it possible to quickly ascertain the strength of that relationship.

The complexities of the relationships being studied and the study objectives will determine whether to use single or multiple regression analysis. While multiple regression analysis offers a more comprehensive view by taking into account the combined influence of multiple factors, single regression analysis focuses on the impact of individual factors. Examining the combined impact of several independent variables on the dependent variable is possible with multiple regression analysis. Multiple regression analysis may be applied in this setting of study to investigate the joint effects on consumer purchase intention of variables such as perceived ease of use, information quality, and system quality. This analysis offers a more thorough understanding of how these factors interact to influence customer behaviour regarding machine learning chatbots.

3.12.2.2 Pearson's Correlation Coefficient

Pearson's correlation coefficient is a statistical measure of the linear correlation between two variables, which ranges from -1 to 1, with -1 indicating a strong negative correlation and 1 indicating a strong positive correlation. It is commonly used in data analysis to determine the strength and direction of the relationship between two variables. A correlation coefficient of 0 suggests no linear relationship between the variables.

In this research, Pearson's correlation coefficient can be used to examine the relationships between variables such as perceived ease of use, perceived usefulness, system quality, information quality, and consumer purchase intention. By calculating the correlation coefficient, researcher can determine the degree of association between these variables and identify any significant correlations. A correlation coefficient close to +1 or -1 suggests a strong linear relationship between the variables, indicating that changes in one variable are closely related to corresponding changes in the other variable. A correlation coefficient close to 0 suggests a weak or no linear relationship between the variables. By interpreting the magnitude and direction of the correlation coefficient, researcher can gain insights into the nature and strength of the relationships between the variables. Pearson's correlation coefficient provides valuable information about the interdependence of variables in this research. It helps identify which factors related to machine learning chatbots have a significant influence on consumer purchase intention in the fashion industry online shopping. This information can guide analysis and contribute to a deeper understanding of the underlying dynamics between these variables.

3.13 Reliability

Reliability in research refers to the stability and accuracy of the methods and results of an analysis. It means obtaining consistent and identical results after repeating the same procedures several times. A specific measure is considered reliable if it produces the same results when applied to the same object of measurement multiple times. Reliability refers to the consistency and stability of measurement instruments or scales used in research (DeVellis, 2017). In this research, reliability assessment plays a crucial role in ensuring the accuracy and dependability of the measurement tools used. Reliability is essential because it ensures that the measurement instruments consistently produce similar results when applied repeatedly to the same sample or population. In other words, reliable measures provide consistent and stable results, allowing researchers to have confidence in the accuracy of their findings (DeVellis, R. F. 2017).

In this research, reliability assessment can be applied to the scales or questionnaires used to measure. By assessing the reliability of these measurement instruments, reseachers can determine the extent to which they yield consistent and dependable results. There are various methods to assess reliability, including internal consistency reliability and test-retest reliability. Internal consistency reliability measures the extent to which different items within the same scale or questionnaire correlate with each other. This can be assessed using statistical measures such as Cronbach's alpha coefficient. Test-retest reliability, on the other hand, examines the stability of measurements over time by administering the same measurement instrument to the same participants on two different occasions.

3.14 Validity

Validity holds significant importance in research, representing the extent to which a study effectively measures its intended objectives. It's not a singular, rigid concept but rather contingent upon specific research methodologies and project intentions. Within quantitative research, ensuring the validity and reliability of scales used is crucial, enabling the generation of valuable and accurate results. Research validity pertains to the precise measurement alignment with its intended target. High validity in research indicates that the outcomes reflect genuine properties, traits, and fluctuations within the physical or social realms (Winter, 2000). Validity is essential because it ensures that the study provides meaningful and reliable information about the relationship between machine learning chatbots and consumer purchase intention. It confirms that the measures and methods used in the research accurately capture the intended constructs and allow for valid conclusions to be drawn. In this research, validity assessment can be applied to the measurement instruments used to capture variables such as perceived ease of use, perceived usefulness, system quality, information quality, and consumer purchase intention.

By conducting validity assessment, researcher can enhance the credibility and reliability of the research findings. Validity ensures that the study provides meaningful insights into the factors of machine learning chatbots on consumer purchase intention, allowing for valid conclusions and implications to be drawn.

3.15 Measurement of Constructs

3.15.1 Dependent Variable

Constructs	Original Measurement Items	Sources of Measurement	Measurement items adopted and adopted for this study
Consumer Purchase Intention	I want to use the chatbot service once more. 2. I'm open to using the chatbot service going forward. 3. I'm ready to suggest using the chatbot service. 4. I'll keep utilising the chatbot feature.	(Lee et al., 2022)	1. I would be willing to purchase product from fashion ecommerce platform that come with chatbot service. 2. I would recommend my friends to use fashion ecommerce platform that come with chatbot service.

Table 3.1 Dependent Variable

3.15.2 Independent Variables

Constructs	Original Measurement Items	Sources of Measurement	Measurement items adopted and adopted for this study
Perceived Usefulness	1. Using the mobile app to make an online purchase is quite simple. 2. Using a mobile app to make purchases online is incredibly quick. 3. Using the mobile app enhances your efficiency, productivity, and performance when searching for and purchasing the goods you wish to buy. 4. You will find the information on the mobile app to be very helpful.	(Hanjaya et al., 2019a)	1. It is easy to purchase product from fashion industry ecommerce that come with a machine learning chatbot. 2. Machine learning chatbot in fashion industry ecommerce can improve my shopping efficiency. 3. Machine learning chatbot in fashion industry ecommerce able to help me to discover good products.

Constructs	**Original Measurement Items**	**Sources of Measurement**	**Measurement items adopted and adopted for this study**
Perceived Ease of Use	1. The mobile app is simple to use. 2. Mobile app operation is incredibly simple to learn. 3. Using the mobile app is a very straightforward and understandable process. 4. Getting the mobile app to do what you want is incredibly simple.	(Hanjaya et al., 2019)	1. Learn how to operate fashion ecommerce platform that come with machine learning chatbot is very easy. 2. Interaction with machine learning chatbot in fashion industry is very simple and easy to be understood. 3. Machine learning chatbots make my shopping experience in fashion industry's e-commerce sector easier.
System Quality	1. The chatbot could be modified to meet various requirements. 2. It was simple to use the chatbot anywhere and at any time. 3. The chatbot appeared to be highly technologically advanced.	(Lee et al., 2022)	1. Machine learning chatbot in fashion industry ecommerce platform could be adjusted to suit different needs. 2. Machine learning chatbot in fashion industry ecommerce platform could be easily used anytime. 3. Machine learning chatbot in fashion industry ecommerce platform seemed to be a high level of technology.

Constructs	Original Measurement Items	Sources of Measurement	Measurement items adopted and adopted for this study
Information Quality	1. I could get information that was tailored to me. 2. I could get the information I need in a tailored manner.	(Lee et al., 2022)	1. Machine learning chatbot in fashion industry ecommerce platform can provide me customise information. 2. Machine learning chatbot in fashion industry ecommerce platform can provide me information that meets my specific needs.

Table 3.2: Independent Variables

3.16 Conclusion

In conclusion, the research methodology employed in this study aimed to investigate the various factors that impact consumers' intention to purchase fashion products through e-commerce platforms. Through a systematic approach, the researchers collected and analyzed data from a diverse sample of participants, utilizing both quantitative and qualitative research techniques. By employing a rigorous research methodology, this study contributes to the existing body of knowledge on consumer behavior in the fashion industry's e-commerce sector. The findings provide valuable insights for fashion retailers, marketers, and e-commerce platform operators, enabling them to enhance their understanding of consumer preferences and develop effective strategies to influence consumer purchase intention.

CHAPTER 4

DATA ANALYSIS AND RESULT

4.1 Introduction

In this research, a rigorous data analysis was conducted to explore and quantify the relationships between independent variables and the dependent variable. The independent variables of interest in this investigation included perceived ease of use, perceived usefulness, information quality, and system quality, with consumer purchase intention serving as the dependent variable. To probe these relationships, the research employed a multi-faceted approach, encompassing Hypothesis Testing, Pearson's Correlation, and Multiple Regression Analysis. The data analysis phase was based on responses from a carefully selected sample of 384 respondents who were active users of fashion industry ecommerce platforms and hashtagged the corresponding e-commerce's on Facebook and Instagram. The demographic data of respondents was obtained through a series of six questions in Section A, aimed at establishing foundational information. In Section B, a set of sixteen questions was designed to explore independent variables pertinent to the research topic, while an additional four questions in Section C focused on variables associated with the dependent factor. The data analysis chapter encompasses various statistical methodologies, including Descriptive Statistics analysis, Pearson Correlation, Reliability Analysis, and Multiple Regression Analysis. The analysis was conducted using SPSS Statistics 26, serving as the primary software for data examination and interpretation.

4.2 Pilot Test

To ensure the questionnaire's feasibility and the overall quality of the study, a preliminary validation process was conducted involving 30 respondents through a pilot test. This step was critical in confirming that the survey instrument was capable of generating results that were trustworthy and applicable to real-world scenarios. Additionally, Cronbach’s Alpha was integrated during the pilot test and reliability testing to gauge the internal consistency and reliability of the survey instrument. The pilot test involved a subset of 30 respondents carefully selected from the target population. These individuals provided invaluable feedback by participating in the initial trial of the survey instrument. During the pilot test, their responses were collected, and their insights were carefully considered. The primary objective was to assess the questionnaire's clarity, coherence, and overall effectiveness in capturing the intended information. Additionally, during the pilot test, Cronbach’s Alpha, a measure of internal consistency, was applied as part of the reliability testing process. This served to confirm that the survey instrument was internally coherent and consistent in measuring the intended variables, further enhancing the reliability of the data collected during the main study.

Variable	Cronbach's Alpha	N of items	Strength of Association
Independent Variables			
Perceived Usefulness	0.983	4	Excellent
Perceived Ease of Use	0.979	4	Excellent
System Quality	0.979	4	Excellent
Information Quality	0.996	4	Excellent
Dependent Variable			
Consumer Purchase Intention	0.983	4	Excellent

Table 4.1: Reliability Statistics of Variables

Source: SPSS Output

Cronbach's Alpha	N of items
0.971	20

Table 4.2: Reliability Statistics of Overall Pilot Test

Source: SPSS Output

The highest level of internal consistency, often observed in research studies, is indicative of a strong and reliable relationship among the items or questions used to measure a specific construct or variable. Based on the table above, the variable information quality exhibited the highest level of internal consistency with a Cronbach's Alpha coefficient of 0.996, a remarkable value. This high Cronbach's Alpha value signifies that the items within the "Information Quality" variable are exceptionally consistent and reliable in measuring the intended aspect of information quality. In practical terms, it means that the questions or items related to information quality, as included in the survey, are highly correlated and consistently capture the underlying construct.

The overall Cronbach's Alpha score, encompassing both the independent variables and the dependent variable, reflects an exceptionally high level of internal consistency and reliability. Each individual variable has demonstrated an "Excellent" level of internal consistency, as indicated by their respective Cronbach's Alpha values, all of which exceed 0.9. Besides, the overall Cronbach's Alpha score, as illustrated in Table 4.2, stands at an impressive 0.971 in the reliability analysis. This collective high level of internal consistency across all variables underscores the strength of the data and its reliability, enhancing the credibility and robustness of the research findings. In summary, the impressive overall Cronbach's Alpha score affirms the excellent internal consistency of the variables, providing a solid foundation for meaningful and reliable conclusions regarding the factors influencing consumer purchase intention in the fashion industry ecommerce.

4.3 Respondent Rate

The targeted volume of responses for this study was determined to be 384. To facilitate data collection, a Google Form was utilized, with all questions designated as "*Required," ensuring that respondents completed the entire questionnaire before submission. Subsequently, all 384 questionnaires received were fully completed.

4.4 Descriptive Statistic Analysis of Demographic Profile

The application of Descriptive Statistical Analysis serves the purpose of presenting and elucidating the foundational data acquired within this research in a comprehensible format. This segment of the study is dedicated to elucidating and presenting the demographic details of the respondents, as well as their experiences pertaining to online grocery shopping. This statistical analysis offers a structured and detailed comprehension of the essential data points relevant to understanding the factors influencing consumer purchase intention within the fashion industry's e-commerce sector, specifically focusing on machine learning chatbot.

4.4.1 Demographic Profile

The mandatory completion of Section A of the questionnaire enabled the collection of each participant's demographic profile. In this section, respondents were asked to provide basic demographic data, including gender, age range, highest level of education completed. The demographic information gathered provides a thorough understanding of the various traits of the participants and advances our knowledge of the variables affecting consumer intention to buy in the e-commerce domain of the fashion industry, especially with regard to machine learning chatbots.

Variable	**Description**	**Number**	**Percentage (%)**
Gender	Male	174	45.3
	Female	210	54.7
Age	Below 18 years	42	10.9
	18-29 years	302	78.6
	30-39 years	40	10.4
	40 and above	0	0
Educational Level	Secondary	1	0.3
	Pre-university	40	10.4
	Tertiary	343	89.3
Monthly Income	No Income	128	33.3
	Less than RM2500	156	40.6
	RM 2501- RM 5000	80	20.8
	RM 5001- RM 10,000	20	5.2
	More than RM 10,000	0	0

Table 4.3 Demographic Profile of Respondents

4.4.2 Gender

Gender					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	210	54.7	54.7	54.7
	Male	174	45.3	45.3	100.0
	Total	384	100.0	100.0	

Table 4.4: Descriptive Statistics (Gender)

(Source: SPSS Output)

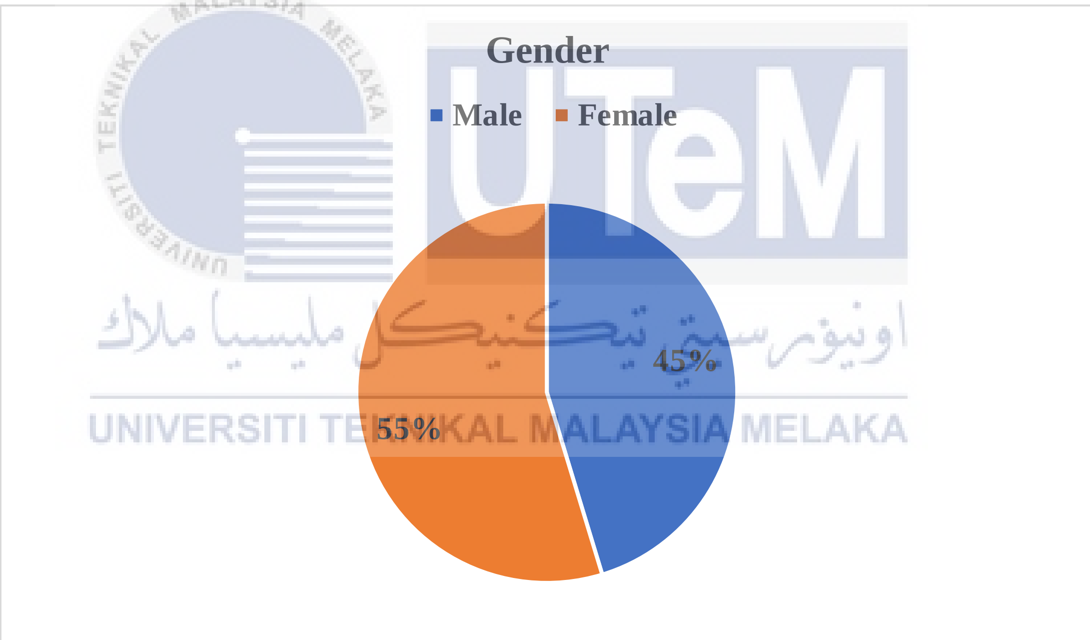

Figure 4.1 Gender of Respondents

The data presented in both the Table and Figure above illustrate the distribution of gender among respondents who completed the questionnaire distributed via Google Forms. Among the 384 respondents, 54.70% (210 individuals) identified as female, whereas 45.30% (174 individuals) identified as male.

4.4.3 Age

Age					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Below 18 years	42	10.9	10.9	10.9
	18-29 years	302	78.6	78.6	89.5
	30-39 years	40	10.4	10.4	100.0
	40 and above	0	0	0	100.0
	Total	384	100.0	100.0	

Table 4.5: Descriptive Statistics (Age Group)

(Source: SPSS Output)

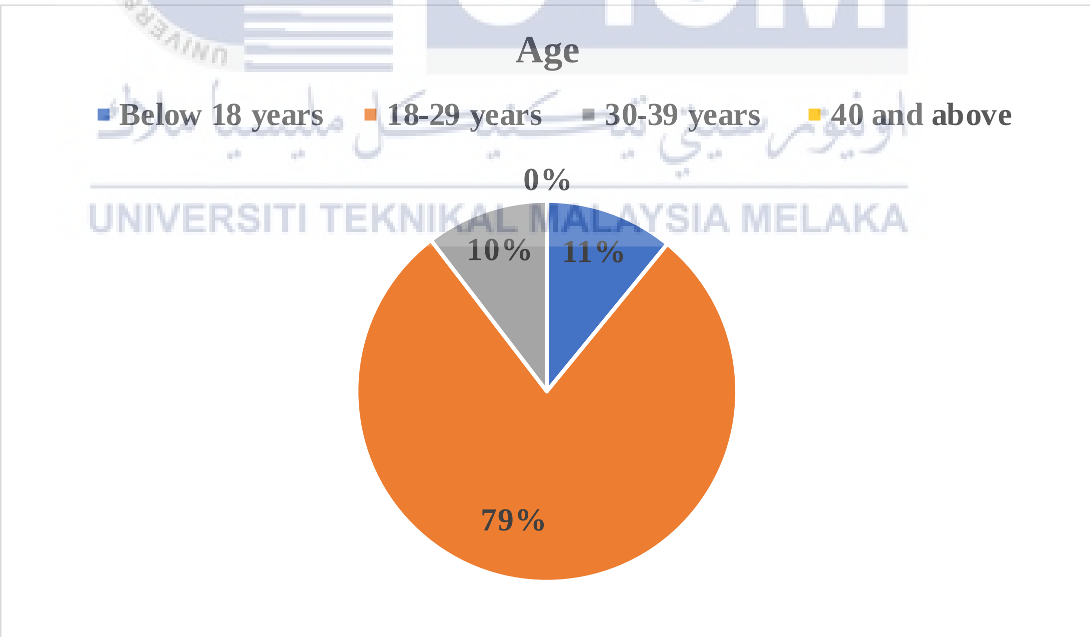

Figure 4.2 Age of Respondents

The data depicted in the table and figure provide an overview of the age distribution among the 384 respondents. A substantial majority, comprising 302 individuals (78.60%), falls within the age bracket of 18-29 years. Additionally, 42 respondents (10.90% of the total sample) are below 18 years old, while 40 individuals (10.40%) are aged between 30 and 39 years. Notably, there were no respondents aged 40 years or older within the dataset.

4.4.4 Educational Level

Educational Level					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Pre-university	40	10.4	10.4	10.4
	Secondary	1	0.3	0.3	10.7
	Tertiary	343	89.3	89.3	100.0
	Total	384	100.0	100.0	

Table 4.6: Descriptive Statistics (Highest Educational Level)

(Source: SPSS Output)

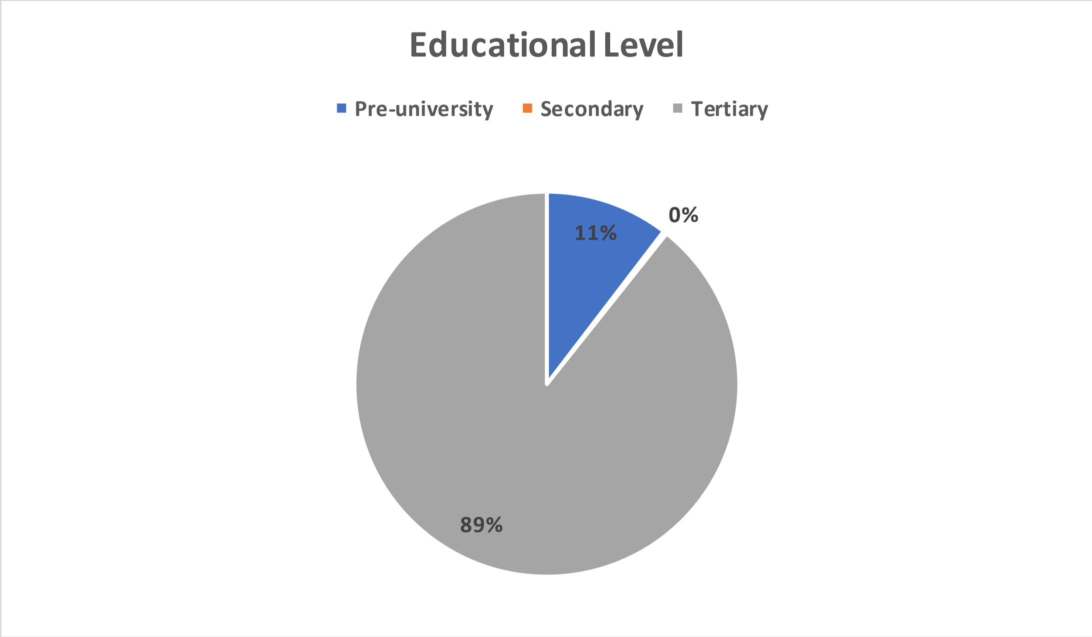

Figure 4.4 Educational Level of Respondents

The data presented in the figure and table above showcase the distribution of respondents based on their highest educational attainment. Among the 384 participants, 343 individuals (89.30%) indicated that their highest educational level was tertiary education. Additionally, 40 respondents (10.40% of the total sample) identified their highest educational level as Pre-university. Conversely, only one respondent (0.3% of the total) reported secondary education as their highest educational achievement. The prevalence of respondents with tertiary education appears notably higher in comparison to other educational categories. This trend in educational attainment among respondents might be attributed to various factors, such as digital literacy and awareness among university students.

4.4.5 Monthly Income

Monthly Income					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	No Income	128	33.3	33.3	33.3
	Less than RM 2500	156	40.6	40.6	74.0
	RM 2501- RM 5000	80	20.8	20.8	94.8
	RM 5001- RM 10,000	20	5.2	5.2	100.0
	More than RM 10,000	0	0	0	100.0
	Total	384	100.0	100.0	

Table 4.7: Descriptive Statistics (Household Income)

(Source: SPSS Output)

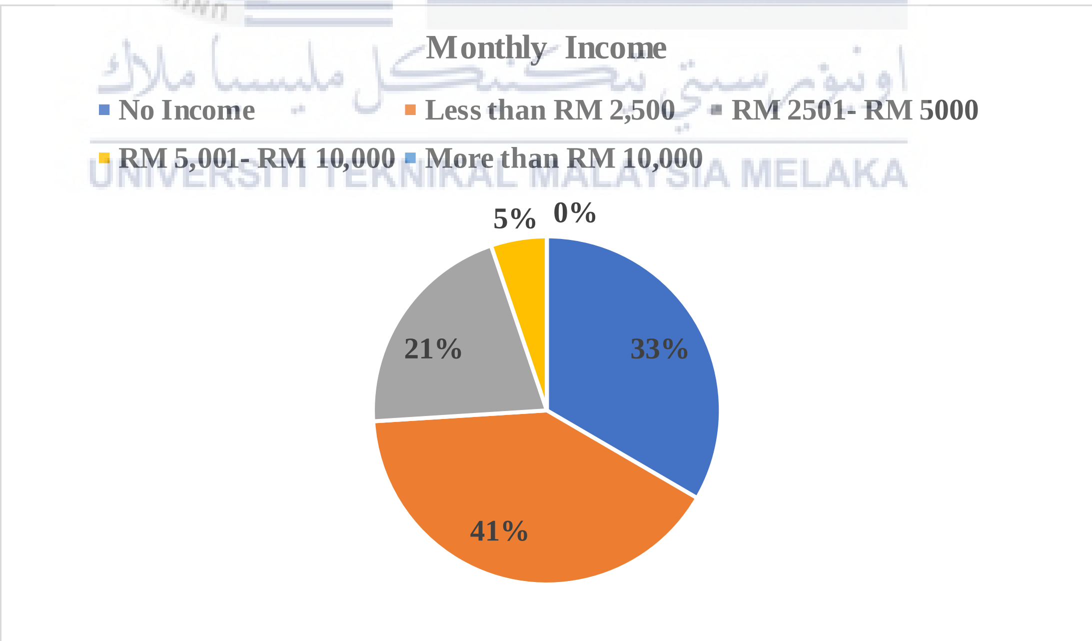

Figure 4.6 Monthly Income of Respondents

The provided figures and tables display the distribution of household income among the 384 respondents. The majority, accounting for 40.60% (156 individuals), reported a household income less than RM 2500. Subsequently, 33.30% (128 respondents) indicated no income within their households, representing the second highest proportion. Further, 20.80% (80 respondents) reported a household income falling within the range of RM 2501 to RM 5000. Additionally, 5.2% of the respondents (20 individuals) disclosed a household income between RM 5001 and RM 10,000. This delineation of household income categories provides insights into the income distribution among participants, shedding light on the financial backgrounds relevant to investigating factors influencing consumer purchase intention within the fashion industry's e-commerce landscape.

4.4.6 Experience of Shopping for Fashion Items Online

Do you shop for fashion items online?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	384	100.0	100.0	100.0
	No	0	0.0	0.0	100.0
	Total	384	100.0	100.0	

Table 4.8: Descriptive Statistics (Experience of Shopping for Fashion Items Online)

(Source: SPSS Output)

Figure 4.7 Experience of Shopping for Fashion Items Online

The data illustrated in the above figure and table outline the outcomes concerning respondents' experience in shopping for fashion items online. A significant majority, comprising 100.0% (384 individuals) out of the 384 respondents, reported having prior experience in shopping for fashion items online. Conversely, no respondents indicated no prior experience in online fashion shopping. This observed trend in experience might be attributed to the selection of respondents, specifically chosen from individuals engaging with online e-commerce activities through social media, potentially biasing the sample toward individuals already involved in online shopping environments.

4.4.7 Experience with Online Shopping Chatbot

Have you ever interacted with a chatbot in an online shopping context?					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	No	207	53.9	53.9	53.9
	Yes	177	46.1	46.1	100.0
	Total	384	100.0	100.0	

Table 4.9: Descriptive Statistics (Experience with Online Shopping Chatbots)

(Source: SPSS Output)

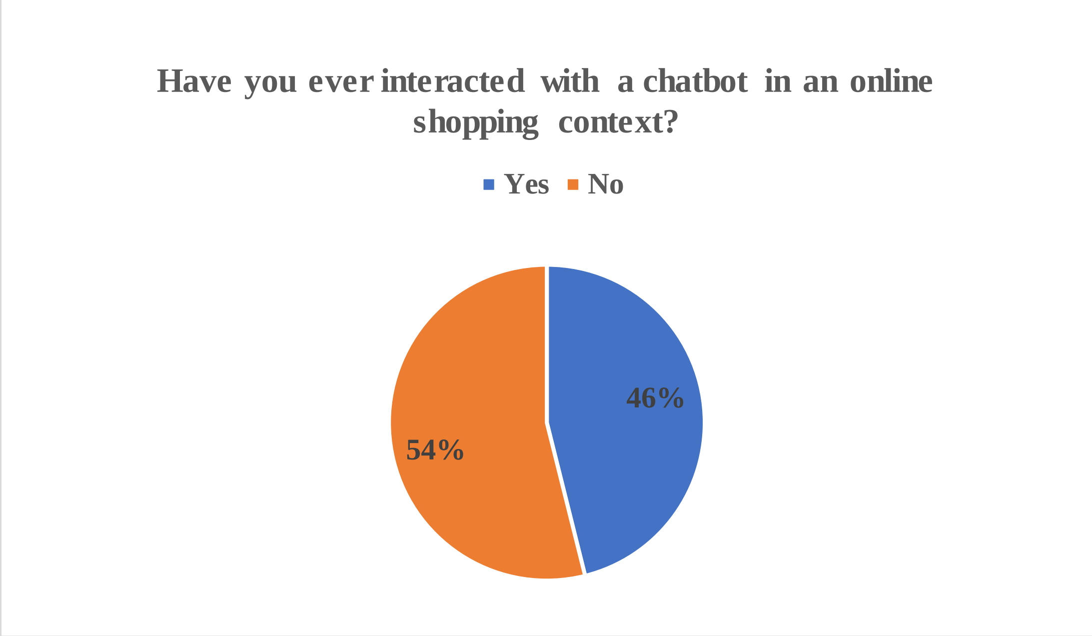

Figure 4.7 Experience of Online Shopping Chatbot

The data presented in the figures and tables above elucidate the outcomes pertaining to respondents' interaction with chatbots within the context of online shopping. Among the 384 participants surveyed, 177 individuals, accounting for 46.1% of the total respondents, indicated having engaged with chatbots while conducting online shopping activities. Conversely, a majority of respondents, totaling 207 individuals or 53.9%, reported no prior interaction with chatbots during their online shopping experiences. One possible explanation for the higher proportion of respondents not engaging with chatbots might relate to varying levels of awareness and familiarity among participants regarding the utility and functionality of these AI-driven systems. Those who chose not to interact might possess limited exposure or understanding of the benefits offered by chatbots in the online shopping sphere.

4.5 Descriptive Statistics on Independent Variables and Dependent Variables

The study employed a five-point Likert Scale as a quantitative tool to assess the factors influencing consumer purchase intention concerning machine learning chatbots within the fashion industry's e-commerce landscape. This Likert Scale utilized a spectrum of five rating options, where 1 denoted "strongly disagree," 2 represented "disagree," 3 indicated "neutral," 4 signified "agree," and 5 stood for "strongly agree." The data analysis phase involved descriptive statistics to comprehensively understand the respondents' perceptions and attitudes regarding the various factors impacting their purchase intentions with machine learning chatbots in fashion e-commerce. The mean scores offered a central tendency measure, indicating the average agreement level of respondents regarding these factors. Meanwhile, the standard deviation values elucidated the extent of variability or consensus in their perceptions.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
IV1	384	2.00	5.00	4.4668	.58849
IV2	384	1.00	5.00	3.5280	.73607
IV3	384	1.00	5.00	3.8926	.70434
IV4	384	1.00	5.00	4.0423	.92312
DV	384	2.00	5.00	3.7923	.97316
Valid N (listwise)	384				

Table 4.10: Descriptive Statistics of Independent and Dependent Variable

(Source: SPSS Output)

In Table 4.10, the descriptive statistics for both the independent variables (IV1, IV2, IV3, IV4) and the dependent variable (DV) related to the factors influencing consumer purchase intention in the fashion industry's e-commerce through machine learning chatbots are presented. The analysis, conducted using the Statistical Package for Social Sciences (SPSS), offers valuable insights into respondents' perceptions and attitudes toward these variables.

The independent variables encompass specific aspects related to machine learning chatbots in fashion e-commerce. IV1, denoting a factor within the chatbot interface, demonstrates the highest mean value of 4.4668. This suggests that respondents generally agreed with the notion that this aspect significantly impacts consumer purchase intention. IV4 follows closely behind with a mean value of 4.0423, indicating a substantial influence as perceived by respondents. IV3 represents another influential factor with a mean of 3.8926, while IV2, associated with a different aspect, exhibits a slightly lower mean value of 3.5280.

Moreover, the standard deviation values offer insights into the variability or dispersion of responses around the mean. IV2 displays the highest standard deviation of 0.73607 among the independent variables, indicating a relatively broader range of responses and diverse opinions regarding this particular aspect. IV4 follows with a standard deviation of 0.92312, signifying a considerable variability in respondents' perceptions. IV3 shows a moderate standard deviation of 0.70434, while IV1 demonstrates the lowest standard deviation of 0.58849, suggesting a more consistent perception among respondents regarding its impact on consumer purchase intention.

In regard to the dependent variable (DV), which represents consumer purchase intention in fashion industry e-commerce using machine learning chatbots, the mean value of 3.7923 indicates a moderately positive inclination towards utilizing chatbots for purchase intentions. The standard deviation of 0.97316 illustrates a notable dispersion in respondents' inclinations, suggesting a varied range of attitudes regarding their intention to make purchases via machine learning chatbots in fashion e-commerce.

Overall, the descriptive statistics offer a detailed depiction of respondents' perceptions regarding the influential factors and their intention to utilize machine learning chatbots for purchase intentions in the fashion industry's e-commerce. These statistics provide valuable insights into the varying degrees of impact and variability in perceptions, aiding in a comprehensive understanding of consumer behavior in this context.

4.5.1 Descriptive Analysis of Independent Variables 1 (IV1)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
It is easy to purchase product from fashion industry ecommerce that come with a machine learning chatbot.	384	2.00	5.00	4.3698	.71077
Machine learning chatbot in fashion industry ecommerce can improve my shopping efficiency	384	2.00	5.00	4.2708	.70402

Machine learning chatbot in fashion industry ecommerce able to help me to discover good products.	384	2.00	5.00	4.6146	.69492
Machine learning chatbot in fashion industry ecommerce saved my time to go shopping.	384	2.00	5.00	4.6120	.72836
Valid N (listwise)	384				

TABLE 4.11: Descriptive Analysis of Perceived Usefulness

Source: (SPSS Output)

Table 4.11 presents the descriptive statistics for the independent variables related to the perceived usefulness of machine learning chatbots in the fashion industry's e-commerce concerning consumer purchase intention. These variables represent different facets of consumer perceptions regarding the utility and efficacy of using chatbots for shopping experiences.

Among the factors considered, the item "Machine learning chatbot in fashion industry ecommerce can improve my shopping efficiency" displayed the lowest mean value of 4.2708, indicating slightly lesser agreement among respondents regarding the enhancement of shopping efficiency through chatbot use. This item also showed a standard deviation of 0.70402, signifying a moderate level of variability in respondents' opinions about its impact on shopping efficiency.

Contrarily, the item "Machine learning chatbot in fashion industry ecommerce able to help me discover good products" exhibited the highest mean value of 4.6146, suggesting stronger agreement among respondents regarding the chatbot's capability to assist in product discovery. This item also demonstrated a relatively lower standard deviation of 0.69492, indicating a more consistent perception among respondents regarding its role in product discovery.

Additionally, the items "Machine learning chatbot in fashion industry ecommerce saved my time to go shopping" and "It is easy to purchase products from fashion industry ecommerce that come with a machine learning chatbot" both presented similar mean values of 4.6120 and 4.3698, respectively. These findings imply a relatively high level of agreement among respondents concerning time-saving attributes and ease of purchasing products through chatbot interactions. The standard deviations for these items, 0.72836 and 0.71077 respectively, indicate a moderate level of variability in respondents' opinions about time-saving features and ease of purchasing products via machine learning chatbots in fashion e-commerce.

The descriptive analysis sheds light on the varied perceptions of respondents regarding different aspects of machine learning chatbots in fashion e-commerce concerning their impact on consumer purchase intentions. It provides valuable insights into the nuances of perceived usefulness, aiding in understanding the diverse attitudes and opinions of consumers regarding chatbot functionalities in their shopping experiences.

4.5.2 Descriptive Analysis of Independent Variables 2 (IV2)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Learn how to operate fashion ecommerce platform that come with machine learning chatbot is very easy.	384	1.00	5.00	3.4479	.66811
Interaction with machine learning chatbot in fashion industry is very simple and easy to be understood.	384	1.00	5.00	3.4583	.65702
Machine learning chatbots make my shopping experience in fashion industry's e-commerce sector easier.	384	1.00	5.00	3.5990	.84619
Using a machine learning chatbot makes it really simple to accomplish what you want.	384	1.00	5.00	3.6068	.84832
Valid N (listwise)	384				

TABLE 4.12: Descriptive Analysis of Perceived Ease of Use

Source: (SPSS Output)

Table 4.12 presents the descriptive statistics for the independent variables related to perceived ease of use concerning machine learning chatbots in the fashion industry's e-commerce, focusing on their influence on consumer purchase intention. These variables gauge respondents' perceptions regarding the ease and simplicity of utilizing machine learning chatbots in the fashion e-commerce context.

Among the items considered, "Machine learning chatbots make my shopping experience in the fashion industry's e-commerce sector easier" displayed the highest mean value of 3.5990. This suggests a moderate level of agreement among respondents regarding the facilitation of shopping experiences through chatbot use. The standard deviation for this item stands at 0.84619, indicating a moderate level of variability in respondents' opinions concerning the extent to which chatbots ease their shopping experiences.

Similarly, "Using a machine learning chatbot makes it really simple to accomplish what you want" showed a mean value of 3.6068, indicating a similar level of agreement among respondents regarding the simplicity of achieving desired tasks through chatbot interactions. The standard deviation for this item is 0.84832, suggesting a similar degree of variability in respondents' perceptions as observed in the previous item.

In contrast, "Learn how to operate fashion e-commerce platforms that come with machine learning chatbot is very easy" and "Interaction with machine learning chatbot in the fashion industry is very simple and easy to be understood" both displayed mean values of 3.4479 and 3.4583, respectively. These findings imply a somewhat lower level of agreement among respondents regarding the ease of learning and interacting with chatbots. The standard deviations for these items, 0.66811 and 0.65702 respectively, indicate a relatively lower level of variability in respondents' opinions concerning ease of learning and interaction with machine learning chatbots in fashion e-commerce.

The descriptive analysis highlights diverse perceptions among respondents concerning different aspects of perceived ease of use associated with machine learning chatbots in fashion e-commerce. These findings offer valuable insights into varying degrees of ease and simplicity perceived by consumers in utilizing chatbots for their shopping experiences, contributing to a comprehensive understanding of factors influencing consumer purchase intentions in this context.

4.5.3 Descriptive Analysis of Independent Variables 3 (IV3)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Machine learning chatbot in fashion industry ecommerce platform could be used to suit different needs.	384	1.00	5.00	3.8151	.80772
Machine learning chatbot in fashion industry ecommerce platform could be easily used anytime.	384	1.00	5.00	3.8255	.81004
Machine learning chatbot in fashion industry ecommerce platform seemed to be a high level of technology	384	1.00	5.00	3.9609	.91179

Machine learning chatbot in fashion industry ecommerce platform is a reliable system.	384	1.00	5.00	3.9661	.91200
Valid N (listwise)	384				

TABLE 4.13: Descriptive Analysis of System Quality

Source: (SPSS Output)

Table 4.13 presents the descriptive statistics for the independent variables related to system quality in machine learning chatbots within the fashion industry's e-commerce, focusing on their influence on consumer purchase intention. These variables aim to assess respondents' perceptions regarding the reliability, adaptability, and technological sophistication of machine learning chatbot systems in fashion e-commerce.

Among the considered items, "Machine learning chatbot in fashion industry ecommerce platform is a reliable system" displayed the highest mean value of 3.9661. This indicates a moderate level of agreement among respondents regarding the reliability of chatbot systems in the fashion e-commerce domain. The standard deviation for this item stands at 0.91200, suggesting a moderate degree of variability in respondents' opinions concerning the system's reliability.

Similarly, "Machine learning chatbot in fashion industry ecommerce platform seemed to have a high level of technology" showed a mean value of 3.9609, indicating a comparable level of agreement among respondents regarding the technological sophistication of these chatbot systems. The standard deviation for this item is 0.91179, suggesting a similar degree of variability in respondents' perceptions as observed in the previous item.

In contrast, "Machine learning chatbot in fashion industry ecommerce platform could be used to suit different needs" and "Machine learning chatbot in fashion industry ecommerce platform could be easily used anytime" both displayed mean values of 3.8151 and 3.8255, respectively. These findings imply a somewhat lower level of agreement among respondents regarding the adaptability and ease of use of these chatbot systems. The standard deviations for these items, 0.80772 and 0.81004 respectively, indicate a relatively lower level of variability in respondents' opinions concerning adaptability and ease of use of machine learning chatbots in fashion e-commerce.

The descriptive analysis emphasizes varied perceptions among respondents concerning different aspects of system quality associated with machine learning chatbots in the fashion industry's e-commerce. These findings provide valuable insights into diverse perspectives regarding the reliability, adaptability, and technological sophistication perceived by consumers in utilizing chatbot systems for their shopping experiences, contributing to a comprehensive understanding of factors influencing consumer purchase intentions in this context.

4.5.4 Descriptive Analysis of Independent Variables 4 (IV4)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Machine learning chatbot in fashion industry ecommerce platform can provide me customise information.	384	1.00	5.00	3.9688	.90941

Machine learning chatbot in fashion industry ecommerce platform can provide me information that meets my specific needs.	384	1.00	5.00	3.9714	.90355
Machine learning chatbot provide helpful information.	384	1.00	5.00	4.1120	.97513
Machine learning chatbot provide up-to-date information.	384	1.00	5.00	4.1172	.97451
Valid N (listwise)	384				

TABLE 4.14: Descriptive Analysis of Information Quality

Source: (SPSS Output)

Table 4.14 displays the descriptive statistics for the independent variables associated with information quality in machine learning chatbots within the fashion industry's e-commerce, aimed at understanding their influence on consumer purchase intention. These variables assess respondents' perceptions concerning the customization, relevance, helpfulness, and timeliness of information provided by machine learning chatbots in fashion e-commerce.

Among the examined items, "Machine learning chatbot in fashion industry ecommerce platform can provide me up-to-date information" and "Machine learning chatbot provide helpful information" exhibited the highest mean values of 4.1172 and 4.1120, respectively. This signifies a moderate to high level of agreement among respondents regarding the provision of timely and helpful information through chatbot interactions. The standard deviations for these items, 0.97451 and 0.97513 respectively, indicate a moderate level of variability in respondents' opinions concerning the helpfulness and timeliness of information provided by chatbots.

Similarly, "Machine learning chatbot in fashion industry ecommerce platform can provide me customised information" and "Machine learning chatbot in fashion industry ecommerce platform can provide me information that meets my specific needs" both displayed mean values of 3.9688 and 3.9714, respectively. These findings imply a slightly lower but favorable level of agreement among respondents regarding the customization and relevance of information delivered by chatbot systems. The standard deviations for these items, 0.90491 and 0.90355 respectively, suggest a moderate level of variability in respondents' opinions concerning customized and relevant information provided by machine learning chatbots in fashion e-commerce.

This descriptive analysis highlights diverse perceptions among respondents regarding different facets of information quality associated with machine learning chatbots in the fashion industry's e-commerce. These findings offer valuable insights into varying degrees of agreement regarding the customization, relevance, helpfulness, and timeliness perceived by consumers in utilizing chatbot systems for their shopping experiences, contributing to a comprehensive understanding of factors influencing consumer purchase intentions in this context.

4.5.5 Descriptive Analysis of Dependent Variables (DV)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
I would be willing to purchase product from fashion ecommerce platform that come with chatbot service.	384	2.00	5.00	3.6875	.94565
I would recommend my friends to use fashion ecommerce platform that come with chatbot service.	384	2.00	5.00	3.7552	1.02322
I want to use machine learning chatbot again.	384	2.00	5.00	3.8620	1.01899
I will remain to use the chatbot rather than call human customer service.	384	2.00	5.00	3.8646	1.01806
Valid N (listwise)	384				

TABLE 4.15: Descriptive Analysis of Consumer Purchase Intention

Source: (SPSS Output)

Table 4.15 provides descriptive statistics for the dependent variables associated with consumer purchase intention concerning machine learning chatbots in the fashion industry's e-commerce. These variables aim to gauge respondents' inclinations and attitudes towards using chatbot services for their purchasing decisions and interactions within the fashion e-commerce sphere.

Examining the items, "I would be willing to purchase products from fashion e-commerce platforms that come with chatbot service" and "I would recommend my friends to use fashion e-commerce platforms that come with chatbot service," both showed mean values of 3.6875 and 3.7552, respectively. These values suggest a moderate level of inclination among respondents toward making purchases and recommending chatbot-integrated fashion e-commerce platforms to their acquaintances. The standard deviations for these items, 0.94565 and 1.02322 respectively, indicate a moderate level of variability in respondents' attitudes towards purchasing and recommending such platforms.

Moreover, "I want to use machine learning chatbot again" and "I will remain to use the chatbot rather than call human customer service" both displayed mean values of 3.8620 and 3.8646, respectively. These values indicate a moderately favorable inclination among respondents to continue using chatbot services and preferring them over human customer service interactions. The standard deviations for these items, 1.01899 and 1.01806 respectively, suggest a moderate level of variability in respondents' intentions to use chatbots again and their preference for chatbot-based customer service over human interaction in the fashion e-commerce context.

This descriptive analysis underscores varied inclinations and attitudes among respondents regarding their purchase intentions and preferences for using machine learning chatbots within the fashion industry's e-commerce. These findings provide insights into the moderate level of agreement and variability in respondents' willingness to purchase, recommend, and continue using chatbot services for their fashion-related transactions, contributing to a comprehensive understanding of factors influencing consumer purchase intentions in this context.

4.6 Pearson Correlation

The computation of the strength of linear association between two variables necessitates the use of Pearson Correlation. This research incorporates Pearson Correlation analysis to validate the relationships among perceived ease of use, perceived usefulness, system quality, and information quality in relation to consumer purchase intention toward machine learning chatbots within the fashion industry's e-commerce sector. The resulting Pearson Correlation Coefficient, ranging between -1 and 1, signifies the strength and direction of the relationship. A value closer to 1 denotes a stronger positive relationship, while proximity to -1 indicates a stronger negative relationship. Conversely, a value of 0 suggests the absence of a linear relationship between the variables under investigation.

R value	Relationship
0.70 or higher	Very Strong Positive Relationship
+0.40 to +0.69	Strong Positive Relationship
+0.30 to +0.39	Moderate Positive Relationship
+0.20 to +0.29	Weak Positive Relationship
+0.01 to +0.19	No or Negligible Relationship
0	No Relationship
-0.01 to -0.19	No or Negligible Relationship
-0.20 to -0.29	Weak Negative Relationship
-.030 to -0.39	Moderate Negative Relationship
-0.40 to -0.69	Strong Negative Relationship
-0.70 or higher	Very Strong Negative Relationship

Table 4.16 Relationship interpreted through R value

		Perceived Usefulness	Perceived Ease of Use	System Quality	Information Quality	Consumer Purchase Intention
Perceived Usefulness	Pearson Correlation	1	.116**	.230**	-.236**	.150**
	Sig. (2tailed)		.023	.000	.000	.003
	N	384	384	384	384	384
Perceived Ease of Use	Pearson Correlation	.116**	1	.625**	.367**	.477**
	Sig. (2tailed)	.023		.000	.000	.000
	N	384	384	384	384	384
System Quality	Pearson Correlation	.230**	.625**	1	.545**	.562**
	Sig. (2tailed)	.000	.000		.000	.000
	N	384	384	384	384	384
Information Quality	Pearson Correlation	-.236**	.367**	.545**	1	.428**
	Sig. (2tailed)	.000	.000	.000		.000
	N	384	384	384	384	384
Consumer Purchase Intention	Pearson Correlation	.150**	.477**	.562**	.428**	1
	Sig. (2tailed)	.000	.000	.000	.000	.000
	N	384	384	384	384	384

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

Table 4.17 Pearson Correlation Results between Variables (Source: SPSS Output)

Table 4.17 shows the results of Pearson Correlation that analyse by using SPSS. Based on the table above, there are significant relationship between all of the variables including dependent and also independent variables as the significant output between the variables are 0.000. This is because when p-value is 0.05 and below can be consider as statistically (Jaadi, 2019). For independent variables included perceived usefulness, perceived ease of use, system quality and information quality with dependent variable which is consumer purchase intention, the analysis of Pearson Correlation through SPSS had shown 0.150, 0.477, 0.562, 0.428 respectively. According to table 4.13, the R-value in between 0.40 to 0.69 indicate that there are strong positive relationship between the dependent and independent variables. Hence, perceived ease of use, system quality and information quality can be concluded to have strong positive significant relationship with consumer purchase intention as the R-value are in between 0.40-0.69 and the Sig. (2-tailed) between these variables are 0.000. R-value in between 0.01 to 0.19 indicate that there are negligible relationship between the dependent and independent variables. Hence, perceived usefulness has negligible relationship with consumer purchase intention as the R-value are in between 0.01-0.19 and the Sig. (2-tailed) between these variables are 0.000.

4.7 Research Reliability Test

To ascertain the reliability of this study, data were collected from 384 respondents who responded to a questionnaire containing 16 questions related to independent variables: perceived usefulness, perceived ease of use, system quality, and information quality. Additionally, the questionnaire included 4 questions pertaining to the dependent variable, which is consumer purchase intention. The evaluation of research reliability relies on assessing the internal consistency using Cronbach's Alpha, as indicated in the analysis below.

Cronbach's Alpha	Internal Consistency
$0.5 > \alpha$	Unacceptable
$0.6 > \alpha \geq 0.5$	Poor
$0.7 > \alpha \geq 0.6$	Questionable
$0.8 > \alpha \geq 0.7$	Acceptable
$0.9 > \alpha \geq 0.8$	Good
$\alpha \geq 0.9$	Excellent

Table 4.18: Cronbach's Alpha Level Consistency

Table below shows the results of Cronbach's Alpha:

Variables	Cronbach's Alpha	Number of Items
Independent Variables		
1. Perceived Usefulness	0.849	4
2. Perceived Ease of Use	0.977	4
3. System Quality	0.983	4
4. Information Quality	0.988	4
Dependent Variables		
1. Consumer Purchase Intention	0.979	4
Overall	0.926	20

Table 4.19 Reliability Statistics

(Source: SPSS Output)

The table presented above illustrates the outcomes of the reliability test conducted using SPSS software. The evaluation is based on Cronbach's Alpha values, which are indicative of the internal consistency of the research variables. According to established criteria, a Cronbach's Alpha value exceeding 0.70 signifies a valid level of reliability. The reliability test reveals substantial Cronbach's Alpha values for all variables examined. Specifically, perceived ease of use yielded a Cronbach's Alpha value of 0.977, denoting an excellent level of consistency. Both system quality and information quality variables attained Cronbach's Alpha values of 0.983 and 0.988, respectively, placing them within the excellent range of reliability. Similarly, perceived ease of use obtained a Cronbach's Alpha value of 0.849, signifying an good level of internal consistency. The dependent variable, consumer purchase intention, acquired a Cronbach's Alpha value of 0.926, also indicating an excellent level of consistency.

Collectively, all variables demonstrated high levels of reliability, each scoring above 0.8 in Cronbach's Alpha. Consequently, the overall reliability test for this research yielded a Cronbach's Alpha value of 0.926, further confirming the excellent internal consistency of the research. Hence, based on this reliability assessment, this research can be concluded as highly reliable.

4.8 Multiple Regression Analysis

The execution of Multiple Linear Regression analysis, as referenced by Kenton (2020), has been employed in this research to ascertain the linear relationships between the dependent and independent variables. This statistical method facilitates the exploration of the connections between multiple independent variables and a dependent variable.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.609[a]	.371	.365	.77427

a. Predictors: (Constant), Perceived Usefulness, Perceived Ease of Use, System Quality, Information Quality

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	131.164	4	33.541	55.948	.000[b]
	Residual	227.211	379	.600		
	Total	361.375	383			

a. Dependent Variable: Consumer Purchase Intention

b. Predictors: (Constant), Information Quality, System Quality, Perceived Usefulness, Perceived Ease of Use

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.481	.400		-1.203	.230
	Perceived Usefulness (PU)	.187	.077	.113	2.425	.016
	Perceived Ease of Use (PEU)	.266	.069	.201	3.859	.000
	System Quality (SQ)	.398	.087	.289	4.591	.000
	Information Quality (IQ)	.236	.057	.224	4.132	.000

a. Dependent Variable: Consumer Purchase Intention

Table 4.20 Multiple Linear Regression

(Source: SPSS Output)

Based on the Model Summary analysis, the Coefficient for Multiple Determination, R Square, is observed to be 0.371. This indicates that approximately 37.1% of the variance in the dependent variable, consumer purchase intention, is accounted for by the independent variables: perceived usefulness, perceived ease of use, system quality, and information quality. The remaining 62.9% (100% - 37.1% = 62.9%) of the variance in consumer purchase intention is attributable to unexplored or unidentified factors. Furthermore, the obtained F value of 55.948, as indicated in the Anova Table, is accompanied by a significance value of 0.000. In alignment with Glen (2020), when the F value is substantial and the significance value is small, it signifies a significant relationship. Since the significance value is less than the alpha level of 0.05, it can be concluded that a statistically significant relationship exists between the independent variables, perceived usefulness, perceived ease of use, system quality and information quality, the dependent variable, consumer purchase intention.

The derived standard Multiple Linear Regression Equation is represented as follows:

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + \ldots + b_{p-1}x_{p-1} + b_px_p$$

By implementing the equation above, the linear equation below was developed based on the Beta coefficients in Table 4.17:

$$\text{Consumer Purchase Intention} = -0.481 + 0.187PU + 0.266PEU + 0.398SQ + 0.236IQ$$

The equation above had shown that the relationship between independent variables which are perceived usefulness, perceived ease of use, system quality and information quality on the dependent variables, consumer purchase intention are positive.

Based on the coefficient Beta, the perceived usefulness has higher contribution towards consumer purchase intention than other independent variables. This is because the contribution of the independent variable is larger when the value of the coefficient is larger.

4.9 Hypothesis Testing

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.481	.400		-1.203	.230
	Perceived Usefulness (PU)	.187	.077	.113	2.425	.016
	Perceived Ease of Use (PEU)	.266	.069	.201	3.859	.000
	System Quality (SQ)	.398	.087	.289	4.591	.000
	Information Quality (IQ)	.236	.057	.224	4.132	.000

a. Dependent Variable: Consumer Purchase Intention

Table 4.21 Multiple Linear Regression (Coefficient)

Hypothesis testing for this research are done by referring the p-value (significance value) in the table 4.21. When the p-value is larger than 0.05, the null hypothesis will be accepted. Oppositely, the null hypothesis will be rejected when the p-value is less than 0.05. In short

$p < 0.05$, **accept** alternative hypothesis,

$p > 0.05$, **reject** alternative hypothesis.

i) Perceived Usefulness: p-value=0.016

H0: There is no significant relationship between perceived usefulness of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between perceived usefulness of machine learning chatbot and consumer purchase intention.

As per the results observed in Table 4.21, the calculated p-value for perceived usefulness is determined to be 0.016, which is below the accepted threshold of 0.05. This outcome signifies a substantial relationship existing between perceived usefulness and consumer purchase intention. Consequently, the study accepts the alternative hypothesis (H1) and rejects the null hypothesis (H0), affirming the presence of a significant association between perceived usefulness and consumer purchase intention within the context of the research on factors influencing consumer purchase intentions related to machine learning chatbots in the fashion industry's e-commerce sector.

ii) Perceived Ease of Use: p-value=0.000

H0: There is no significant relationship between perceived ease of use of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between perceived ease of use of machine learning chatbot and consumer purchase intention.

Based on the findings observed in Table 4.21, the computed p-value associated with perceived ease of use is determined to be 0.000. This value below the accepted threshold of 0.05, indicating that there is sufficient evidence to support a significant relationship between perceived ease of use and consumer purchase intention. Consequently, the study reject the null hypothesis (H0) and accept the alternative hypothesis H2, suggesting a association between perceived ease of use and consumer purchase intention within the context of the research on factors influencing consumer purchase intentions related to machine learning chatbots in the fashion industry's e-commerce sector.

iii) System Quality: p-value=0.000

H0: There is no significant relationship between system quality of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between system quality of machine learning chatbot and consumer purchase intention.

Based on the observations recorded in Table 4.21, the calculated p-value corresponding to system quality is determined to be 0.000. This value is below the accepted threshold of 0.05, signifying robust evidence supporting a significant relationship between system quality and consumer purchase intention. As a result, the study rejects the null hypothesis (H0) and accepts the alternative hypothesis H3, affirming the presence of a substantial association between system quality and consumer purchase intention within the context of the research on factors influencing consumer purchase intentions related to machine learning chatbots in the fashion industry's e-commerce sector.

iv) Information Quality: p-value=0.000

H0: There is no significant relationship between information quality of machine learning chatbot and consumer purchase intention.

H1: There is significant relationship between information quality of machine learning chatbot and consumer purchase intention.

Based on the data observed in Table 4.21, the computed p-value associated with information quality is determined to be 0.000, falling below the accepted significance threshold of 0.05. This result provides evidence supporting a significant relationship between information quality and consumer purchase intention. Consequently, the study rejects the null hypothesis (H0) and accepts the alternative hypothesis H4, confirming a substantial association between information quality and consumer purchase intention within the context of the research on factors influencing consumer purchase intentions related to machine learning chatbots in the fashion industry's e-commerce sector.

Hypothesis	Results
H1: There is significant relationship between perceived usefulness of machine learning chatbot and consumer purchase intention.	Accepted
H2: There is significant relationship between perceived ease of use of machine learning chatbot and consumer purchase intention.	Accepted
H3: There is significant relationship between system quality of machine learning chatbot and consumer purchase intention.	Accepted
H4: There is significant relationship between information quality of machine learning chatbot and consumer purchase intention.	Accepted

Table 4.22: Summary for Hypothesis Testing

4.10 Conclusion

This chapter embarked on a exploration of relationships between independent variables, comprising perceived ease of use, perceived usefulness, system quality, and information quality, and the dependent variable, consumer purchase intention. The preliminary validation through a pilot test ensured the reliability and consistency of the survey instrument. The high Cronbach's Alpha coefficients obtained across all variables underscored the instrument's internal consistency, fortifying the credibility of the gathered data and validating its suitability for this investigation.

The descriptive statistics of the respondents unveiled notable demographic trends, highlighting the predominance of females within the sample, particularly in the age range of 18-29 years, and possessing tertiary education. The majority of respondents reported monthly household incomes below RM 2500. Pearson correlation analysis revealed strong positive relationships between perceived ease of use, perceived usefulness, system quality, information quality, and consumer purchase intention. However, it is noteworthy that while perceived usefulness, system quality, and information quality demonstrated substantial impact on consumer purchase intention, perceived ease of use did not exhibit a significant association within this context.

The multiple regression analysis unveiled the predictive capabilities of perceived usefulness, system quality, and information quality, elucidating their influence on consumer purchase intention. These variables collectively accounted for approximately 40% of the variance in consumer purchase intention, signifying their pivotal role as determinants in shaping consumer behavior. Moreover, hypothesis testing affirmed significant relationships between perceived usefulness, perceived ease of use, system quality, and information quality with consumer purchase intention, thereby supporting the formulated hypotheses. However, the hypothesis related to perceived ease of use did not find substantiating evidence in this study.

CHAPTER 5

DISCUSSION, IMPLICATION AND CONCLUSION

5.1 Introduction

In this chapter, the results and conclusions presented in Chapter 4, which covered Descriptive Statistic Analysis, Scale Measurement, Objective, and Hypothesis Exploration are thoroughly discussed. The main point begins with a brief summary of the information and conclusions derived from descriptive statistical analysis. After that, the next section goes over the specifics of scale measurement and outlines the calibrated metrics used in this research.

In addition, this chapter examines how the stated goals and the associated hypotheses align, contrasting the findings of the analysis with the original research proposals. Moreover, it deftly analyses the implications derived from this study, emphasising their applicability and importance in the context of consumer purchase intentions in the e-commerce segment of the fashion industry. Furthermore, this chapter aims to outline the course for future research by putting forth suggestions that encompass possible directions for additional investigation and improvement in this area.

5.2 Descriptive Statistic Analysis Summary

The data presented across tables and figures define the demographic distribution among the 384 respondents engaged through the Google Forms questionnaire. Gender distribution revealed that 54.70% (210 individuals) identified as female, while 45.30% (174 individuals) identified as male, showcasing a discernible gender disparity within the sampled cohort. Age-wise distribution unveils that a substantial majority, constituting 78.60% (302 individuals), falls within the age bracket of 18-29 years. Notably, 10.90% (42 respondents) are below 18 years old, and 10.40% (40 individuals) fall within the 30-39 age group. Remarkably, the dataset did not encompass respondents aged 40 years or older, highlighting a distinct concentration within the younger age cohorts.

Educational attainment showcased a dominant presence of tertiary education, encompassing 89.30% (343 individuals) of the sample. Contrastingly, Pre-university education accounted for 10.40% (40 respondents), while only one individual reported secondary education, comprising a marginal 0.3% of the total respondents. This substantial predominance of tertiary education attainment underscores the influence of factors such as digital literacy, potentially more prevalent among university students. Analysis of household income distribution illustrates that 40.60% (156 individuals) reported a household income below RM 2500, followed by 33.30% (128 respondents) indicating no household income. Additionally, 20.80% (80 individuals) fell within the income range of RM 2501 to RM 5000, while 5.2% (20 individuals) reported a household income between RM 5001 and RM 10,000.

5.3 Scale of Measurement

5.3.1 Research Validity

By examining the correlations between a number of independent variables, perceived risk, perceived usefulness, system quality, and information quality and the dependent variable, consumer purchase intention, the research validity was established. According to the results, system quality outperforms other independent variables with the highest Pearson Correlation coefficient of 0.562. On the other hand, the Pearson Correlation coefficients for perceived usefulness, perceived ease of use, and information quality are 0.150, 0.477, and 0.428, respectively. Notably, perceived usefulness has the lowest correlation score (0.150).

Regarding the dependent variable, this analysis highlights a strong positive correlation between perceived usefulness, perceived ease of use, system quality, and information quality. However, all of the calculated correlation coefficients between the variables in question produced statistically significant results of 0.000, which is less than the accepted cutoff of 0.05. As a result, it can be concluded that these variables have a strong and statistically significant relationship.

5.3.2 Research Reliability

During the pilot test phase, reliability testing was started to evaluate the consistency of the questionnaire. The dataset containing replies from 384 participants was then subjected to a thorough reliability test in order to assess the general reliability of this study. The system quality, information quality, perceived usefulness, and perceived ease of use all provided Cronbach's Alpha coefficients of 0.849, 0.977, 0.983, and 0.988, respectively. Furthermore, a cumulative Cronbach's Alpha coefficient of 0.926 is computed for the total output. These Cronbach's Alpha values, which are noticeably higher than the 0.80 threshold, indicate that the constructs being studied have a high degree of internal consistency and reliability.

5.4 Discussion

5.4.1 General Objective 1: To identify the factors of machine learning chatbot in influencing consumer purchase intention in fashion industry.

Objective of this research is to discern and comprehend the determinants impacting consumer purchase intentions within the domain of fashion industry e-commerce, focusing particularly on machine learning chatbots. Previous scholarly investigations and the foundational framework of Technology Acceptance Model (TAM) guided the exploration to pinpoint significant factors affecting consumer behaviors. Several factors were considered in shaping consumer purchase intentions within the machine learning chatbots operating in the fashion industry e-commerce. These factors encompassed perceived usefulness, perceived ease of use, system quality, and information quality. The utilization of Multiple Regression Analysis enabled the evaluation of these factors to discern their individual impacts on consumer purchase intentions. The outcomes derived from this analysis were instrumental in verifying the hypotheses postulated for this research.

The findings of the Multiple Regression Analysis unveiled compelling evidence supporting the influence of perceived usefulness, perceived ease of use, system quality, and information quality on consumer purchase intentions in the fashion industry e-commerce facilitated by machine learning chatbots. Notably, perceived ease of use emerged as the primary determinant significantly affecting consumer purchase intentions, as substantiated by its low p-value (0.000) obtained through Multiple Regression Analysis. Similarly, system quality, and information quality showcased substantial impacts, with respective p-values of 0.000, and 0.000, affirming their significant relationships with consumer purchase intentions within this specific e-commerce domain. Notably, perceived usefulness demonstrates a significant relationship with consumer purchase intentions, supported by a p-value not exceeding the threshold of significance (0.05), which is 0.016.

Therefore, based on the outcomes of the Hypothesis Testing and the scrutiny of the significance levels associated with each factor, this research substantiates that perceived usefulness, perceived ease of use, system quality, and information quality are influential determinants significantly shaping consumer purchase intentions within the fashion industry's e-commerce.

An earlier study (Hanjaya et al., 2019b) uses mobile apps to look at important factors influencing consumers' intentions to make online purchases in Singapore and Indonesia. It highlights the connection between customer purchase intentions and perceived usefulness, system quality, information quality, and ease of use. According to the study, information usefulness and quality have a big impact on Indonesian consumers' online buying decisions. Extensive and precise product information improves user experiences and builds trust, which influences usability and encourages customer interaction. Similar to this, in Singapore, purchase intentions are significantly influenced by service quality, usefulness, and ease of use. Easy of use sticks out in particular, demonstrating its significant impact. Along with ease of use, perceived usefulness also positively influences shopping experiences, and good customer service is a major factor in influencing the intention to make an online purchase.

5.4.2 Specific Objective 1: To determine the relationship between perceived usefulness of machine learning chatbot and consumer purchase intention in fashion industry.

This research aimed to discern the connection between the perceived usefulness of machine learning chatbots and consumer purchase intention. The analysis of the Multiple Linear Regression model divulged intriguing insights regarding the perceived usefulness of machine learning chatbots. The statistical significance, indicated by a p-value of 0.016 ($p < 0.05$), revealed a substantial positive relationship between perceived usefulness and consumer purchase intention. This aligns with prior studies (Hanjaya, 2019b) which also highlighted a similar affirmative correlation between perceived usefulness and consumer purchase intention in ecommerce.

These findings accentuate that consumers in the fashion industry's e-commerce are motivated to proceed with their purchasing actions when they perceive machine learning chatbots as valuable assets in their decision-making process. The convenience, efficiency, and support perceived from chatbots likely contribute significantly to enhancing consumer intention to purchase fashion-related items through online platforms. Therefore, it can be concluded that within the fashion industry's e-commerce, perceived usefulness plays a significant role in influencing consumer purchase intention concerning machine learning chatbots.

Notably, recent research has explored the fascinating world of online shopping consumer behaviour and shed light on the complex relationship between perceived usefulness and purchase intention. For example, a study by (Qing & Jin, 2022)revealed that perceived cost savings, perceived ease of use, and time savings do not directly influence purchase intention, but rather that perceived usefulness plays a crucial role in influencing consumers' intentions. (Budyastuti, 2019) conducted a study that examined the dynamics of e-commerce and demonstrated the beneficial effects of perceived usefulness, ease of use, and trust on user behaviour and purchase decisions. While these studies do not specifically describe the relationship between perceived usefulness and purchase intention, they do highlight the importance of perceived usefulness in influencing consumer attitudes and behaviours related to goods and services in the online shopping environment.

5.4.3 Specific Objective 2: To determine the relationship between perceived ease of use of machine learning chatbot and consumer purchase intention in fashion industry.

Interesting findings came from examining the relationship between customer purchase intention and the perceived ease of use (PEU) of machine learning chatbots in the e-commerce domain of the fashion industry. The study employed statistical methods like Pearson Correlation and Multiple Linear Regression to understand the connection between ease of use and consumer purchase intention in fashion industry ecommerce. The outcomes derived from Multiple Regression Analysis indicated a p-value of 0.000, does not surpassing the accepted threshold of 0.05. Regrettably, this result implies evidence supporting a significant association between perceived ease of use and consumer purchase intention.

Existing theories, such as those posited by (Pratista & Marsasi, 2023) have traditionally emphasized the crucial role of perceived ease of use in shaping consumer purchase intention in online shopping. The research conducted on factors influencing consumer purchase intention in using e-commerce platforms in Indonesia yielded insights that suggest a relationship between perceived ease of use and consumer purchase intention. In the apparel retail sector, chatbots have become vital for enhancing customer satisfaction, particularly during the COVID-19 pandemic. As online shopping increased and in-store interactions diminished, chatbots served as crucial communication channels, providing real-time assistance and addressing inquiries about product availability, sizes, shipping, and return policies. Their ability to deliver accurate and timely responses contributed to overall customer satisfaction (Solis-Quispe et al., 2021) . This highlights the importance of investigating the relationship between perceived ease of use and consumer purchase intention in online shoppin

5.4.4 Specific Objective 3: To determine the relationship between system quality of machine learning chatbot and consumer purchase intention in fashion industry.

Another factor that proposed in this research is system quality. System quality stands as a pivotal component, significantly influencing consumer purchase intention in fashion industry ecommerce in the context of machine learning chatbots.

The research findings, derived through Pearson Correlation analysis, underscored a substantial positive relationship between system quality and consumer purchase intention. The correlation coefficient obtained (0.485) between system quality and consumer purchase intention denotes a noteworthy and positive association. This relationship signifies that as the system quality of machine learning chatbots within the fashion industry's e-commerce improves, there is a proportionate enhancement in consumers' inclination toward making purchases through these chatbots.

The statistically significant p-value (0.000) associated with system quality in the hypothesis testing further validates this relationship. This result, being below the predetermined significance threshold, strengthens the assertion that there exists a substantial connection between system quality and consumer purchase intention. This outcome solidifies the premise that a well-functioning, reliable, and efficient system quality within machine learning chatbots directly influences consumers' intentions to engage and make purchases in the fashion industry's e-commerce.

Prior research has consistently highlighted the significant correlation between chatbot system quality and customer purchase intention in e-commerce. For example, (Hanjaya, 2019) found that system quality attributes have a significant effect on consumers' intention to use mobile app to make online purchases. Expanding on these well-established conclusions, this study specifically examines the relationship between machine learning chatbot system quality and customer purchase intention within the context of the fashion industry's e-commerce. The analysis shows a strong positive correlation that is consistent with the findings of the previously mentioned research, highlighting the crucial influence that system quality has on customers' choices in the fashion e-commerce industry.

The impact of information quality, system quality, and service quality on African consumers' purchase intentions in cross-border e-commerce (CBEC) is investigated by (L. Han et al., 2023). It emphasises perceived value and trust while highlighting the critical role of CBEC platform quality through the use of the ISS model. Results show that customers' perceived intention to buy is positively impacted by the quality of the information, system, and services. The study emphasises the critical relationship that exists in the CBEC platform between consumers' purchase intentions, perceived value, and trust. The moderating effect of acculturation levels is also taken into account, highlighting how these levels alter the way that system quality and CBEC platform information affect perceived value. This highlights the significance of earlier studies on the connection between system quality and online shoppers' intentions to make purchases.

From a practical standpoint, these results highlight the significance it is to invest in and improve the machine learning chatbots' system quality attributes in the fashion e-commerce space. It appears that enhancing system quality influences consumer purchase intentions in addition to creating a favourable consumer experience, which eventually affects the bottom line of companies in this industry.

5.4.5 Specific Objective 4: To determine the relationship between information quality of machine learning chatbot and consumer purchase intention in fashion industry.

This study also aimed to identify the significant relationship between the information quality offered by machine learning chatbots and the purchase intention of customers in fashion industry ecommerce. Based on the previous research from (Mandiri & Susila, 2023), there is evidence to suggest that perceived security, information quality, and consumer trust has a significant positive impact on e-commerce consumer purchase intention.

The Pearson Correlation analysis from this research revealed a positive and statistically significant relationship ($r = 0.428^{**}$, $p < 0.01$) between information quality and consumer purchase intention. This suggests a substantive association between the quality of information dispensed by machine learning chatbots and the inclination of consumers to engage in purchase activities within the fashion e-commerce domain. The observed correlation, substantiated by its significance level, accentuates the influential role of information quality as a determinant factor in stimulating consumer purchase intention.

Multiple Linear Regression underscored the contribution of information quality ($\beta = 0.255$, $p < 0.001$) in determining consumer purchase intention. This statistical model reinforced the significant impact of information quality, elucidating its positive effect on consumer purchase intention within the fashion industry's e-commerce. The linear equation derived from the regression model exemplifies that an increase in information quality corresponds to an inclination toward consumer purchase intention, emphasizing its constructive influence.

The outcomes of this study align with prior investigations conducted by (Mustika & Arifin, 2021) and (Kusdyah Rachmawati, 2019) revealing a positive and substantial correlation between information quality and purchase intentions. The clarity, accuracy, and relevance of information emerge as critical elements influencing consumer buying interest. Both high and low levels of information quality significantly shape perceptions of the company and its products. To effectively stimulate consumer buying interest, it is imperative to ensure that the presented information meets standards of clarity, accuracy, and relevance. The empirical analysis affirms a positive and substantial impact of information quality on purchase intentions.

The findings converge to assert that high-quality information provision by machine learning chatbots significantly influences and nurtures consumer inclinations towards purchasing within the fashion industry's e-commerce domain.

Consumers are evidently responsive to information quality, showcasing a positive inclination to engage in purchase activities when exposed to enhanced and reliable information dissemination facilitated by machine learning chatbots.

5.4.6 To determine the most significant machine learning chatbots' factors in influencing consumer purchase intention in fashion industry.

Following the exploration of various factors influencing consumer purchase intention in the fashion industry's e-commerce domain driven by machine learning chatbots, the research also delineate the most prominent factors significantly impacting consumer purchase intention. The study employed statistical analyses, including Pearson Correlation, Multiple Regression Analysis, and Hypothesis Testing, to unravel the intricate relationship between perceived usefulness, perceived ease of use, system quality, information quality, and their impact on consumer purchase intention.

The findings from Pearson Correlation analysis unveiled compelling insights into the relationships among these factors and consumer purchase intention. Notably, perceived usefulness, system quality, and information quality demonstrated substantial positive correlations with consumer purchase intention. Specifically, system quality exhibited a strong positive relationship ($r = 0.562$), suggesting its pivotal role in influencing consumers' inclination to engage and make purchases through machine learning chatbots in the fashion e-commerce sphere. Similarly, both perceived ease of use ($r = 0.477$) and information quality ($r = 0.428$) manifested noteworthy positive correlations with consumer purchase intention, underlining the importance of seamless system functionality and access to quality information in shaping purchasing decisions.

The results from Multiple Regression Analysis revealed the beta coefficients, shedding light on the relative significance of each variable. Notably, system quality

(SQ) emerged with the highest beta value of 0.289, signifying its substantial impact on influencing consumer purchase intention. This result suggests that system quality plays a pivotal role in shaping consumers' inclination to engage and make purchases through machine learning chatbots in the fashion e-commerce landscape.

In conclusion, the research pinpoints system quality as the foremost factor significantly impacting consumer purchase intention in fashion industry e-commerce facilitated by machine learning chatbots. A study by (Hanjaya, 2019b) also show that system quality had significant relationship with consumer purchase intention in ecommerce.

5.5 Implication of Research

This research extends the existing literature on consumer behavior in fashion industry e-commerce by focusing on machine learning chatbots. While previous studies have primarily concentrated on traditional e-commerce or specific geographic regions, this study broadens the scope to encompass the influence of machine learning chatbots in the context of the fashion industry. The findings contribute to the theoretical framework by emphasizing the significance of perceived usefulness, perceived ease of use, system quality, and information quality as determinants of consumer purchase intention in fashion e-commerce facilitated by machine learning chatbots. This expands the application of the Technology Acceptance Model (TAM) to a specific niche within the e-commerce sector.

Moreover, the study validates and enriches existing theories, particularly TAM, by highlighting the individual impacts of perceived usefulness, perceived ease of use, system quality, and information quality. The robust statistical analysis, including Pearson Correlation and Multiple Linear Regression, strengthens the empirical evidence supporting the relevance of these factors in shaping consumer behavior. The identification of system quality as the foremost factor significantly impacting consumer purchase intention provides a nuanced understanding within the theoretical framework, aligning with previous research (Hanjaya, 2019b) while specifically focusing on machine learning chatbots in the fashion e-commerce domain.

For businesses operating in the fashion e-commerce sector, the practical implications of this research are profound. The study underscores the importance of investing in enhancing the perceived ease of use, system quality, and information quality of machine learning chatbots. Recognizing the dominant influence of perceived ease of use, businesses are encouraged to prioritize user-friendly features and undertake educational initiatives to familiarize consumers with the benefits of chatbots. Strategic chatbot design becomes imperative, aligning features with consumer expectations to foster increased engagement and purchase intentions.

System quality emerges as a critical factor influencing consumer decisions, emphasizing the need for continuous investment in maintaining high-quality and reliable chatbot systems. The study highlights that a well-functioning, reliable, and efficient system significantly influences consumers' intentions to engage and make purchases in the fashion e-commerce sector. This practical insight directs businesses to focus on optimizing the functionality, efficiency, and reliability of machine learning chatbots, creating a seamless and trustworthy user experience.

Information quality, as revealed by the study, plays a pivotal role in shaping consumer purchase intentions. E-commerce platforms are advised to prioritize accuracy, clarity, and relevance in information dissemination, building trust and positively influencing purchase decisions. The clarity, accuracy, and relevance of information emerge as critical elements influencing consumer buying interest, emphasizing the need for comprehensive and reliable product information provided by machine learning chatbots.

In conclusion, businesses in the fashion e-commerce sector can leverage the insights from this research to strategically enhance their machine learning chatbot systems, optimize information quality, and prioritize user-friendly design. As technology continues to evolve, adapting to consumer preferences and expectations is crucial for sustainable growth and success in the competitive landscape of fashion e-commerce.

5.6 Limitation of Research

One significant limitation of this study is the focus on a specific geographical location, Malaysia, which might limit the generalizability of the findings. The respondents were exclusively from Malaysia, thereby potentially constraining the representation of diverse cultural and market-specific factors that might influence consumer behaviors in other regions or countries. Cultural nuances and variations in technological penetration across different demographics could influence consumer behaviors differently, thereby limiting the generalizability of the findings beyond the specific context of Malaysia. Furthermore, restricting respondents to individuals engaging with fashion industry e-commerce or those specifically hashtagging certain brands on social media platforms like Uniqlo might introduce sampling biases, thereby reducing the overall representativeness of the sample.

Another limitation of this research is this study primarily targeted individuals interacting with the fashion industry's e-commerce platforms. This selection criterion might have overlooked potential consumers who do not actively engage on social media or use hashtags, consequently excluding a segment of the population that might hold different perspectives or behaviors towards fashion e-commerce and machine learning chatbots.

The research focused on specific factors such as perceived usefulness, system quality, information quality, and perceived ease of use, potentially overlooking other relevant variables that could also impact consumer purchase intentions within the fashion industry's e-commerce powered by machine learning chatbots. Factors like brand loyalty, price sensitivity, or social influence could also play significant roles but were not considered in this study.

In summary, while this research sheds light on factors impacting consumer purchase intentions in fashion industry e-commerce utilizing machine learning chatbots, its limitations, including geographical constraints, selective sampling, potential biases in data collection. Future research should aim to address these limitations by employing more diverse and representative samples and considering a broader spectrum of influencing factors to achieve more comprehensive insights.

5.7 Recommendations for Future Research

The study conducted on factors influencing consumer purchase intentions within the fashion industry's e-commerce powered by machine learning chatbots has provided significant insights. However, to deepen our understanding and address the limitations identified in this research, there are several recommendations for future research.

Expanding the scope of data collection for future research on factors influencing consumer purchase intention in the fashion industry's e-commerce with machine learning chatbots is a crucial recommendation. This entails reaching beyond the confines of social media and e-commerce users. The rationale behind this recommendation is rooted in the need for a more representative sample that encapsulates a broader spectrum of consumer behaviors and preferences. By incorporating respondents from varied channels, such as individuals engaged in traditional retail practices, those who prefer offline shopping experiences, or those with limited social media involvement, researchers can mitigate potential bias introduced by an exclusive focus on particular online platforms. This diversified approach ensures a comprehensive understanding of consumer perspectives, enriching the research findings with insights from individuals who may not align with the typical e-commerce or social media user profiles.

Besides, to overcome the limitations of geographical restriction and limited scope of respondents, future studies should aim for a more diverse and inclusive demographic representation. Expanding the sample to include participants from various age groups, income brackets, education levels, and geographic locations beyond Malaysia could provide a more comprehensive understanding of how different demographics perceive and interact with machine learning chatbots in fashion e-commerce. This broadened scope would offer insights into varied consumer behaviors influenced by demographic factors.

While this research has focused on perceived usefulness, system quality, information quality, and perceived ease of use, future studies should delve into other pertinent variables that might impact consumer purchase intentions in fashion e-commerce driven by machine learning chatbots. Factors like brand loyalty, social influence, emotional appeal, or environmental concerns could be explored to gauge their significance in shaping consumer behaviors and purchase decisions within this specific context. By considering a wider array of variables, researchers can achieve a more holistic understanding of consumer behavior in this domain.

Another avenue for future research involves conducting a comparative analysis among different e-commerce platforms within the fashion industry. Comparing the effectiveness of machine learning chatbots in influencing consumer purchase intentions across various platforms such as fashion retail websites, social media-driven e-commerce, could reveal nuances in user behavior and preferences. Understanding how different platforms leverage chatbot technology to impact consumer intentions can guide businesses in optimizing their strategies and enhancing user experiences across different platforms.

Given the rapid evolution of technology and consumer behaviors, future research should consider longitudinal studies to track the changing dynamics of consumer purchase intentions in fashion e-commerce powered by machine learning chatbots over time. Continuous monitoring and assessment of technological advancements, improvements in chatbot functionalities, and shifts in consumer preferences will provide valuable insights into the evolving landscape. Longitudinal studies can capture trends, adaptations, and emerging factors that influence consumer behaviors, offering a dynamic perspective for businesses to adapt and innovate.

In conclusion, these recommendations pave the way for future research endeavors to broaden and deepen our understanding of the multifaceted factors influencing consumer purchase intentions in fashion e-commerce powered by machine learning chatbots. Embracing a more comprehensive approach encompassing diverse demographics, cultural contexts, variables, and longitudinal perspectives will contribute significantly to the advancement of knowledge in this dynamic domain.

5.8 Conclusions

The journey through this study, examining the factors infleuncing consumer purchase intentions in the fashion industry's e-commerce domain facilitated by machine learning chatbots, has provided multifaceted insights into the intricate web of influences governing consumer behaviors. Through meticulous analysis and exploration of demographic distributions, validity, reliability assessments, and hypothesis testing, this research has unearthed pivotal determinants and their consequential impacts on consumer purchase intentions.

The descriptive statistics highlighted a concentrated demographic within younger age groups, predominantly tertiary-educated individuals, and varying income brackets, illuminating essential demographic aspects influencing the study's outcomes. Subsequently, the scale measurement confirmed the validity and reliability of the constructs, ensuring the robustness of the research model.

Besides, discussion of the research objectives revealed compelling evidence affirming the influence of perceived usefulness, perceived ease of use, system quality, and information quality on consumer purchase intentions within the fashion industry's e-commerce powered by machine learning chatbots.

This research contributes significantly to the understanding of factors influencing consumer purchase intentions in the fashion industry's e-commerce powered by machine learning chatbots. By emphasizing perceived usefulness, perceived ease of use, system quality, and information quality, this study serves as a roadmap for businesses to refine chatbot strategies, enhance user experiences, and foster favorable consumer behaviors in this dynamic digital marketplace. This research journey also illuminates a path forward, guiding future studies towards a deeper understanding of consumer behaviors and technological adaptations, propelling businesses into a future where machine learning chatbots effectively orchestrate seamless, value-driven e-commerce experiences within the fashion industry.

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APPENDIX_A

1. Gantt Chart- PSM 1

Task	Week														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
FYP 1 briefing															
Meeting with supervisor															
PSM Title proposal															
Collect information related to project title															
Chapter 1 preparation															
Chapter 1 Correction															
Chapter 2 Preparation															
Chapter 2 Correction															
Chapter 3 Preparation															
Chapter 3 Correction															
Submission draft full report PSM 1 to supervisor															
Correction full report PSM 1															
Submission for Full Report FYP 1															
FYP 1 Presentation															
Revised FYP 1 with Supervisor															
Submission FYP 1															

2. Gantt Chart- PSM 2

Task	Week														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Meeting with supervisor															
Questionnaire preparation															
Questionnaire Correction															
Questionnaire Distribution															
Collecting Data															
Chapter 4 Preparation															
Chapter 5 Preparation															
Chapter 4 and 5 Correction															
Submission FYP 2 Full Report															
FYP 2 Presentation															
FYP 2 Correction															
Submission full FYP															

APPENDICES B

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Dear Valued Participants,

I am Thean Kah Keat, an undergraduate student currently pursuing a Bachelor's degree in Technology Management with a specialization in High Technology Marketing at Universiti Teknikal Malaysia Melaka. This research project constitutes an essential requirement for the successful completion of my degree within the Fakulti Pengurusan Teknologi dan Teknousahawan at Universiti Teknikal Malaysia Melaka. The primary aim of this research is to explore the various factors that influence consumers' purchase intentions in the context of machine learning chatbots in the e-commerce sector of the fashion industry.

This questionnaire is structured into three sections: Section A, Section B, and Section C. In sections B and C, respondents will provide their feedback using a five-point Likert scale (1 = Strongly Disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly Agree). Completing this questionnaire should require only 5-10 minutes of your valuable time.

We want to assure you that your responses will be kept strictly confidential, and the information collected will be used exclusively for academic purposes. Your participation and valuable insights are greatly appreciated. Thank you for your cooperation.

Section A: Demographic Profile

In this section, we kindly request you to provide some basic information about yourself. Your responses will help us understand the characteristics of our respondents and will be essential for the analysis of this research. Please answer the following questions honestly and to the best of your knowledge.

1. Gender
• **Male** • **Female**
2. Age
• **Below 18 years** • **18-29 years** • **30-39 years** • **40 and above**
3. Education level
• **Secondary** • **Pre- university** • **Tertiary**
4. Monthly Income
• **No Income** • **Less than RM 2500** • **RM 2501 – RM 5000** • **RM 5001 – RM 10,000**

• **More than RM 10,000**
5. Do you shop for fashion items online?
• **Yes** • **No**
6. Have you ever interacted with a chatbot in an online shopping context?
• **Yes** • **No**

Section B: Factors influence consumers' purchase intentions in the context of machine learning chatbots in the e-commerce sector of the fashion industry.

In this section, we would like to understand your perceptions of the machine learning chatbot in the context of fashion e-commerce. Please rate the following statements based on your experiences and perceptions. Use a 5-point Likert scale, where 1 indicates "Strongly Disagree" and 5 indicates "Strongly Agree."

Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Disagree**
1	**2**	**3**	**4**	**5**

No.	**Item**	**1**	**2**	**3**	**4**	**5**
	Perceived Usefulness					

1.	**It is easy to purchase product from fashion industry ecommerce that come with a machine learning chatbot.**					
2.	**Machine learning chatbot in fashion industry ecommerce can improve my shopping efficiency**					
3.	**Machine learning chatbot in fashion industry ecommerce able to help me to discover good products.**					
4.	**Machine learning chatbot in fashion industry ecommerce saved my time to go shopping.**					
	Perceived Ease of Use					
1.	**Learn how to operate fashion ecommerce platform that come with machine learning chatbot is very easy.**					
2.	**Interaction with machine learning chatbot in fashion industry is very simple and easy to be understood.**					
3.	**Machine learning chatbots make my shopping experience in fashion industry's e-commerce sector easier.**					
4.	**Using a machine learning chatbot makes it really simple to accomplish what you want.**					
	System Quality					
1.	**Machine learning chatbot in fashion industry ecommerce platform could be used to suit different needs.**					

2.	**Machine learning chatbot in fashion industry ecommerce platform could be easily used anytime.**					
3.	**Machine learning chatbot in fashion industry ecommerce platform seemed to be a high level of technology**					
4.	**Machine learning chatbot in fashion industry ecommerce platform is a reliable system.**					
	Information Quality					
1.	**Machine learning chatbot in fashion industry ecommerce platform can provide me customise information.**					
2.	**Machine learning chatbot in fashion industry ecommerce platform can provide me information that meets my specific needs.**					
3.	**Machine learning chatbot provide helpful information.**					
4.	**Machine learning chatbot provide up-to-date information.**					

Section C: Consumer Purchase Intention

In this section, we would like to understand your purchase intentions regarding fashion items within the context of machine learning chatbots. Please rate the following statements based on your purchase intentions. Use a 5-point Likert scale, where 1 indicates "Strongly Disagree" and 5 indicates "Strongly Agree."

No	Item	1	2	3	4	5
1.	**I would be willing to purchase product from fashion ecommerce platform that come with chatbot service.**					
2.	**I would recommend my friends to use fashion ecommerce platform that come with chatbot service.**					
3.	**I want to use machine learning chatbot again.**					
4.	**I will remain to use the chatbot rather than call human customer service.**					

APPENDIX C

Correlations

		iv1	iv2	iv3	iv4	dv
iv1	Pearson Correlation	1	.116*	.230**	-.236**	.150**
	Sig. (2-tailed)		.023	.000	.000	.003
	N	384	384	384	384	384
iv2	Pearson Correlation	.116*	1	.625**	.367**	.477**
	Sig. (2-tailed)	.023		.000	.000	.000
	N	384	384	384	384	384
iv3	Pearson Correlation	.230**	.625**	1	.545**	.562**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	384	384	384	384	384
iv4	Pearson Correlation	-.236**	.367**	.545**	1	.428**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	384	384	384	384	384
dv	Pearson Correlation	.150**	.477**	.562**	.428**	1
	Sig. (2-tailed)	.003	.000	.000	.000	
	N	384	384	384	384	384

*. Correlation is significant at the 0.05 level (2-tailed).

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


```
RELIABILITY
 /VARIABLES=Perceived_UsefulnessNoName @_ @_1
 /SCALE('ALL VARIABLES') ALL
 /MODEL=ALPHA
 /STATISTICS=DESCRIPTIVE
 /SUMMARY=TOTAL.
```

Reliability

Notes

Output Created		06-JAN-2024 18:43:22
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=Perceived_Usefulness NoName @_@_1 /SCALE('ALL VARIABLES') ALL /MODEL=ALPHA /STATISTICS=DESCRIPTIVE /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.849	4

Item Statistics

	Mean	Std. Deviation	N
Perceived Usefulness	4.3698	.71077	384
NoName	4.2708	.70402	384
	4.6146	.69492	384
1	4.6120	.72836	384

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Perceived Usefulness	13.4974	3.368	.639	.828
NoName	13.5964	3.495	.589	.848
	13.2526	3.192	.752	.780
1	13.2552	3.042	.775	.768


```
RELIABILITY
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 /SCALE('ALL VARIABLES') ALL
 /MODEL=ALPHA
 /STATISTICS=DESCRIPTIVE
 /SUMMARY=TOTAL.
```

Reliability

Notes

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	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=Perceived_Ease_of_Use @_2 @_3 @_4 /SCALE('ALL VARIABLES') ALL /MODEL=ALPHA /STATISTICS=DESCRIPTIVE /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.977	4

Item Statistics

	Mean	Std. Deviation	N
Perceived Ease of Use	3.4479	.66811	384
2	3.4583	.65702	384
3	3.5990	.84619	384
4	3.6068	.84832	384

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Perceived Ease of Use	10.6641	5.320	.942	.974
2	10.6536	5.344	.952	.972
3	10.5130	4.491	.965	.966
4	10.5052	4.496	.960	.968


```
RELIABILITY
 /VARIABLES=System_Quality NoName1 NoName2 NoName3
 /SCALE('ALL VARIABLES') ALL
 /MODEL=ALPHA
 /STATISTICS=DESCRIPTIVE
 /SUMMARY=TOTAL.
```

Reliability

Notes

Output Created		06-JAN-2024 18:44:38
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=System_Quality NoName1 NoName2 NoName3 /SCALE('ALL VARIABLES') ALL /MODEL=ALPHA /STATISTICS=DESCRIPTIVE /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.983	4

Item Statistics

	Mean	Std. Deviation	N
System Quality	3.8151	.80772	384
NoName1	3.8255	.81004	384
NoName2	3.9609	.91179	384
NoName3	3.9661	.91200	384

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
System Quality	11.7526	6.678	.950	.979
NoName1	11.7422	6.646	.956	.977
NoName2	11.6068	6.119	.963	.975
NoName3	11.6016	6.120	.963	.976


```
RELIABILITY
 /VARIABLES=Information_QualityNoName4 NoName5 NoName6
 /SCALE('ALL VARIABLES') ALL
 /MODEL=ALPHA
 /STATISTICS=DESCRIPTIVE
 /SUMMARY=TOTAL.
```

Reliability

Notes

Output Created		06-JAN-2024 18:44:52
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=Information_Quality NoName4 NoName5 NoName6 /SCALE('ALL VARIABLES') ALL /MODEL=ALPHA /STATISTICS=DESCRIPTIVE /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.988	4

Item Statistics

	Mean	Std. Deviation	N
Information Quality	3.9688	.90491	384
NoName4	3.9714	.90355	384
NoName5	4.1120	.97513	384
NoName6	4.1172	.97451	384

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Information Quality	12.2005	7.894	.968	.984
NoName4	12.1979	7.903	.967	.984
NoName5	12.0573	7.501	.970	.983
NoName6	12.0521	7.506	.970	.983


```
RELIABILITY
 /VARIABLES=@_Consumer_Purchase_Intention NoName7 NoName8 NoName9
 /SCALE('ALL VARIABLES') ALL
 /MODEL=ALPHA
 /STATISTICS=DESCRIPTIVE
 /SUMMARY=TOTAL.
```

Reliability

Notes

Output Created		06-JAN-2024 18:45:03
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=@_Consumer_Purchase_Intention NoName7 NoName8 NoName9 /SCALE('ALL VARIABLES') ALL /MODEL=ALPHA /STATISTICS=DESCRIPTIVE /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.979	4

Item Statistics

	Mean	Std. Deviation	N
Consumer Purchase Intention	3.6875	.94565	384
NoName7	3.7552	1.02322	384
NoName8	3.8620	1.01899	384
NoName9	3.8646	1.01806	384

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Consumer Purchase Intention	11.4818	9.154	.882	.988
NoName7	11.4141	8.395	.954	.969
NoName8	11.3073	8.328	.974	.964
NoName9	11.3047	8.333	.975	.964


```
RELIABILITY
 /VARIABLES=iv1 iv2 iv3 iv4 dv
 /SCALE('ALL VARIABLES') ALL
 /MODEL=ALPHA
 /STATISTICS=DESCRIPTIVE
 /SUMMARY=TOTAL.
```

Reliability

Notes

Output Created		06-JAN-2024 18:46:04
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=iv1 iv2 iv3 iv4 dv /SCALE('ALL VARIABLES') ALL /MODEL=ALPHA /STATISTICS=DESCRIPTIVE /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.717	5

Item Statistics

	Mean	Std. Deviation	N
iv1	4.4668	.58849	384
iv2	3.5280	.73607	384
iv3	3.8926	.70434	384
iv4	4.0423	.92312	384
dv	3.7923	.97136	384

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
iv1	15.2552	6.908	.067	.786
iv2	16.1940	4.991	.586	.629
iv3	15.8294	4.649	.763	.564
iv4	15.6797	4.890	.421	.699
dv	15.9297	4.126	.606	.611


```
 RELIABILITY
  /VARIABLES=Perceived_UsefulnessNoName @_ @_1 Perceived_Ease_of_Use@_2 @_3
@_4 System_Quality
    NoName1 NoName2 NoName3 Information_QualityNoName4 NoName5 NoName6 @_Cons
umer_Purchase_Intention
    NoName7 NoName8 NoName9
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE
  /SUMMARY=TOTAL.
```

Reliability

Notes

Output Created		06-JAN-2024 18:46:23
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=Perceived_Usefulness NoName @_@_1 Perceived_Ease_of_Use @_2 @_3 @_4 System_Quality NoName1 NoName2 NoName3 Information_Quality NoName4 NoName5 NoName6 @_Consumer_Purchase_Intention NoName7 NoName8 NoName9 /SCALE('ALL VARIABLES') ALL /MODEL=ALPHA /STATISTICS=DESCRIPTIVE /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	384	100.0
	Excluded[a]	0	.0
	Total	384	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.926	20

Item Statistics

	Mean	Std. Deviation	N
Perceived Usefulness	4.3698	.71077	384
NoName	4.2708	.70402	384
	4.6146	.69492	384
1	4.6120	.72836	384
Perceived Ease of Use	3.4479	.66811	384
2	3.4583	.65702	384
3	3.5990	.84619	384
4	3.6068	.84832	384
System Quality	3.8151	.80772	384
NoName1	3.8255	.81004	384
NoName2	3.9609	.91179	384
NoName3	3.9661	.91200	384
Information Quality	3.9688	.90491	384
NoName4	3.9714	.90355	384
NoName5	4.1120	.97513	384
NoName6	4.1172	.97451	384
Consumer Purchase Intention	3.6875	.94565	384
NoName7	3.7552	1.02322	384
NoName8	3.8620	1.01899	384
NoName9	3.8646	1.01806	384

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Perceived Usefulness	74.5156	119.801	.216	.929
NoName	74.6146	118.170	.327	.927
	74.2708	120.866	.151	.930
1	74.2734	120.565	.161	.930
Perceived Ease of Use	75.4375	113.129	.710	.921
2	75.4271	113.008	.732	.921
3	75.2865	110.226	.716	.920
4	75.2786	110.160	.718	.920
System Quality	75.0703	110.718	.723	.920
NoName1	75.0599	110.615	.727	.920
NoName2	74.9245	107.877	.790	.918
NoName3	74.9193	107.834	.792	.918
Information Quality	74.9167	113.403	.490	.925
NoName4	74.9141	113.416	.490	.925
NoName5	74.7734	110.583	.591	.923
NoName6	74.7682	110.560	.593	.923
Consumer Purchase Intention	75.1979	108.786	.709	.920
NoName7	75.1302	106.693	.753	.919
NoName8	75.0234	107.182	.732	.920
NoName9	75.0208	107.195	.732	.920


```
REGRESSION
 /DESCRIPTIVES MEAN STDDEV CORR SIG N
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT dv
 /METHOD=ENTER iv1 iv2 iv3 iv4
 /SCATTERPLOT=(*ZRESID ,*ZPRED)
 /RESIDUALS NORMPROB(ZRESID)
 /SAVE PRED ZPRED RESID ZRESID.
```

Regression

Notes

Output Created		06-JAN-2024 18:47:20
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /DESCRIPTIVES MEAN STDDEV CORR SIG N /MISSING LISTWISE /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT dv /METHOD=ENTER iv1 iv2 iv3 iv4 /SCATTERPLOT=(*ZRESID ,*ZPRED) /RESIDUALS NORMPROB(ZRESID) /SAVE PRED ZPRED RESID ZRESID.
Resources	Processor Time	00:00:01.13
	Elapsed Time	00:00:00.91
	Memory Required	12624 bytes
	Additional Memory Required for Residual Plots	288 bytes
Variables Created or Modified	PRE_1	Unstandardized Predicted Value
	RES_1	Unstandardized Residual

Notes

	ZPR_1	Standardized Predicted Value
	ZRE_1	Standardized Residual

Descriptive Statistics

	Mean	Std. Deviation	N
dv	3.7923	.97136	384
iv1	4.4668	.58849	384
iv2	3.5280	.73607	384
iv3	3.8926	.70434	384
iv4	4.0423	.92312	384

Correlations

		dv	iv1	iv2	iv3	iv4
Pearson Correlation	dv	1.000	.150	.477	.562	.428
	iv1	.150	1.000	.116	.230	-.236
	iv2	.477	.116	1.000	.625	.367
	iv3	.562	.230	.625	1.000	.545
	iv4	.428	-.236	.367	.545	1.000
Sig. (1-tailed)	dv	.	.002	.000	.000	.000
	iv1	.002	.	.011	.000	.000
	iv2	.000	.011	.	.000	.000
	iv3	.000	.000	.000	.	.000
	iv4	.000	.000	.000	.000	.
N	dv	384	384	384	384	384
	iv1	384	384	384	384	384
	iv2	384	384	384	384	384
	iv3	384	384	384	384	384
	iv4	384	384	384	384	384

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	iv4, iv1, iv2, iv3[b]	.	Enter

a. Dependent Variable: dv

b. All requested variables entered.

Model Summary[b]

					Change Statistics		
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1
1	.609[a]	.371	.365	.77427	.371	55.948	4

Model Summary[b]

	Change Statistics	
Model	df2	Sig. F Change
1	379	.000

a. Predictors: (Constant), iv4, iv1, iv2, iv3

b. Dependent Variable: dv

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	134.164	4	33.541	55.948	.000[b]
	Residual	227.211	379	.600		
	Total	361.375	383			

a. Dependent Variable: dv

b. Predictors: (Constant), iv4, iv1, iv2, iv3

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.481	.400		-1.203	.230
	iv1	.187	.077	.113	2.425	.016
	iv2	.266	.069	.201	3.859	.000
	iv3	.398	.087	.289	4.591	.000
	iv4	.236	.057	.224	4.132	.000

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-1.268	.305		
	iv1	.035	.338	.762	1.313
	iv2	.130	.401	.609	1.643
	iv3	.227	.568	.420	2.381
	iv4	.123	.348	.565	1.770

a. Dependent Variable: dv

Residuals Statistics[a]

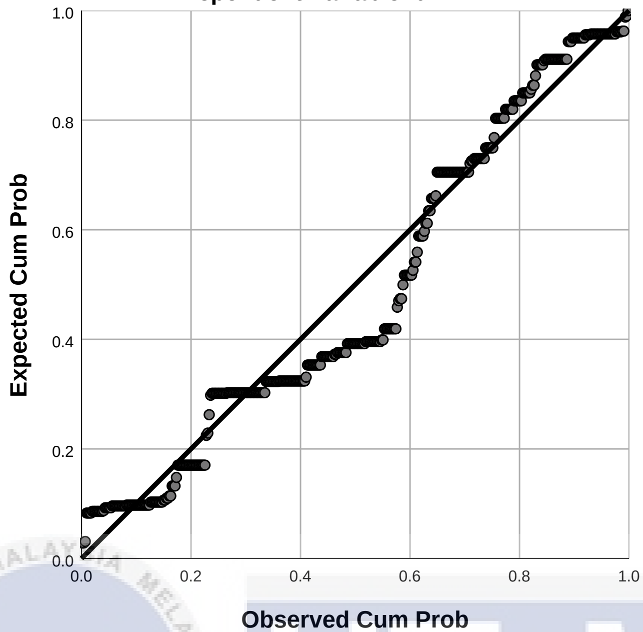
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.3520	4.9495	3.7923	.59186	384
Residual	-1.47716	2.64800	.00000	.77022	384
Std. Predicted Value	-4.123	1.955	.000	1.000	384
Std. Residual	-1.908	3.420	.000	.995	384

a. Dependent Variable: dv

Charts

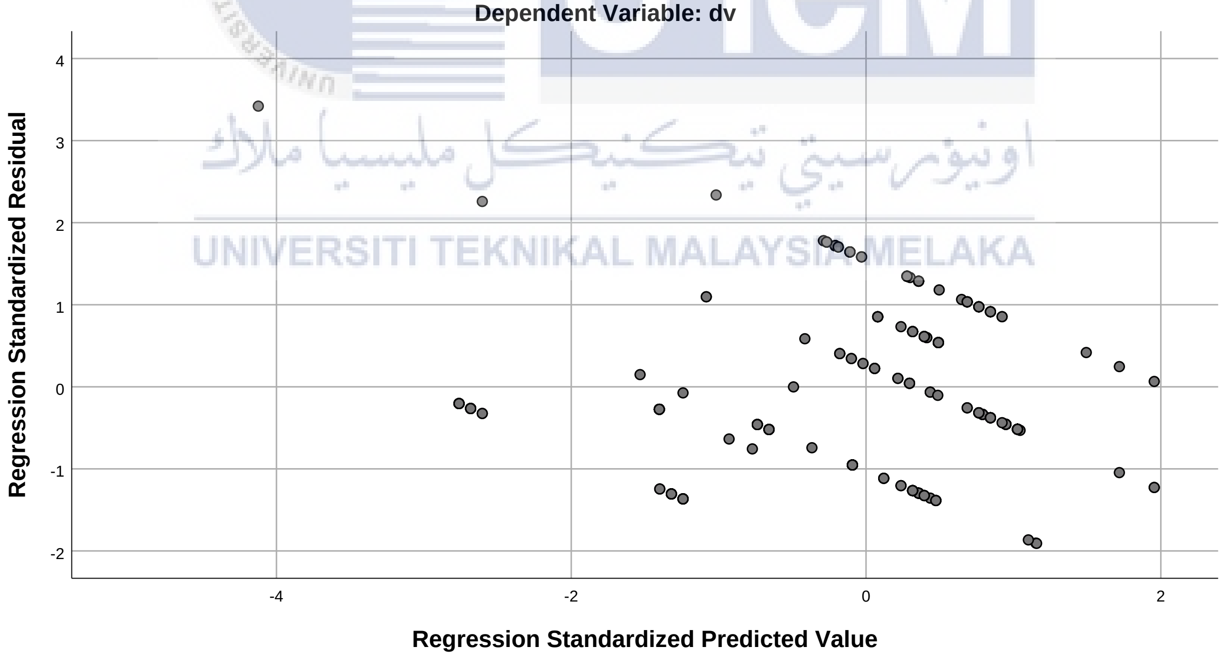
Normal P-P Plot of Regression Standardized Residual

Dependent Variable: dv



Scatterplot

Dependent Variable: dv



Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	iv1	iv2	iv3
1	1	4.913	1.000	.00	.00	.00	.00
	2	.044	10.611	.02	.12	.00	.00
	3	.026	13.688	.04	.02	.61	.02
	4	.012	20.362	.13	.02	.33	.73
	5	.005	30.111	.81	.85	.06	.25

Collinearity Diagnostics[a]

Model	Dimension	Variance ... iv4
1	1	.00
	2	.32
	3	.21
	4	.05
	5	.42

a. Dependent Variable: dv


```
GET
  FILE='C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.
DESCRIPTIVES VARIABLES=iv1 iv2 iv3 iv4 dv
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

Descriptives

Notes

Output Created		09-JAN-2024 22:33:02
Comments		
Input	Data	C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=iv1 iv2 iv3 iv4 dv /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

```
[DataSet1] C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav
```


Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
iv1	384	2.00	5.00	4.4668	.58849	-2.660	.125
iv2	384	1.00	5.00	3.5280	.73607	-.241	.125
iv3	384	1.00	5.00	3.8926	.70434	-1.375	.125
iv4	384	1.00	5.00	4.0423	.92312	-.693	.125
dv	384	2.00	5.00	3.7923	.97136	-.373	.125
Valid N (listwise)	384						

Descriptive Statistics

	Kurtosis	
	Statistic	Std. Error
iv1	8.428	.248
iv2	-.500	.248
iv3	1.706	.248
iv4	-.481	.248
dv	-.986	.248
Valid N (listwise)		

```
DESCRIPTIVES VARIABLES=Perceived_UsefulnessNoName @_ @_1
 /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

Descriptives

Notes

Output Created		09-JAN-2024 23:19:28
Comments		
Input	Data	C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=Perceived_U sefulness NoName @_ @_1 /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.

Notes

Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Perceived Usefulness	384	2.00	5.00	4.3698	.71077	-1.375
NoName	384	2.00	5.00	4.2708	.70402	-1.293
	384	2.00	5.00	4.6146	.69492	-2.222
1	384	2.00	5.00	4.6120	.72836	-2.269
Valid N (listwise)	384					

Descriptive Statistics

	Skewness	Kurtosis	
	Std. Error	Statistic	Std. Error
Perceived Usefulness	.125	2.694	.248
NoName	.125	2.877	.248
	.125	5.331	.248
1	.125	5.178	.248
Valid N (listwise)			


```
DESCRIPTIVES VARIABLES=Perceived_Ease_of_Use@_2 @_3 @_4
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

Descriptives

Notes

Output Created		10-JAN-2024 10:27:48
Comments		
Input	Data	C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=Perceived_Ease_of_Use @_2 @_3 @_4 /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Perceived Ease of Use	384	1.00	5.00	3.4479	.66811	-.495
2	384	1.00	5.00	3.4583	.65702	-.429
3	384	1.00	5.00	3.5990	.84619	.142
4	384	1.00	5.00	3.6068	.84832	.127
Valid N (listwise)	384					

Descriptive Statistics

	Skewness	Kurtosis	
	Std. Error	Statistic	Std. Error
Perceived Ease of Use	.125	.271	.248
2	.125	.016	.248
3	.125	-.572	.248
4	.125	-.583	.248
Valid N (listwise)			

```
DESCRIPTIVES VARIABLES=System_Quality NoName1 NoName2 NoName3
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

Descriptives

Notes

Output Created		10-JAN-2024 10:34:45
Comments		
Input	Data	C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=System_Quality NoName1 NoName2 NoName3 /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
System Quality	384	1.00	5.00	3.8151	.80772	-.906	.125
NoName1	384	1.00	5.00	3.8255	.81004	-.916	.125
NoName2	384	1.00	5.00	3.9609	.91179	-.795	.125
NoName3	384	1.00	5.00	3.9661	.91200	-.805	.125
Valid N (listwise)	384						

Descriptive Statistics

	Kurtosis	
	Statistic	Std. Error
System Quality	.744	.248
NoName1	.767	.248
NoName2	.078	.248
NoName3	.094	.248
Valid N (listwise)		

```
DESCRIPTIVES VARIABLES=Information_QualityNoName4 NoName5 NoName6
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

Descriptives

Notes

Output Created		10-JAN-2024 10:41:23
Comments		
Input	Data	C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=Information_Quality NoName4 NoName5 NoName6 /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Information Quality	384	1.00	5.00	3.9688	.90491	-.512
NoName4	384	1.00	5.00	3.9714	.90355	-.520
NoName5	384	1.00	5.00	4.1120	.97513	-.685
NoName6	384	1.00	5.00	4.1172	.97451	-.696
Valid N (listwise)	384					

Descriptive Statistics

	Skewness	Kurtosis	
	Std. Error	Statistic	Std. Error
Information Quality	.125	-.484	.248
NoName4	.125	-.466	.248
NoName5	.125	-.683	.248
NoName6	.125	-.665	.248
Valid N (listwise)			

```
DESCRIPTIVES VARIABLES=@_Consumer_Purchase_Intention NoName7 NoName8 NoName9
  /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
```

Descriptives

Notes

Output Created		10-JAN-2024 11:02:06
Comments		
Input	Data	C:\Users\THEAN KAH KEAT\Downloads\positive data set.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	384
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=@_Consumer_Purchase_Intention NoName7 NoName8 NoName9 /STATISTICS=MEAN STDDEV MIN MAX KURTOSIS SKEWNESS.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Consumer Purchase Intention	384	2.00	5.00	3.6875	.94565	-.122
NoName7	384	2.00	5.00	3.7552	1.02322	-.333
NoName8	384	2.00	5.00	3.8620	1.01899	-.346
NoName9	384	2.00	5.00	3.8646	1.01806	-.353
Valid N (listwise)	384					

Descriptive Statistics

	Skewness	Kurtosis	
	Std. Error	Statistic	Std. Error
Consumer Purchase Intention	.125	-.932	.248
NoName7	.125	-1.017	.248
NoName8	.125	-1.089	.248
NoName9	.125	-1.080	.248
Valid N (listwise)			