The moderating role of perceived risk between AI chatbots, purchase intentions and customer loyalty in customer service

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Attestation of Authorship

"I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning."

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Ethics Approval

This research was been approved by the Auckland University of Technology Ethics Committee (AUTEC) on June 24, 2021, for three years (i.e. through June 24 2024) with the ethics application number 21/162.

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Abstract

Artificial Intelligence (AI) has increasingly permeated the service industry as new innovations have rapidly allowed the development of new channels for interacting with consumers. Among these is the development of AI based Chatbots for customer services online. This research was conducted on American consumers to examine their attitudes towards AI based Chabot service agents, and whether perceived risk of these chatbots has an impact on the relationship between chatbot quality and their purchase intentions or loyalty with a company. Using a sample of 198 American respondents, the relationship between chatbot quality with purchase intentions and loyalty as two separate variables was examined (Study 1), and perceived risk was used as a moderator variable in these relationships (Study 2).

The results of the study showed that there was a positive impact of the quality of AI based chatbots on the purchase intentions as well as loyalty of American consumers. However, contrary to predictions perceived risk was found to not be a moderating variable of this relationship. This study provides a number of contributions to the literature around AI based chatbots and marketing literature. It offers academics as well as marketers a deeper understanding of the influences of AI based chatbots on long term loyalty among consumers. Additionally, by highlighting the lack of impact from perceived risk in this relationship, it has helped to reduce the burden of marketers to reassure consumers with regarding to potential risks related to AI based chatbots when implementing them within the organisation. Thus, the findings that have been presented in this study provide a variety of uses to managers, marketers and researchers in terms of practical engagement with consumers as well as future research directions.

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Chapter 1: Background

1.1. Introduction

As businesses continue to seek better ways to enhance the customer experience, artificial intelligence (AI) has quickly established itself has a critical tool for service improvements in the 21st century. Indeed, AI-driven technology such as chatbots has helped drive success among many industries in the last decade (Cheng & Jiang, 2020). According to Business Insider (2020), the use of AI-based chatbots is predicted to experience an annual growth of 29.7%, and jump from 2.6 billion to 9.4 billion USD between 2019 and 2024. In particular, the service industry has seen the largest increase in AI, due to its ability to transform online consumer experiences by using natural (human like) dialogue to interact with customers. Chatbots allow companies to offer immediate communicative services on any online channel such as social media, websites and messaging applications, while using customised language to mimic human speech, in order to provide a seamless user experience that can help foster loyalties (Huang & Rust, 2018). As a result, not only can chatbots increase the efficiency of online services, but they can also dramatically improve customer perceptions of a business. However, because of the customer orientation of AI-based chatbots and their predicted effect on business-customer relationships, the quality of chatbot systems are essential to their success.

As Prentice, Dominique and Wang (2020) discovered, AI quality (as with employee based service quality) has a significant connection to long-term customer loyalty. Delone and McLean (2003) established the information system (IS) success model, which viewed IS success in terms of three quality dimensions: service quality, system quality and information quality. According to Huber, Piercy and Mckwown (2008), information systems can be used to describe any information technology or business process that is designed to translate inputs into outputs to achieve goals. This study will examine chatbots through an information system perspective and survey the influences that the three quality dimensions have on customer loyalty and intention to purchase.

It is undeniable that user technology in general (such as mobile devices and the internet) has had major impacts on customers' decision-making processes. However, this has not been fully explored, due to the contemporary nature of chatbot services. The use of AI-based chatbots is expected to dramatically alter the business-customer relationship, due to their ability to increase customer convenience when performing desired tasks (Dawar and Bendle, 2018). Various brands have already attempted to integrate AI-base chatbots into their online customer communication media, such as Microsoft's digital chatbot solution that provides personalised information and answers to open-ended questions (Yao, 2017). However, extant literature about chatbots remains limited, not only in terms of alternative uses for business communication, but also research on the outcomes and satisfaction of chatbot users due to a heavier focus on social media and traditional service users where contact occurs in physical stores (Galert, 2018). In particular, there has been a lack of focus on the impact of perceived risk on customer satisfactions and intention to continue using the products or brands offering chatbot service, which is of significant importance since perceived risk has traditionally been a major hinderance to initial technological innovations in the pass such as smartphones and the internet etc. (Sundar &Kim, 2019). Thus, the full effect of using chatbots on consumers is unclear.

1.2. Research problem

Technologies based on AI capabilities have been developed to improve consumer experiences when shopping, in an attempt to maximise their purchase intentions (Frank, 2021). This technology is desirable, as it eliminates a significant component of costly labour, while concurrently increasing the convenience and speed of purchase processes for consumers (McKendrick, 2017). Therefore, there is a clear need for business leaders and company stakeholders to develop their understanding of consumer reactions to the adoption of AI-based technologies, which includes AI-based chatbots, in order to determine the best way of implementing them. This will allow organisations to maximise the utility and effectiveness of AI chatbots within their organisations and find strategies to improve consumer responses toward them. Previous studies have shown that adopting new technologies can be a challenging process for consumers within retail settings. The level of perceived risk customers feel toward new technologies in terms of privacy, security, and reliability is a key factor that influences their decisions to use them (Ho, Ocasio-Velazquez & Booth, 2017). As such, one of the key areas of investigation for new technologies being adopted across industries is the impact of trust and perceived risk. For example, statistically significant influences of perceived risk have been found for technologies such as cloud-based solutions (Ho et al., 2017), internet banking (Kesharwani & Bisht, 2012), and online applications (Lu et al., 2005) among others. When taking the adoption of AI chatbots within retail into consideration, perceived risk could be an important factor influencing consumer attitudes, acceptance and judgement of AI chatbots.

Therefore, the current research project aims to investigate the impact of perceived risk to moderate the relationship between the quality of AI chatbots with consumers' purchase intentions and loyalty. The expectation is that the perceived risk of AI chatbots decreases the purchase intentions as well as loyalty of consumers during AI chatbot interactions. Ultimately, the research aims to produce reliable information for stakeholders of retail organisations, to help them develop a deeper understanding of interactions that influence the effectiveness of AI chatbots that replace human labour, while maintaining or improving customer purchase intentions and loyalty.

1.3. Research Question(s)

Traditionally, there are significant interactions between the retailer and consumer during the checkout or information-gathering process, typically with cashiers or customer service agents. However, the introduction new technological solutions through AI-based chatbots reduces the required level of interaction between consumers and human representatives of an organisation. These technologies have the potential to improve consumer service experiences by reducing waiting times and checkout processes. Yet, the willingness of consumers to adopt AI chatbots may depend on their perceived risk, which, in turn, may influence their purchase intentions.

The purpose of this study is to develop an understanding of how the perceived risk of using AI chat services affects the relationship between AI chatbot quality, customer purchase intentions and loyalty. Specifically, it aims to analyse how different levels of perceived risk moderate the customer's experience of the quality of AI chat services, and how this affects their willingness to return to the company again through purchase intentions and customer loyalty. As such, two research questions are posited:

1. How does the quality of AI chat services affect the two variables of consumer purchase intentions and loyalty?

2. How does perceived risk moderate the relationship between the quality of AI chat services and the two variables of purchase intentions and loyalty?

1.4. Significance of the Research

Most businesses want to develop positive interactions between consumers and organisations in an attempt to maximise customer numbers and achieve greater purchase intentions with long-term loyalty (Sherman et al., 1997). Successfully introducing AI-based chatbots into the retail sector as checkout solutions or information providers requires knowledge about the quality of this new technology and how it can influence the purchase intentions of consumers when it enters the market. It is also valuable to know whether there are moderating factors that could affect chatbots' success and help companies develop mitigating strategies.

This study is one of the first to examine how the level of perceived risk potential moderates the quality of AI chatbots and the purchase intentions of consumers. This study views AI chatbots as providing significant advantages to the consumer experience and examines its connection to consumer purchase intentions through perceived risk. This research will make contributions to academia and business practitioners and expand the literature around technological adoption and its facilitation, while helping companies understand whether they need to develop strategies to help appease consumer concerns. Therefore, this analysis will also be able to help marketers be more successful when encouraging consumers to adopt this technology and use it to promote greater purchase intentions. Understanding the influence of perceived risk helps companies design strategies that mitigate negative experiences as AI chatbots are rolled out, improving the retail consumer experience.

1.5. Methodology

The study was carried out during the Covid-19 pandemic, making it necessary for researchers to concentrate on online methodologies in order to guarantee validity and reliability. This study was carried out across two separate studies with randomised sampling. IBM SPSS simple regression was used to examine the relationship between AI-based chatbot quality and purchase intentions, while SPSS PROCESS macro (Model 1, 10,000 bootstrapped samples; Hayes 2018) was used to conduct the moderation analysis using perceived risk.

1.6. Definition of Key Terms

AI-based chatbots refer to technologies that allow consumers or website viewers to interact with a company chat service who respond to customer inquiries through artificially intelligence bots (Wankhede et al., 2018), where all processes are devoid of direct employee participation.

Perceived risk refers to the customers' perception of the level of uncertainty or negative consequence when purchasing goods or services, or interacting with the AI-based chatbot (Dowling & Staelin, 1994).

Purchase intention refers to the likelihood of consumers engaging in purchase decisions with the organisation using AI-based chatbots online or elsewhere during an interaction with a consumer (Kang et al.,2015).

Loyalty refers to the strength of consumers repeat patronage and tendency to recommend the product to others (Kang et al., 2015).

1.7. Thesis Outline

The organisation of this thesis is divided into six primary chapters. The first chapter highlights the objectives of the study and the related research terms, settings, aims, problems and questions. The second chapter is comprised of the literature review that examines the research hypotheses and conceptual framework. The third chapter highlights the methodology of the study including the approach utilised in data collection, measurement development, and analytical methods. The fourth chapter provides analyses of the raw data that was collected for the study, including the use of SPSS software to test for validity and significance in the target relationships. The fifth chapter is a detailed discussion of the results of the investigation, how it contributes to extant literature, as well as the potential implications. The final chapter sets out the limitations of the research as well potential areas for improvement or expansion in future investigations.

Chapter 2: Literature Review

2.1. Introduction

New technology is often readily embraced by marketers due to its proven benefits in terms of improved customer insights and service quality, as well as overcoming difficult situations as found in the Covid-19 pandemic (Kopalle, Kumar & Subramaniam, 2020; Lau, 2020). As a result, research into the current evolution of digital technologies in marketing has been fast-paced (Crittenden & Peterson, 2019), with researchers looking into how artificial technology is capable of assisting and managing customer needs (Kumar et al., 2019). However, research has only recently been positioned at the intersection of marketing and AI, especially in response to consumer responses to AI-based marketing (Prentice et al., 2020). Companies such as Sephora, MasterCard, Spotify and Google are among the growing list of organisations using AI-based platforms to improve their services and develop new competitive advantages. In particular, the widespread adoption of AI-based chatbots has been a response to chat services becoming the preferred option for consumer support (Charlton, 2013), primarily due to evidence that AI-based chatbots provide cost and time saving opportunities (Reddy, 2017).

Organizations have traditionally been keen to adopt new technologies that may provide competitive advantages to their products or services (Baldwin, 2019). Artificial intelligence has been an area of particularly important growth for firms across many industries, primarily because of its unique competitive advantage of personalising customer service and high-level analytics (Fowler, 2020). Despite their invention in the 1960s, one of the most notable developments for AI-based chatbots was its dissemination in the 2010s, when companies such as Facebook began allowing businesses to deliver automated customer support and interactive experiences through chatbots (Deloitte, 2017).

However, despite the potential benefits of AI-based chatbots, companies have had a hard time using them to meet consumer expectations, which could lead to a decline in compliance with chatbot services (Adam et al., 2020). One area that only few researchers have considered is the impact of perceived risk in terms of the acceptance of chatbots, which plays a critical role in the public's acceptance of new technologies (Zhang et al., 2019). Here, the focus is on the impact that perceived risk potentially has on the future acceptance of AI-based chatbots in the marketing industry, including its moderating role between AI quality and purchase intentions.

This chapter reviews the extant literature in the areas of artificial intelligence, chatbots, and intention to purchase/brand loyalty in order to develop the proposed model and hypotheses.

2.2. Artificial intelligence

AI commonly refers to digital computerised systems that are able to carry out the same tasks as human subjects, including but not limited to tasks that require logical thinking and intelligence (Van Esch et al., 2020). Visvikis, Le Rest, Jaouen and Hatt (2019) described AI as one of the most promising emergent technologies within business and marketing, as it provides software (used in computers or robots) that is capable of independent thinking in ways that are highly similar to human intelligence. This not only allows AI to complete tasks equally if not better than humans, but also to respond to problems in similar ways. Patrick and Williams (2020) reflected a similar viewpoint by defining AI as machines capable of simulating a level of intelligence on par with humans, while also performing tasks that traditionally would be thought to need human intelligence to complete. AI's ability to interact with environments was also highlighted by Wirth (2018), where AI was referred to as machines capable of recognising their surroundings and responding in ways that maximise the successful rate of designated tasks. Therefore, extant literature appears to have developed a consensus around the definition of AI as a level of intelligence that is at least equivalent to human intellect, which can engage in problem solving within its immediate environment.

AI allows machines to make use of their experiences as mechanisms for learning, yet the way that they are designed to use these experiences has led to the divergence of two types of AI that are either narrow (weak), or general (strong) (Wirth, 2018). Narrow AI have been designed to complete one task at a time, thereby continually improving their execution for a specific function selected by a human operator. Due to the fact this only focuses on a single task at any point in time, this type of AI is unable to readily adapt to novel applications. As a result, it is commonly referred to as "business automation," since it often automates activities previously performed by humans in order to maximise efficiency for a specific task beyond what a human might be capable of (Kaplan and Haenlein, 2019). Example functionalities include recognising human faces for more personalised experiences at stores, or asking smartphones to report weather etc. The second form of AI is general AI, which is considered to be a more comprehensive machine intelligence due to its development of the ability to think generally (Patrick and Williams, 2020). Thus, general AI are taught to make decisions based on learning instead of prior training, and are not limited to a specific problem or task. Although both general and narrow AI have the potential to go beyond what humans might be capable of, general AI has the ability to expand into new domains, which makes it more similar to actual human intelligence. When adapting these AI into practical solutions, determining the type of AI being used can heavily influence the cost and quality of an AI-based service.

In real world contexts, AI has quickly become one of the leading areas of technological development in multiple fields of both business and science. For instance, the past decade has seen AI being adapted into computer systems for automated driving, big data analysis, and customer services. This highlights the versatility as well as the problem solving capabilities of AI. Indeed, in the application of AI systems, it is clear that existing smart systems already exceed the processing and problem solving capabilities of human intelligence. Technology that allows businesses to offer 24/7 AI service agent support has increased exponentially, allowing organisations to provide services with not only fewer human resources, but at lower costs within a reduced timeframe. Businesses are now able to use IBM's Watson in order to provide services for chatting, personalized reactions to customers (i.e. emotions, tone, personality), as well as individual recommendations (Akkiraju, 2017). This has resulted in a large number of businesses adopting AI-based service agents and "bots" to assist with consumer inquires and complaint procedures, etc. They have also begun to inhabit other ecosystems such as social media and are capable of increasingly complex feats such as the autonomous production of content and social media interactions (Varol, Ferrara, Davis, Menczer & Flammini, 2017). This has caused a dramatic growth in literature regarding this advance in technology, as well as a greater understanding of AI's effects on consumer perceptions and behaviours.

Although one of the primary objectives of adopting AI-based service agents is to elevate the user experience and improve information quality, studies have found that there is no guarantee that individual needs can be completely satisfied (Yoon, 2010). There have been a wide range of reports regarding to negative consumer inquiry experiences with AI-based service agents. Many consumers that are not satisfied with AI chatbots often highlight a lack of authenticity as a primary contributing factor to the negative mediated experience (Dwivedi et al., 2019). Additionally, AI-based service bots have also been called "dumb" in response to their occasional inability to provide an answer that matches questions that were asked of them, which many perceive as a risk in their ability to keep personal information safe (Bishop, 2021). Consequently, these types of perceptions could lead to consumers avoiding AI-based interactions, which could cause major issues for organisations that invested heavily in their implementation.

2.3. Artificial Intelligence and customer service

The last decade has seen a significant rise in the popularity of chat services that provide customer services (Xu, Shieh, Esch, Ling, 2020). This is primarily being fuelled by advances in AI, which have allowed human chat service agents to be replaced by conversation software agents or chatbots that are significantly more cost effective (Pfeuffer et al., 2019). For instance, a chatbot is not only able to reduce the queue and wait times for online customer service, but it can also significantly reduce labour costs for organizations (Ostrom et al., 2019). For many service organizations, the question being asked is not whether they should begin using AI, but to what extent should they use it to maximize its capability to improve the effectiveness and efficiency of services (Rust, 2020). Companies such as Apple and Google have developed general AI programs (Siri and Allo) based on natural language processing that are capable of responding to a variety of information-seeking or functionality requests (Xu et al., 2020). They have been adopted by a wide array of consumers who search for information and personalise technological devices that AI are incorporated into (Tussyadiah & Miller, 2019). However, whether consumers of these electronic devices know it or not, their utilisation of these AI programs also facilitates the improvement of customer services during information searches and purchases. This is because many of these large companies use this data to improve future personalised experiences for their customers, while also advancing their algorithms to provide more expedient and improved AI services (Xu et al., 2020).

There is some scepticism and resistance against this type of technology and its ability to provide adequate service and replace human interaction, especially in terms of negative perceived risk (Van Doorn, Mende & Noble, 2017). Additionally, many believe AI chatbots are unable to appropriately utilise context, sentiment and emotion in the same way as humans (Xu et al., 2020), which creates more of a handicap on the adoption of AI-based chatbots within consumer retail settings. This can trigger unwanted behaviours among the consumers (such as avoiding the company’s services) that could end up having negative consequences for service providers, such as reduce purchase intentions and loyalty (Bowman et al., 2004). Since AI chatbots are still relatively new in many sectors, it is understandable that there is an element of potential perceived risk. However, many consumers may not realise the significant advantages of AI in recent years that may have helped address many of these issues.

Customers think that they might not get a task done due to a lack of information on bots or an incomplete understanding of chatbots. For instance, Dreyer (2016) conducted a survey that found that many consumers considered chatbots to be incapable of offering effective solutions to complex problems, and their main use was limited to primary information only. Puntoni, Reczek, Giesler & Botti (2021) found that while customers may accept AI, they negatively evaluate AI-created emotional elements, which many feel are important in service environments. This points to a heightened level of perceived risk seen with consumers who are using chatbots. Although AI is already being used across many sectors including the service industry, more research is required to explore AI as an end-to-end service solution rather than as a small component of a customer service system that has traditionally been the domain of human service providers (Xiao and Kumar, 2019). The trust that consumers lack in terms of AI-based chatbots within retail settings will depend on companies’ communicative ability to address these issues, as newer versions of AI are increasingly being developed that can analyse emotional responses.

In recent years, one of the most common AI chatbots that has been integrated into the consumer experience is customer service chatbots, which answer complex customer inquiries through machine learning and artificial intelligence programs. According to Andrews (2009), although human employees are capable of improving customer experiences through their own experience and knowledge, the hiring and retention of employees keeps overhead costs high. AI chatbots have the advantage of being able to carry out similar functionalities (i.e. answer basic inquires), but at a significantly reduced cost. They use existing resources and information to recognise and answer multiple forms of identical questions, and can also be trained by handlers to provide responses in preferred tones or voices. Therefore, new AI-based technology solutions such as chatbots can improve the quality of customer service experiences, while also increasing company effectiveness and competitiveness.

Retail organisations that want to find new ways of integrating AI into the consumer experience are motivated by the advantages it has the potential to provide. As highlighted by Xu et al. (2020), many retail AI are increasingly becoming able to provide much more expedited services, since they are automated and do not require human labour throughout the entire process. This cuts down labour costs for companies while maximising the speed that tasks are completed, reducing the resources required. At the same time, advances within AI technologies continue to improve their ability to enhance customer shopping experiences by providing increasingly useful and effective assistance (Pantano & Timmermans, 2014). This is a major competitive advantage for organisations within the current business environment; as the technology improves, it will also help anticipate consumer needs and enhance consumer lifetime value.

Most importantly, a well-positioned AI-based customer service chatbot will be able to help drive interactions with the company at levels that exceed human capability, reducing overall costs. This is particularly relevant for multinational companies that have massive consumer bases, as it is very expensive to hire enough customer service agents to address inquires that could be handled instantly by an online AI chat service as an initial line of customer support. By freeing human agents to do other work and decrease response times, it is estimated that AI-based chatbots will be able to help decrease the current global business costs of around $1.3 trillion USD, which is 30% of the cost of 265 billion customer service inquires that companies take on each year (Reddy, 2017; Techlabs, 2017). By 2022 alone, AI-based chatbots are expected to save businesses more than $8 billion USD a year, which is a massive increase from only $20 million in 2017 before AI-based chatbots began to be more widely adopted (Reddy, 2017). The provision of these types of AI chatbot services are increasingly what is differentiating large retailers and organisations from smaller competitors. Using an automated computer system, customers can get answers to questions on their own, while saving valuable time traditionally used for calling and being transferred through calls within customer service agencies (Hauser, Gunther, Flath & Thiesse, 2019). For many of today's large retailers, a competent AI-based chatbot system will significantly reduce the amount of effort and cost that an organisation will need to go through in order to satisfy the consumer.

Consumers typically appreciate the advantages of accessibility and flexibility within self-service channels, but they also value personalisation. Therefore, it is important that companies do not entirely transition toward a fully self-service model, especially when beginning relationships with consumers (Scherer, Wunderlich & Von Wangenheim, 2015), since this can lead to a loss in sales when there are no personal social actors during an online transaction (Kirkpatrick, 2017). However, when AI-based chatbots are able to mimic social actors, they can potentially play a more active role within service encounters and even substitute positions traditionally held by employees of the organisation (Verhagen et al., 2014). Verhagen et al. (2014) highlighted how this has already become a growing reality, with many AI-based chatbots being able to signal human characteristics like being friendly during every encounter, which is viewed as a critical component when addressing customer inquiries. As a result, compared to what traditional online service experiences used to be, AI-based chatbots can not only improve accessibility and flexibility within self-service channels, but they can also reduce the risk of undesirable social interactions by guaranteeing consistent personalisation and social presence.

Therefore, AI-based chatbots have the ability to dramatically change how consumers access information, services and even transactions within online retail settings (Pantano & Timmermans, 2014). Consumers' involvement with AI-based chatbots represents one of the most significant advancements of evolving retail environments, especially since the majority of retailers have been transitioning to online channels. This growth within the AI-based chatbot sector is demonstrated in how the number of chatbots on Facebook saw a jump between 2016 and 2019 from 11,000 to 300,000 (Johnson, 2019). According to Van Esch & Black (2019), as consumers' confidence in a specific technology rises due to increased familiarity, their willingness to use it in the future also sees a concurrent increase. Additionally, when using technological tools or devices, consumer behaviours and needs play a major part in what they expect AI-based chatbots to be able to do in general service environments. Extant literature has shown that when variables such as ease of use and perceived usefulness increase for a new technology, so do the behavioural adoptions and attitudes toward the technology (Venkatesh & Bala, 2008). Over time, retailers have consistently made improvements to AI-based chatbots through the adoption of new AI technologies and innovations (Hagberg et al., 2016). As these improvements continue to increase in the future, so does the willingness of consumers to adopt AI-based chatbots within retail service settings.

2.4. Perceived risk

In Mayer et al. (1995)'s widely used definition of trust, trust is considered "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part" (p.712). As a result, a critical element of trust lies in the vulnerability or risk that humans are willing to put themselves in at any given point in time. Thus, the ways consumer perceive risk from this will influence the degree of trust they have for another party, tool,or technology.

Considering extant literature, perceived risk has been defined as a customer's perception of the level of uncertainty or negative consequence when purchasing goods or services (Dowling & Staelin, 1994). The potential impact of perceived risk has been demonstrated in other relationships. Tam (2012) previously established that the level of perceived risk had a moderating effect on relationships between consumer satisfaction and loyalty. His research indicated that when there was a high level of performance risk (i.e. the perceived risk that products or services will not be able to deliver as expected or fail), consumers might develop increased loyalty to incumbent product or service providers. Since chatbots are a relatively new technological development within multiple industries, customers might have increase performance risk perceptions that could impact their experiences when using the technology. Im et al. (2008) suggested that when technologies fail to provide consumers with the desired outcomes, they will feel a loss that negatively impacts their judgement. Additionally, Im et al. (2008) also highlighted that there are often discrepancies between users' judgements and actual technological performance, which leads to greater perceived 'risk,' because users are unaware of potential consequences relating to such discrepancies. Therefore, it is crucial that research investigates the role of risk in new technologies, and whether the levels of perceived risk regarding the ability of chatbots to actually perform their desired functions will moderate relationships between dependent and independent variables.

Chatbots are somewhat unique in that the personal data that people send them is not always appropriate for commercial uses by businesses (Sundar & Kim, 2019). This has contributed to uncertainty around possible negative outcomes related to the disclosure of personal consumer information (Wang & Lin, 2017). Studies have shown that consumers automatically develop concerns over the collection of personal information when they are given access to personalisation services on normal webpages (Ho, 2006). It has also been foundthat system-initiated personalisation services (i.e. when the consumer did not personally seek the service out) cause a particular increase in privacy concerns, despite the convenience they might provide during web browsing (Sundar & Marathe, 2010). In the service industry, prior literature has shown that from a user's perspective, new technology always contains a certain amount of performance and privacy risk, from mobile payments to the use of smartwatches (Gao & Waechter, 2017; Dehghani, 2018). There is a high likelihood that chatbot services will face similar challenges regarding threats to personal privacy. This is because when customers are engaged with chatbots for service/product purchases, they might be required to enter personal information (such as name, address and phone number) that could be viewed potentially dangerously. As a result, perceived risk plays a critical role in the adoption of AI-based chatbotservices.

In this study, perceived risk is only examined from the perceptive of performance related risk as this provides a more encompassing variable. It can be argued that privacy risk can be incorporated into the umbrella of performance risk, as the more online centered consumers nowadays have a basic and reasonable expectation that online stores can protect their privacy (Mendoza, 2020). As a result, protection of privacy could also be considered a basic element of their performance expectations, making it closely related to perceived performance risk.

2.5. Quality of AI chatbots

According to Delone and McLean (2003), the quality of technology from the 'information systems' perspective has three quality dimensions: service quality, system quality and information quality. This model is selected over other models, because it is more convenient in its applicability and measurement of commercially relevant components such as service quality, as well as technical components such as system and information quality. This model will also provide more relevant information to marketers and developers in order to make potential improvements.

Thus, the quality of AI in this study will be conceptualized according to all three dimensions of the IS mode, encompassing system quality, service quality as well as information quality within its measurement for this study.

2.5.1. System Quality

According to Delone and Mclean (1992), system quality measures within the Information Systems success model are related to the level of technical success for whatever information system is being considered. This has a strong relationship to factors such as the adaptability, availability, reliability, useability, and response time of the information system, especially its capability to respond to necessary changes within environments based on user needs (Liu & Wang, 2005). As such, whether chatbot developers are able to adapt chatbots to the needs of their intended users should play a significant factor in their success. For example, Schou (1996) pointed out that system availability should refer to how likely users are able to access the needed information at specific times within required formats. However, one of the difficulties this presents to developers is the fact that users often expect information systems to provide 100% availability (Martin & Khazanchi, 2006). This means that if chatbot developers are unable to use services to provide accurate information on time and in the correct formatting, user experiences are guaranteed to be negatively affected. Reliability faces similar difficulties, as this refers to the ability to provide information under different operating conditions, which can be challenging when customers expect good information systems performance even with low internet speeds (Reibman & Veeraraghavan, 1991). Useability and response time are both related to the ease of use of the system, frequent users of modern technology expect very quick response times (Hoxmeier & DiCesare, 2000). In sum, based on the IS model put forward by Delone and McLean (2003), these factors contribute to the system quality of IS such as chatbots.

2.5.2. Service Quality

Service quality is the second component within the IS model (Delone and McLean, 2003). They determined it as an essential component of IS success due to the rise of service-oriented functionalities provided by online channels and computer technology. In particular, the dimensions of empathy, assurance and responsiveness were essential to IS service quality. Gorla, Somers and Wong (2010) explained these dimensions in detail. Empathy is argued to evaluate whether the needs and interests of consumers are understood by the IS. Assurance is whether the IS is able to maintain a high level of expertise in the provision of service, such that customers can get their problems solved through professional communication. Lastly, responsiveness is related to the speed at which the IS provider is able to offer their services to customers. One of the major reasons that service quality has a much more significant impact on IS nowadays is due to the established impact that service quality has on factors such as satisfaction and loyalty (Sivadas & Baker-Prewitt, 2000). Companies that want to include chatbots in their offerings to consumers are using them as direct service providers and replacements for human service providers. As a result, it is reasonable to assume that the importance of service quality would transfer over to chatbots as well. Indeed, Delone & McLean (2003) claimed that if the overall performance of an information system needs to be measured, service quality may be the most important component. This was supported in other studies such as one by Brown and Jayakody (2008), which investigated the different determinants of service sector IS success and found that service quality was more important that the majority of other quality factors. Therefore, it is reasonable to incorporate service quality as a core component of chatbot quality using the IS model.

2.5.3. Information Quality

Delone & McLean (2003) defined information quality as a measurement of the semantic success of technologies. Under the IS model, this refers to whether the information presented to users was relevant, accurate and timely. In this case, information quality can play an essential role within the overall quality of chatbot services. If chatbots do not produce relevant information when customers ask for it, this may lead to negative perceptions of the service, reduced trust, and discontinued use of the IS. A study conducted by Swanson (1997) found that information quality had varied impacts on factors such as organisational performance by increasing costs associated with maintenance and operations. Additionally, more recent studies have also found that information quality affects the perceived value of websites, which, in turn, influences loyalty to the websites (Pearson et al., 2012). Indeed, the information provided by chatbots is vital to consumers' experiences and the quality of their interactions with a company. Thus, information quality is a reasonable determinant of the overall quality of chatbots in this study.

2.6. Purchase Intentions

According to Pavlou (2003), from an online perspective, purchase intentions can be understood as "the degree to which a consumer is willing to buy a product through an online store." Engaging within specific behaviours is a reflection of the likelihood that someone will favour the performance of the actions. Based on the theory of reason action, attitudes toward specific behaviours are able to act as direct predictors for intentions to perform actions within the consumer decision-making process (Ajzen & Fishbein, 1975). This has been proven across a number of different studies, and there has been evidence showing how it is important when purchasing any type of product. Yoo and Lee (2009) empirically demonstrated how when a consumer develops a positive attitude toward counterfeit products, their purchasing intention toward counterfeits also concurrently increases. As a result, purchase intentions and any associated positive attitude plays a vital role in marketing, regardless of the type of product that is being marketed.

The impact of variables on purchase intentions is likely one of the most important aspects of marketing, since it has potential financial consequences for organizations. Kang et al. (2015) demonstrated how human-to-human live chat can have a marked positive influence on customer experiences, which increases the purchase intention of said customers. There have also been other studies highlighting how live chat services could become an essential component within online service interactions (McLean and Osei-Frimpong, 2017). However, the potential of this effect transferring to an AI chatbot setting, where AI replace the human component of live chats, remains relatively unexplored across any industry. Considering the growth of this technology and adoption by a wide range of sectors (Mehr, Ashe & Fellow, 2017), this presents a potentially impactful and interesting area to examine.

Thus, in the case of this study, purchase intentions are conceptualized as the willingness of the consumer (i.e. participant) to purchase a product or service from a company if they have a need for that product. In addition, only online purchase intentions are considered, excluding offline purchase intentions, as chatbot services are typically used in conjuncture with online stores in order to help resolve immediate doubts or hesitations so that the company can drive an immediate sale on their online platform. Thus, taking this into consideration online only purchase intentions are considered.

2.7. Loyalty

At a general level, there is no unified definition of loyalty from a consumer toward any products, services, activities or brands. Some researchers have argued that loyalty is a display of strong "attitudinal commitment towards brands (Uncles et al., 2003). In this case, such attitudes could be determined by asking consumers about their commitment toward a brand, or whether they would recommend it to their acquaintances positively (Uncles et al., 2003). In turn, whether someone would engage in repeated purchases for a brand would also be determined by the strength of their positive feelings or attitudes toward said brand. This "attitude defines loyalty" perspective suggests that relationships can be developed between a brand and the consumer. However, another perspective claims that loyalty is primarily expressed in terms of revealed behaviour, meaning their repurchase behaviour and not their attitudes (Uncles et al., 2003). This places the primary on the purchase patterns of consumers, which have often be found to be “an ongoing propensity to buy the brand, usually as one of several” (Ehrenberg and Scriven, 1999). The third perspective is that of customer loyalty being moderated by situational factors, which is a contingency approach arguing that loyalty should be conceptualised as a relationship between behaviour and attitude while being influenced by immediate context (Uncles et al., 2003). Thus, strong attitudes toward brands may not be capable of producing strong purchase patterns if the context is not desirable (i.e. budget, occasion, or habits).

For online retail, customer loyalty is recognised as the preference or intention to repurchase products from a website or e-store, or the positive feelings consumers have towards an online store. It is widely understood that the development of customer loyalty occurs slowly over time. Oliver (1999) clarified the distinction between satisfaction and loyalty by highlighting how the former “is a fairly temporal post-usage state for one - time consumption or a repeatedly experienced state for ongoing consumption” (p. 41), while the latter is a preference that endures over time due to consistent satisfactory experiences. Satisfaction-influenced loyalty only becomes aggregated over time (Oliver, 1999), but remains independent such that consumers who feel satisfaction in the moment are not always loyal. Yi and La (2004) emphasized that loyalty develops after cumulative post-purchase evaluations of experiences with a company, and not through the evaluation of a single purchase.

Loyalty is a significant factor in customer service, as it directly impacts the future sales and long-term predictability and profitability of firms (Kandampully et al., 2015). It has been established that employees’ behaviour and performance over service counters or other environments constitutes the experiences and perceptions of customers with regard to service quality, which further influences their level of commitment and involvement with a company (Delcourt et al., 2013). This loyalty is manifested through an increased frequency of engagement and recommendations to others (Delcourt et al., 2013). However, while this has been supported within a human-to human-environment, there has been a marked lack of evidence looking at similar situations featuring an AI service provider.

In the case of this study, loyalty is conceptualized as the tendency to engage in repeat patronage of the service and products of the company over the long term on a consistent basis, while concurrently recommending the brand to others. Thus, loyalty in this case is not simply a willingness to purchase a product from the company, but instead the commitment to select them as the first company from which they will purchase products from (over potential competitors) and demonstrate their commitment by sharing it with others in their social circles.

2.8. Conceptual Framework

A detailed review of the literature regarding the quality of AI, perceived risk, purchase intentions and loyalty has been provided in the development of the conceptual framework. This study examined the moderating role that perceived risk had on the relationship between the quality of AI and purchase intentions, and was based on existing research of technology acceptance models and organization demands for greater innovations to reduce costs, while making consumer experiences more convenient and expedient.

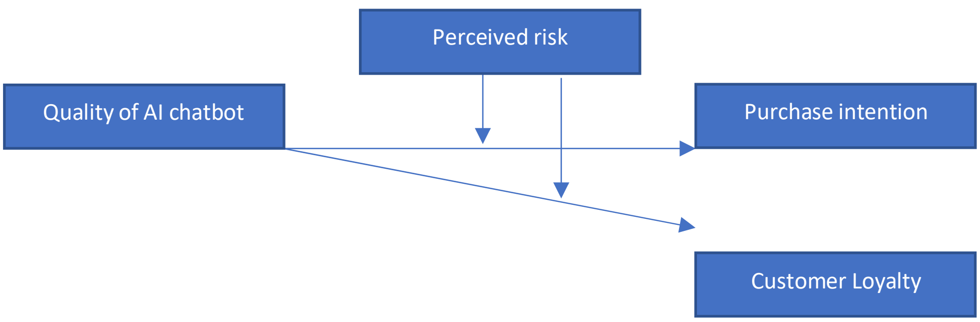

Figure 1. Conceptual Framework

2.9. Development of Hypotheses

Several variables were used in the development of the hypotheses for this study, which include the quality of AI-based chatbots as the independent variable, purchase intentions and customer loyalty as the dependent variables, and perceived risk as the moderator. An array of studies have looked at the influence of new technology on consumer behavioural intentions, and how perceived risk can influence various factors such as brand loyalty (Yasin & Shamim, 2013).

2.9.1. The direct effect of AI-based chatbots on customer purchase intentions and Customer Loyalty

Due to the propagation of digital services and restrictions implemented by Covid-19, the rise in online shopping and consumer interactions means that customers have increasingly been willing to try new technologies such as online AI chatbots. The increased involvement of technologies such as AI chatbots in the online retail experience such as information research has positive impacts for organisation costs as well as consumer conveniences (Pantano & Timmermans, 2014; Reddy, 2017). When consumers have increased feelings of satisfaction from greater service quality, this increase the likelihood that they will purchase the product again in the near future, as well as continue to patronize thecompany and their products in the long run (Xu et al., 2020), and in many cases recommend the product or brand to others (Coker, 2013). Therefore, the following hypotheses were developed:

H1: The quality of AI-based chatbots has a positive impact on purchase intentions.

H2: The quality of AI-based chatbots has a positive impact on customer loyalty.

2.9.2. The moderation effect on the relationship between AI-based chatbots and purchase intention and loyalty

As AI-based chatbots have been rapidly introduced across multiple businesses within the retail sector, perceived risk is a real concern that has been found to affect consumer acceptance of new technologies (Gao & Waechter, 2017; Dehghani, 2018). The potential perceived risk related to AI-based chatbots includes concerns regarding their ability to satisfy information or inquiry needs, as well as the sharing of search history or other potential personal information disclosed during communications. Researchers have found that the most common concern related to online technologies is the perceived risk due to the ambiguity of online environments (Frost et al., 2014). Considering this factor, the following hypotheses were developed:

H3: The level of perceived risk with regard to an AI-based chatbot moderates the relationship between the quality of the AI chatbot and purchase intentions.

H4: The level of perceived risk with regard to an AI-based chatbot moderates the relationship between the quality of the AI chatbot and customer loyalty.

Chapter 3: Methodology

3.1. Introduction

The methodology seeks to answer the questions 1) How does the quality of AI chat services affect consumer purchase intentions and loyalty?, and 2) How does perceived risk moderate the relationship between the quality of AI chat services and the two separate variables of purchase intentions and loyalty? This chapter provides an outline of the research methodology of the study in relation to the quantitative study design and its justification, inclusion criteria and sampling method of participants, the design of the data gathering instrument (structured questionnaire), and procedures that researchers followed in orderto carry out the study and analyze the resulting data. Any ethical issues that were identified and considered are also discussed.

As justified by Gosling, Vazire, Srivastava and John (2004), an online quantitative research design was carried out that gathered data from American participants for the four variables 1) quality of AI chatbots, 2) perceived risk, 3) purchase intentions and 4) loyalty across two separate studies. The first study examined the connection between quality of AI chatbots with purchase intentions and loyalty, while the second examined the moderating effect of perceived risk on the relationships identified in the first study. The outcomes were analyzed through IBM's SPSS statistical software to answer the research questions.

3.2. Aim of the Research

The aim of this research was to discuss the relationship between the quality of AI chatbots within businesses and their connection to the two variables of purchase intentions and customer loyalty among American citizens, and how the perceived risk of AI chatbots may influence this relationship. The research focused on four key variables, which included the 1) quality of AI chatbots, 2) perceived risk, 3) purchase intentions and 4) loyalty. The research was divided into two studies that allowed the researchers to first determine the relationship between the quality of AI-based chatbots onpurchase intentions and loyalty, and then the moderating effect that the level of perceived risk had on theinteraction between the quality of AI chatbots on purchase intentions and loyalty. Therefore, this researchwas designed to test the main effect between the independent variable (AI chatbot quality) on the dependent variables (purchase intention, loyalty), as well as the moderating variable of perceived risk.

3.3. Implementation of Methodology

For the purpose of this study, a quantitative research paradigm was followed throughout both studies the use of structured questionnaire. Eyisi (2016) explains the advantages of quantitative research by highlighting the fact that it uses statistical data as a tool that both saves resources and research time. Additionally, by placing an emphasis on the figures and numbers within the collection and analysis of data, generalisation becomes possible. This increases the usefulness of data not only for researchers, but for users of the study results as well. Thus, a quantitative research method is the able to produce results that are more objective and statistically accurate.

An online structured questionnaire was selected as the method for this study because it is essential to gather customer data to provide rich insights into the relationships between relevant variables within the study. A seven-point Likert Scale ranging from "strongly disagree"to "strongly agree" was used to measure the consumers' perceptions of the independent,dependent and moderating variables. The survey was designed on Qualtrics, which was then linked to Amazon Mechanical Turk (M-Turk)'s platform for participates to access through M-Turk.

Therefore, the data was gathered through Amazon Mechanical Turk (M-Turk), which is aplatform that allows individuals to perform market research from a wide pool of online workersprimarily from the US. The raw data that is gathered through the Amazon Mechanical Turk (M-Turk) was downloaded onto the researcher's computer, which was then transferred to

Excel for data cleaning, followed by SPSS for statistical analyses.

The research project was divided into two separate studies, where Study 1 focused on gathering data on the relationship between the quality of AI chatbots and purchase intentions and loyalty, while Study 2 focused on gathering data on the moderating role of perceived risk on the relationship between the quality of AI chatbots and purchase intentions and loyalty. For both studies, the quality of AI was measured based on participant responses to two separate scenarios, where one showed a scenario for a low quality chatbot, and one showed a scenario for a high quality chatbot. Qualtrics software automatically divided participants at rando between these two conditions, which people read before taking their survey to judge the quality of the AI put forward.

3.4. Rationale for Utilizing this Method

Based on the methodology of this study, a two-experiment research design was carried out using American participants through M-Turk. Using two experiments was done because it can provide and improve internal validity for the results (Hampton, 2018). Furthermore, as recommended by Calder, Phillips and Tybout (1981), a sample that is homogenous on non-theoretical variables such as occupation or geographical location helps to minimize internal validity threats. The division between two different studies helped to confirm the relationship between the quality of AI chatbots and purchase intentions as well as loyalty by using two different sets of participants. Covid-19 made data collection within smaller regions such as New Zealand more challenging, and as such, an online questionnaire was created using Qualtrics that was then distributed through M-Turk within the US in order to collect data for the study. This method is justified based on Gosling, Vazire, Srivastava and John (2004), where the authors found that internet quantitative data collection methods are consistent with findings from traditional methods, and in some cases facilitate improved outcomes due to greater diversity of participants from online channels. Additionally, online quantitative research has been used in previous studies that involved investigations of consumer purchase intentions (e.g. Ariffin, Mohan & Goh, 2018) and loyalty (e.g. Aldas-Manzano, Ruiz-Mafe, Sanz-Blas & Lassala-Navarre, 2011). Ariffin et al. (2018) also made use of SPSS in their statistical analysis of consumer purchase intentions, highlighting is viability as a reliable statistical analytical tool. This helped to ensure validity and reliability, and confirmed interaction effects between AI chatbot quality, purchase intentions and loyalty.

3.5. Objectives of the Study

The objective of this study was to detect whether the quality of AI chatbots created any differences in purchase intentions and loyalty as supplied through the written scenarios, and then to determine whether perceived risks of AI chatbots have an effect on this relationship. Accordingly, the focus was placed on:

- Influences of AI chatbot quality on purchase intentions
- Influences of AI chatbot quality on customer loyalty
- Whether perceived risk had statistically significant moderating effects on the relationship between AI chatbot quality and purchase intention and customerloyalty

3.6. Measurements

The scenario for distinguishing between conditions of low and high chatbot quality from consumers was developed by the researcher based on a review of prior literature in relation to the information systems model of technology quality judgments (system quality, service quality, information quality). Thus, each scenario for low- and high-quality visions of AIcontained 3 sentence descriptions of the AI (for both Study 1 and Study 2). The first sentence descriptions (The chatbot gives limited information vs. the char bot gives sufficient information) reflects *system quality* as it relates to level of technical success for the information system being considered since it concerns the availability of information in the system. The second sentence descriptions (the chatbot takes too long to respond vs. the chatbot responds quickly) relate to *service quality* in its measurement of responsiveness of the AI. And the third sentence descriptions (The information is not helpful vs. the information is very helpful) relate to *information quality* as it relates to whether information presented to users was relevant, accurate and timely. Only one scenario was shownto each participant based on a random assignment from the Qualtrics software to equally divide participants between the two conditions. The developed scenarios and associated measurementof perceptions for the AI-based chatbot are shown below.

Table 1. Scenario conditions for measuring perceptions of AI chatbot Quality

Condition	**Scenario**
Low Quality	You are engaging with a chatbot to get information on a product you are about to purchase. During the interaction, you notice the following: - The chatbot gives limited information - The chatbot takes too long to respond - The information is not helpful
High Quality	You are engaging with a chatbot to get information on a product you are about to purchase. During the interaction, you notice the following: - The chatbot gives sufficient information - The chatbot responds quickly - The information is very helpful

The scale used to measure perceptions of the quality of the provided AI chatbot scenario was - How would you rate the quality of the chatbot?, which also served as a manipulation check. This question was measured on a 7-point Likert scale. The other questions used to measure the other variables were sourced from extant literature, and are listed in the following table.

Table 2. Measurement variables

Variable	**Source**	**Measures**	**Scale**
Purchase Intention	Chiu, Hsieh & Kuo (2012)	- I am likely to purchase products from this company	7-point Likert
		- I would consider buying the product from this company if I needed products of this kind?	7-point Likert
Perceived Risk	Agarwal & Teas (2001)	- How confident are you that the product will perform as described?	7-point Likert
		- How certain are you that the product will work satisfactorily?	7-point Likert
Customer Loyalty	Bobalca, Gatej & Ciobanu (2012)	- I would recommend this brand to those who ask my advice.	7-point Likert
		- I say positive things about this brand to other people.	7-point Likert
		I consider this company as my first choice when I want to buy such products.	7-point Likert

All questionnaires for Study 1 contained: 2 items for demographics (age and gender); 1 item relating to AI chatbot quality; 2 items relating to purchase intention; and 3 items relating to customer loyalty. All questionnaires for Study 1 contained: 2 items for demographics (age and gender); 1 item relating to AI chatbot quality; 2 items relating to purchase intention; 2

items relating to perceived risk; and 3 items relating to customer loyalty. After the participants had finished answering these questions, the Qualtrics software directed them to exit the questionnaire. The questionnaire was designed and constructed using English, ensuring the American participants could fully understand the questions.

As highlighted in Table 2, the items for the moderator variable were designed to measure the moderating effect of perceived risk on the relationship between the quality of AI and purchase intentions as well as loyalty, and were based on Agarwal & Teas (2001). The measures for the dependent variable purchase intention were designed based on similar measures used in Chiu et al. (2012). Lastly, the dependent variable customer loyalty was measured using measures adopted from Bobalca et al. (2012).

3.7. Sampling Plan

In the study, participants were sourced from 'Amazon Mechanical Turk' Participants. Although this sampling method increases the risk of bias such as sampling bias (where some people are more likely to respond to invitations), it has the advantage of being very easy to carry out with relatively low costs and time requirements. The participants in the study were sampled through the online panel on 'Amazon Mechanical Turk,' and included working professionals from the US that were paid for their participation. Therefore, the survey targeted US citizens above the age of 18, including both men and women, which was done by setting the qualifications settings (requirements for participation in the survey) within Amazon Turk, making the survey available to people that met these criteria.

In order to collect the relevant customer data, a questionnaire was created through 'Amazon Mechanical Turk.' The target number of participants was expected to be around 200 for each of Study 1 and Study 2 based on the sample size calculator for Qualtrics, with a confidence level of 95% and a margin of error of 5% for the US population. The final number of participants that answered the survey questionnaires was 195 for Study 1 and 194 for Study

2. Each participant in the study was paid $0.10 per person. The targeted participants were those currently living in the US with a HIT score higher than 93%. A HIT score in Amazon Mechanical Turk is the score assigned to potential participants based on the qualifications or criteria that the researcher wants them to have. In our case, participants that joined our study were restricted to those that had been a score of 93% based on the accuracy of previous HITS (which are other jobs/surveys) they had done. In the end, a total of 198 participants were successfully recruited for the study.

3.8. Survey Procedure

The Ethics Committee of the Auckland University of Technology provided approval for the research instrument to undergo data collection. The first page of the questionnaire that was posted on the invitation page on M-Turk was an information sheet containing all the details of the study and necessary disclosures about potential risks, which ensured all participants were well-informed of the study details. After reading the information sheet on M-Turk, participants were then directed via web-link to the questionnaire located on Qualtrics. Qualtrics is where the information from the participants was gathered and used to provide the results. The timeframe for the study was between June 30th 2021 and July 6th 2021, which was selected to help maximise the chance for the gathering of an appropriate sample size.

3.9. Data Analysis

Raw data gathered from M-Turk was transferred to Excel for data cleaning, after which it was transferred to SPSS to be used to model and analyse the data (Ariffin et al., 2018). The researcher analysed the data from the study by performing the following statistical analysis through SPSS:

- Frequency, to examine distribution and identify potential missing values.
- Descriptive analysis, to examine mean and standard deviation.

- Reliability, using the Cronbach's alpha to determine validity.
- Correlation, to determine the relationships between variables, as this provides a simple but reliable method for determining the potential connection between the variables based on questionnaire data.

- PROCESS macro moderation analysis, to determine the influence of the moderating variable on the relationship between independent and dependent variables.

3.10. Research Ethics

Ethics approval was a foundational requirement for this study due to the involvement of human participants. Therefore, the researcher met with the Auckland University of Technology Ethics Committee (AUTEC) and received ethics approval for the research to be undertaken, and ensured the method of data collection abided by ethical requirements and was within the bounds of the law. After careful review, all ethical issues related to participants in the study were adequately addressed and approved by the ethics board. The actual participation of respondents involved sharing information about their experiences and feelings using AI-enabled chatbot services, and required no personal or sensitive data related to their identities. All participant results will remain confidential to the primary researcher and not be used for anything else other than what is stated on the information sheet to complete the objectives of this study. Additionally, all surveys and other data will be deleted after 7 years of storage, and raw data will remain confidential. Any demographic information such as gender and income will not be attached to names or IDs, and will only be exposed to the research as a tool for raw data analysis. A basic information sheet informing participants of the study's purpose and their rights were attached, as per requirements from AUTEC.

Chapter 4: Data Analysis

4.1. Introduction

This chapter provides the analysed information that was taken from the raw data collected from both Study 1 and Study 2. The analysis includes frequency analysis, describe analysis, regression/correlation, and Hayes's PROCESS macro moderation analysis. All statistical analyses were replicated in both Study 1 and 2, besides Hayes's PROCESS macro moderation analysis, which only occurred in Study 2 to examine the potential moderating role of perceived risk on the relationship between AI chatbot quality with purchase intentions and loyalty.

4.2. Experimental Study 1

The between-subject questionnaires for both studies (Study 1 and Study 2) both included identical designs and questions, other than Study 2's inclusion of items to measure perceived risk. The "compute variable" function within SPSS was used to sort answers to different items into the three categories of purchase intentions, perceived risk and customer loyalty as required, followed by an appropriate statistical analyses as needed and as shown below. These included frequency analysis, describe analysis, regression/correlation, and Hayes's PROCESS macro moderation analysis.

4.2.1. Response rate of the two questionnaires

The two questionnaires were published on M-Turk with a paid reward of $0.1 USD per response from 30th of June 2021 to July 6th 2021. The number of respondents for Study 1 was 195, while the number of respondents for Study 2 was 194, for a response rate of 100%. Everyone that was entered into the Qualtrics questionnaires completed all answers as required, and there were no aberrant responses.

4.2.2. Respondent Characteristics for Study 1

The demographic data that was gathered from the participants of Study 1, including age and gender, are shown in Table 3 below:

Table 3. Frequency Statistics (study 1)

Variables	**Option**	**Frequency**	**Percentage (%)**
Gender	Male	115	59.0
	Female	80	41.0
Age Group	Under 19	3	1.5
	20-29	49	25.1
	30-39	79	40.5
	40-49	40	20.5
	50-59	15	7.7
	60+	8	4.1

The outcomes show a relatively even number of men and women respondents, with only a slight skew towards there being more males. In terms of the age group of respondents, the largest group is within the 30s range, followed by those in their 20s and then 40s, which indicates that the sample size was more towards the middle age group.

4.2.3. Regression test

A regression test was conducted in order to examine the relationship between the quality of AI chatbots and the purchase intentions of respondents. and whether ratings of AI quality predicted this. Scores for the variables were coded along a 7-point Likert scale, with a maximum score of 7 and a minimum score of 1. The results showed that the perception of the quality of the AI chatbot explained a significant amount of variance in purchase intentions in a scenario interacting with AI-based chatbots, $F(1, 193) = 372.14$, $p<.01$, R-square = .658. The regression coefficient ($B = .650$, 95%) indicated that an increase in one rating of quality for AI chatbots corresponded, on average, to an increase in purchase intention of .650 points (Appendix 3). The results suggested a significant positive relationship between the quality of chatbots and purchase intentions.

A regression test was conducted in order to examine the relationship between the quality of AI chatbot and the customer loyalty of respondents, and whether ratings of AI qualitypredicted customer loyalty. Scores for the variables were coded along a 7-point Likert scale, with a maximum score of 7 and a minimum score of 1. The results showed that the perceptionof the quality of the AI chatbot explained a significant amount of variance in customer loyaltyin a scenario interacting with AI-based chatbots, $F(1, 193) = 324.14$, $p<.01$, R-square = .627. The regression coefficient (B = .645, 95%) indicated that an increase in one rating of quality for AI chatbots corresponded, on average, to an increase in purchase intention of .645 points (Appendix 3). The results suggested a significant positive relationship between the quality of chatbots and customer loyalty.

4.3. Experimental Study 2

This was a replication of Study 2 with a different sample that was intended to confirm the results of Study 1, while also introducing the variable of perceived risk as a potential moderating factor in the relationship. 195 participants completed the questionnaire, and the same statistical analysis measures were repeated from Study 1, with the addition of a moderation analysis.

4.3.1. Respondents characteristics for Study 2

The demographic data that was gathered from the participants of Study 2, including age and gender, are shown in Table 3 below:

Table 4. Frequency Analysis (Study 2)

Variables	**Option**	**Frequency**	**Percentage (%)**
Gender	Male	99	51.0
	Female	95	49.0
Age Group	Under 19	4	2.1
	20-29	46	23.7
	30-39	65	33.5
	40-49	44	22.7
	50-59	16	8.2
	60+	19	9.8

The outcome of the demographic variables for Study 2 show an almost even distribution between male and female participants. Similar to Study 1, the age group for 30-39 was the largest number of participants in the sample, which was followed by the 20-29 age group and then by then 40-49 age group. This is a similar age distribution to Study 1.

4.3.2. Regression test

A regression test was conducted in order to examine the relationship between the quality of AI chatbots and the purchase intentions of respondents, and whether ratings of AI quality predicted the purchase intentions of customers. Scores for the variables were coded along a 7-point Likert scale, with a maximum score of 7 and a minimum score of 1. The resultsshowed that the perception of the quality of the AI chatbot explained a significant amount of variance in purchase intention in a scenario interacting with AI-based chatbots, $F(1, 192) = 435.48$, $p<.01$, R-square = .694. The regression coefficient (B = .650, 95%) indicated that an increase in one rating of quality for AI chatbots corresponded, on average, to an increase in purchase intention of .701 points (Appendix 3). The results suggested a significant positive relationship between the quality of chatbots and purchase intentions.

A regression test was conducted in order to examine the relationship between the quality of AI chatbots and the loyalty of respondents, and whether ratings of AI quality predicted the loyalty of customers. Scores for the variables were coded along a 7-point Likert scale, with a maximum score of 7 and a minimum score of 1. The resultsshowed that the perception of the quality of the AI chatbot explained a significant amount of variance in loyalty in a scenario interacting with AI-based chatbots, $F(1, 192) = 654.34$, $p<.01$, R-square = .773. The regression coefficient ($B = .650$, 95%) indicated that an increase in one rating of quality for AI chatbots corresponded, on average, to an increase in loyalty of .713 points (Appendix 3). The results suggested a significant positive relationship between the quality of chatbots and loyalty.

4.3.4. Moderation Analysis

In order to examine the moderating role of perceived risk on the relationship between the quality of AI chatbots and purchase intentions and customer loaylty, the researcher conducted a moderation analysis using Hayes's (2018) PROCESS macro in SPSS (Model 1, 10,000 bootstrapped samples). During this analysis, the independent variable was the quality rating for the AI chatbot, while purchase intention and customer loyalty were the dependent variables, and perceived risk was the moderator. Contrary to the prediction of this study, the analysis yielded an insignificant interaction effect of perceived risk with the AI chatbot technology and purchase intention ($b=-.012$, $t(244)=-.59$, $p=.559$) (Appendix 4).

The same moderation test was done to examine the moderating role of perceived risk on the relationship between the quality of AI chatbots and customer loyalty. The researcher conducted a moderation analysis using Hayes's (2018) PROCESS macro in SPSS (Model 1, 10,000 bootstrapped samples). During this analysis, the independent variable was the quality rating for the AI chatbot, while customer loyalty was the dependent variable, and perceived risk was the moderator. Contrary to the prediction of this study, the analysis yielded an insignificant interaction effect of perceived risk with the AI chatbot technology and loyalty ($b = -.023$, $t(427) = -1.49$, $p = .135$) (Appendix 4).

Chapter 5: Discussion and Contributions

5.1. Introduction

This chapter provides an in-depth discussion of the outcome and findings of the current study, as detailed in Chapter 4 regarding the two studies. Conclusion are draw as to their potential implications and alignment with prior literature, and whether they support the hypotheses of this study and are consistent with prior predictions.

5.2. Interpretation of the Results

5.2.1. The interaction between quality of AI chatbots and purchase intentions

The objective of Study 1 was to measure the interaction effects between the quality of AI chatbots and the purchase intention and loyalty of consumers. Firstly, the results showed that therewas indeed a significant positive correlation between the quality of AI chatbots during the encounter with an AI chatbot service agent and the purchase intentions of consumers. Chen (2013) pointed out that with most technologies such as mobile shopping systems, quality (as described by the information systems model with the three components of system, information, and service quality) has a significant influence on purchase intentions across multiple business sectors. Our results aligned with this, in that purchase intentions were closely influenced by perceived AI quality. Conceptually, the quality of AI chatbots not only correlates but predicts the purchase intentions of consumers.

There are various reasons for the results that Study 1 highlighted. The most likely and significant reason that the quality of AI is connected to purchase intentions and loyalty is that consumers are getting their needs met by the AI chatbot, which, from a customer service perspective, is largely about whether the information consumers are seeking is effectively provided to them (Martin & Khazanchi, 2006). This was supported by Cheng & Jiang (2020), who demonstrated that fulfilling the information needs of consumers was a key gratification of chatbot usage. Thus, considering chatbots as simple information business tools, they provide a utilitarian purpose such as the delivery of news, recommendations and other needs related to customer services.

AI-based chatbots generally provide not only a much more convenient experience to consumers, but they also save time, as consumers do not need to deal with a human service agent (Reddy, 2017). Another potential advantage of AI chatbots that contributes to the quality of service that promotes greater purchase intentions is the privacy of the customer service experience, as no interaction with a store employee is necessary. Indeed, Yadav and Pavlou (2020) highlighted how AI-enabled online checkdowns were preferred by some consumers due to their higher level of privacy. Thus, the major benefits of an AI-based chatbot lie in the potential technological and utilitarian advantages relevant to the user experience.

One of the variables that significantly influenced this outcome was the ages of the participants. Looking at the demographic variable of age as a factor related to online consumer purchase intentions, the people dealing with the technology (AI-based chatbots) were from a younger age group, shown to be much more likely to prefer advanced technological solutions (Hoyer et al., 2020). This would understandably lead to a higher purchase intention among consumers as reflected in this study, while older people showed a declining purchase intention. Therefore, those participants that tended to be younger found AI-based chatbot service agents more attractive, thereby encouraging their continued use of products from a company in comparison to older age groups.

5.2.2. The interaction between the quality of AI chatbots and customer loyalty

In the case of this study, researchers also measured the interaction between the quality of AI-based chatbots and customer loyalty as a separate factor. In this case, customer loyalty was defined according to the behavioural intentions of consumers to spread news or recommend products from the company using AI-based chatbots in their customer services. This is based on Bobalca et al. (2012)'s customer loyalty scale and the perspective that customer loyalty is based on actions by the consumer that influence the company in the long run (Uncles et al., 2003). This places the primary on the behavioural patterns of consumers, which not only relates to the "ongoing propensity to buy the brand," but also on their behavioural intentions to spread news about the brand (Ehrenberg and Scriven, 1999). As Zhang et al. (2018) highlighted, one of the most significant influences on the consumer decision-making process is online product recommendations, a critical factor in fostering long-term relationships with a wider array of customers. Therefore, customer loyalty based on participants' recommendations is an equally important factor when determining the advantages of AI-based chatbots in the long-run, if organisations plan to use it to facilitate future expansions of their services or products.

The results from Study 1 showed a significant influence between ratings for AI-based chatbot quality and the customer loyalty of participants. The regression results provided evidence of the AI chatbot quality's ratings having a significant influence on customer loyalty, validating the initial hypothesis. Similar results were also obtained within Study 2 that replicated the same study design with a different sample of participants, providing strong internal validity of these findings. These results are consistent with findings demonstrated in Gretzel (2011), where the customer experience that participants while using AI-based chatbots demonstrated a significant influence on brand love, which is closely related to and has influence on brand loyalty (Drennan et al., 2015). Since brand love has been found to be a significant mediator in word-of-mouth marketing (Yasin & Shamim, 2013), this could translate to brand loyalty, and highlights how AI-based chatbots can help customers recommend a product online to others during an online service experience.

5.2.3. The moderation interaction of perceived risk

Study 2 applied a moderation analysis in order to determine whether there was a conditional effect on purchase intention/loyalty due to the quality of AI chatbots driven by perceived risk. The findings from study 2 showed that perceived risk had no interaction effect on the relationship between the quality of AI-based chatbots and purchase intentions. Previous studieshave commonly found perceived risk to be a relevant moderator for purchase intentions in new technologies such as mobile payments or smartwatches (Gao & Waechter, 2017; Dehghani, 2018). Additionally, in an analysis of perceived risk as a moderating variable between AI-basedchatbots and brand love, a positive result was obtained that indicated the importance of perceived risk in the determination of customers' behavioural intentions in response to the use of AI (Yasin & Shamim, 2013). However, the present study found that there was no moderatinginteraction of perceived risk in the relationship between AI-based chatbot quality and purchaseintentions.

The negative effect refers to the perceived risk that consumers had in relation to AI-based chatbots. Therefore, from the current findings of this study, whether consumers believe AI-based chatbots are a trustworthy source of information for a product or company did not significantly influence their intentions to purchase. Although this differs from prior literature significantly, the results of this study could be a consequence of the pre-conceived notions that consumers have about AI-based chatbots before they engage with them. Specifically, Seiler and Schar (2021) have found that the stereotype content model holds true for human judgments of AI chatbots. The stereotype content model rates human interactions according to two dimensions, which include competence and warmth (perceived likeability), and can be applied not only to social context but also to AI-based chatbots due to their increasing similarity to human interactions (Seiler & Schar, 2021). Seiler and Schar (2021) discovered that chatbots accompanied by images showed higher values of competence and warmth, while those without images or associated material were rated low in warmth and competence. As a result, the use of pictures or other material can effect consumers' judgements with regard to AI-based chatbot quality. This is significant because the same study also found that these initial judgements influenced the level of trust that consumers had for the chatbots from their initial interaction with them (Seiler & Schar, 2021). Since this study used AI-based chatbot scenarios where all AI (according to the descriptions provided by Seiler & Schar, 2021) would be rated as relatively lower in warmth and competence, this could have affected both the trust and perceived risk in a relatively similar way, no matter the ratings regarding the quality of services provided by the AI-based chatbots. This, in turn, would negate any interactive effects that the perceived risk might have had on the relationship between the quality of AI chatbots and purchase intentions and loyalty.

Several studies have found other factors that have a significantly more influentialeffect on purchase intentions when using AI-based chatbots. For example, Zsarnoczky (2017)found that tourists will use AI-based chatbots to find objects and locations, and solve doubts and obtain information. These do not require a high level of trust or low levels of perceived risk, since they does not require the entering of personal information. Instead, among a numberof different variables, Morosan & DeFranco (2016) found that adopting new user technologiesin situations where they are no longer novel is primarily driven by usefulness and performance across both voluntary and mandatory settings. Therefore, it is conceivable that due to AI-based chatbots being introduced across a number of platforms for years, they are no longer novel and are thus more dependent on performance-related issues rather than on the level of perceived risk consumers have regarding the use of AI-based chatbots.

Another explanation for the lack of moderating interaction for perceived risk is because of the AI-based chatbot services under investigation, where simple customer service agents focused on information provision rather than the processing of sensitive information, such AI checkouts that process transactions directly. Thus, the perceived risk of consumers in this study may not have had significant effects on the relationship between AI quality and purchase intentions/loyalty. Additionally, the scenarios provided by the study in order to condition participants to recognize high or low quality AI situations may have negated pre-conceived notions about the level of risk of the AI they were judging, since the scenarios stated whether the AI had a high or low success rate when providing relevant information (See Questionnaire in Appendix 1 and 2). Thus, there is a real potential that the design of this study affected the way that participants judged the level of perceived risk they felt toward AI-based chatbots while they were answering the questions, and did not reflect their true perceptions of AI-based chatbots in real life (i.e. novel) situations.

5.3. Contributions to the Literature

Due to the rapid advancements within the artificial intelligence space, there is a strong implication for its use within retail environments that both practitioners and academics should develop a more detailed understanding of, in order to facilitate its integration into the consumer experience. Prior research has demonstrated a strong relationship between the quality of AI and variables such as brand love and loyalty. These outcomes offer practitioners (i.e. marketers) within business retail environments important considerations in terms of AI's incorporation into marketing strategies across online outlets. The statistical analysis of this study showed that the quality of AI chatbots in terms of the three quality dimensions of service, information and system performance was statistically related to purchase intentions and customer loyalty. This analysis also found that the perceived risk of using AI chatbots did not have a moderation interaction effect between these relationships. The results of this study would be able to assist businesses in increasing the potential of AI-based chatbots in terms of their ability to drive greater purchase intention and loyalty among consumers. Therefore, there are theoretical and practical implications of the results of this study in relation to AI-based chatbots within the

American online retail environment.

5.3.1. Theoretical contribution

Concerning the sourcing of company or product information, AI-based chatbots were still considered a relatively new technology within retail spaces, as only the major organisations were using them. There has been a limited amount of empirically supported evidence that has looked at the influence that AI-based chatbots or services have on attitudinal and behavioural variables among consumers (Van Esch et al., 2020). Additionally, there has been no research examining the influence that perceived risk has on the relationship between AI chatbot quality and the behavioural variables of purchase intentions and customer loyalty. This leaves a gap in the literature regarding perceived risk that has traditionally been a significant factor in the adoption of new technologies within marketplaces (Gao & Waechter, 2017; Dehghani, 2018). This study extended the theory in relation to technology acceptance in the inclusion of AI-based chatbots, specifically in relation to perceived risk, purchase intentions and consumer loyalty.

The findings have also contributed to literature surrounding AI in relation to the long-term value of consumers. Specifically, the study provided internally validated findings on the influential relationship between the quality of AI and long-term purchase intentions and customer loyalty (i.e. word of mouth). These findings corroborate prior studies connecting AI-based chatbot quality and brand love (Yasin & Shamim, 2013), and highlight how AI quality plays an important role in the long-term value of consumers using AI chatbots online in terms of information, system and service factors.

The perceived risk of AI-based chatbots did not play and important moderating role in the relationship between the quality of AI-based chatbots and purchase intentions or customer loyalty. This contradicts research in relation to other technologies, and is thus an invitation for further research to understand these results in terms of their reliability and the potential underlying reason why perceived risks of AI chatbots might not affect purchase intentions or customer loyalty. This could be due to a potential lack of personal information gathering from simple customer service related chatbots (unlike AI chatbots used in checkout services), or a stereotyped understanding of AI chatbots among general consumers that negates the effects of perceived risk.

5.3.2. Practical Implications

As the quality of these systems increases, AI-based chatbots used in customer service and the provision of information offers benefits in terms of increased purchase intentions and customer loyalty. This contributes to marketing literature related to the long-term value of consumers that interact with AI-based chatbots online, suggesting that investments to improve their quality is a worthwhile investment for companies looking to adopt new technologies to improve services and reduce costs. As a result, it should also encourage retailers to adopt other AI-enabled technologies in order to increase convenience and reduce costs for both businesses and consumers. This would increase their purchase intentions and loyalty, while keeping in mind that AI have dramatic benefits toward the reduction of labour costs (Ostrom et al., 2019). Much of the research within the current environment has focused on the technological features of new solutions while ignoring relationships with critical business outcomes like loyalty, purchase intentions and satisfaction due to the burgeoning nature of AI-based chatbots (Yasin & Shamim, 2013, Dehghani, 2018). However, as AI-based chatbots become increasingly recognised as significant contributors to long-term consumer value through marketing communications, studies that investigate the impact of these technologies on such business outcomes are essential.

The results in relation to the lack of perceived risk as a moderating factor demonstrate that the core variable for consumers is the performance and strength of the AI-based chatbot, As such, concerns about the perceived risk of the system do not provide a significant impact, as long as their performance levels remain high. This would also mean that companies would be free to gather and utilize consumer data through AI chatbots with simple measures to reassure potential performance concerns such as a transparent chatbot policies and clear performance expectations, providing them with an avenue for developing consumers insights that would be less contentious that other customerservice avenues.

In summary, this study has provided important insights in terms of the role of AI-based chatbots in marketing/business communications, while offering guidance on how the quality of AI-based chatbots could be used to improve purchase intentions and customer loyalty. This would significantly benefit companies using strategies capable of improving and promoting the continued utilisation of AI-based chatbot customer service agents. A corporate service provider needs to make sure that consumers are able to easily access chatbots, reduce time spent in inquires, and can meet or exceed information needs. Additionally, results showed thatperceived risk was not a major concern that reduced purchase intention or loyalty rates, thus giving marketers increased freedoms when using AI chatbots, as long as their quality remainshigh.

Chapter 6: Conclusion

6.1. Introduction

The objective of this chapter is to provide a conclusion of the key findings and implications of this research on AI-based chatbots as customer service agents, as well as the research limitations and potential areas that future research could expand on.

6.2. Summary of the Research

The quality of AI-based chatbots was defined in the context of the information system model based on service, information and system quality (Delone & McLean, 2003). Purchase intentions and customer loyalty were defined according to the behavioural intentions perspective, with purchase intentions relating to the tendency to re-purchase from the same brand (Pavlou, 2003), and consumer loyalty as an indication of whether consumers would be willing to recommend the product externally (Delcourt et al., 2013). Perceived risk was defined according to Agarwal & Teas (2001), based on the idea that consumers thought that the product would be able to satisfy their needs when using AI-based chatbots. The overall aim of this study was to develop a deeper understanding of the interactions that influence the effectivenessof AI chatbots as customer service agents replacing humans within online retail environments.More specifically, by conducting two experimental online investigations, the researcher examined the moderation effect of perceived risk on the relationship between AI-based chatbotquality and purchase intentions, as well as customer loyalty.

The primary discovery of this research is as follows. Firstly, there was a strong positive connection between the quality of AI-based chatbots and purchase intentions. Secondly, there was a strong positive connection between the quality of AI-based chatbots and customer loyalty. Lastly, there was no moderation interaction effect for perceived risk between the quality of AI-based chatbots and purchase intentions or customer loyalty. Therefore, the hypothesis of this study regarding the moderating effect of perceived risk was disproved, highlighting a potential area of future research to understand why this specific perceived risk factor was not relevant, and whether other types of perceived risks may be able to demonstrate a significant moderation effect.

Ultimately, this study has contributed to the literature within marketing. Firstly, the scenarios that have been developed to measure the quality of AI-based chatbots can be used in future marketing research. Secondly, the study has provided evidence of the effects of AI-based chatbot quality (based on the information system model) on purchase intentions and customer loyalty during online AI chatbot interactions. Lastly, it removes some doubt about whether perceived risk will influence relationships between AI and purchase intentions or loyalty, as it does across multiple other forms of new technology.

6.3. limitations of the Study

This study was subject to a number of different limitations, which need to be acknowledged in order to effectively identify the constraints that may have potentially influenced its findings and interpretations. The limitations also present potential areas for future research. The current study was carried out through an online medium and involved the collection of data through M-Turk. Although the findings found a significant connection between the quality of AI-based chatbots and purchase intentions as well as customer loyalty, the findings were based on artificial scenarios provided to consumers, with no reference to brands or consideration for actual participant experiences with AI-based chatbots. As such, the strong relationship seen in this study may be reduced significantly when actual AI chatbots are weighted against associated brands, real life benefits, experiences and performance, which cannot be factored into such an online experiment. Due to the widespread nature of the Covid-

19 pandemic, field studies were impractical and the study needed to rely on online questionnaires as the primary form of data collection. Since AI-based chatbots are a new but increasingly widespread technology, there may also be other unexamined variables that could influence consumer attitudes toward them, or their purchase intentions/loyalty towards brands using AI-based chatbots that remain to be explored.

Another limitation is that samples for both studies were sourced from American populations, which limits the generalisability of the findings to non-Western cultures. This is an important factor, because individualistic cultures could potentially have a much lower level of perceived risk towards AI mimicking human interactions, in comparison to more collectivist cultures where human interaction and connections are primary within society. Thus, the findings of this study should be replicated within a more collectivist culture to ensure a wider generalisability of the results. Furthermore, there was no major moderating effect of perceived risk on the relationship between the quality of AI-based chatbots and purchase intentions and loyalty. However, the current study only examined perceived risk based on Agarwal & Teas (2001), who categorised it as the risk that the AI-based chatbot fails to perform its designed task. However, there may be other forms of risk that were not examined in the current study that may have a significant moderation effect on the investigation relationships, including but not limited to perceived risk of personal data loss.

6.4. Suggestions for Future Research

The study indicates a number of directions that future research could take in the investigation of AI-based chatbots and consumer behavioural intentions. For instance, due to the limitation of the current study to online methodologies as a result of the current global Covid-19 pandemic, future research could employ a more detailed experimental field study in the investigation of these relationships (i.e. introducing practice testing of AI chatbots on computers) in order to enhance the results and understand consumers' attitudes and behavioural intentions after interacting with AI-based chatbots of various quality. Additionally, this study has contributed to the first wave of investigations into the influence that customer service-based AI chatbots have on customer behaviours such as purchase intentions and long-term customer loyalty (i.e. word of mouth). It is also the first to examine the level of perceived risk's moderation effect on these relationships. Further research should similarly expand on this study to explore other ways that variables may be able to help propel the use of this technology forward. For instance, by exploring new moderating or mediating factors between AI-based chatbots and purchase intentions/loyalty, future research could help identify other factors that promote a strong relationship between AI chatbots and positive customer outcomes.

A potential perspective as to why the moderating effect was not confirmed in this study is due to the perception of warmth regarding the target AI that could have potentially acted as a confounding variable. In future studies, in order to confirm this speculative result, it would be prudent to take into consideration the perception of warmth vs. coldness by utilizing different descriptions of AI that incorporate images. Additionally, this should be confirmed with wider and more generalizable studies by using a larger sample that is more internationally representative.

6.5. Conclusion

As the propagation of AI-based chatbots as online customer service agents continues to increase within the retail and business sectors, organisations have to find new ways toovercome competition, as well as the potential reluctance of consumers to use this 'new' technology. AI-based chatbots have been launched by a wide array of multinational companiessuch as Google, Apple and Amazon, and have the ability to dramatically improve services that help with information searching and improve perceptions of a product or brand. Therefore, a need exists for companies to develop a deeper understanding of AI-based chatbots and their effect on consumers' behavioural intentions after use, in order to determine whether they can be successfully implemented, and what kind of adoption strategies would be needed.

The research gathered American consumer behavioural intents regarding purchase intentions and customer loyalty (word of mouth intentions) based on responses regarding the quality of an AI chatbot. A potential moderation effect of perceived risk on these relationships was also analysed to determine potential influencing factors that companies need to be aware of when implementing AI-based chatbots. The results revealed a significant relationship between the quality of AI-based chatbots and purchase intentions as well as customer loyalty, but no moderating effect of perceived risk on these relationships. Thus, practitioners and academics will need to further expand the potential factors that influence AI chatbots and customer behavioural intentions among consumers, which will help with the appropriate integration of AI chatbots as a cost-reducing customer service strategy in the future.

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Appendix 1 – Sample Questionnaire for Study 1

1. Do you consent to participate in this study?

Yes

No

2. What is your Age? Please fill in the provided space.

______

Scenario

(low quality condition) You are engaging with a chatbot to get information on a product you are about to purchase. During the interaction you notice the following:

- The chatbot gives limited information
- The chatbot takes too long to respond
- The information is not helpful

Or

(High quality condition) You are engaging with a chatbot to get information on a product you are about to purchase. During the interaction you notice the following:

- The chatbot gives sufficient information
- The chatbot responds quickly
- The information is very helpful

3. How would you rate the quality of the chatbot?

Very low quality	1	2	3	4	5	6	7	Very high quality

4. Please indicate how much you agree or disagree with the following statements based on the initial scenario with the chatbot.

	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
I am likely to purchase the products from this company	1	2	3	4	5	6	7
I would consider buying the product from this company if I need products of this kind	1	2	3	4	5	6	7

5. Please indicate how much you agree or disagree with the following statements based on the initial scenario with the chatbot.

	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
I would recommend this brand to those who ask for my advice	1	2	3	4	5	6	7
I say positive things about this brand to other people	1	2	3	4	5	6	7
I consider this company as my first choice when I want to buy such products	1	2	3	4	5	6	7

The End

Appendix 2 – Sample Questionnaire for Study 2

Do you consent to participate in this study?

Yes

No

2. What is your Age? Please fill in the provided space.

_____

Scenario

(low quality condition) You are engaging with a chatbot to get information on a product you are about to purchase. During the interaction you notice the following:

- The chatbot gives limited information
- The chatbot takes too long to respond
- The information is not helpful

Or

(High quality condition) You are engaging with a chatbot to get information on a product you are about to purchase. During the interaction you notice the following:

- The chatbot gives sufficient information
- The chatbot responds quickly
- The information is very helpful

3. How would you rate the quality of the chatbot?

Very low quality	1	2	3	4	5	6	7	Very high quality

4. Please indicate how much you agree or disagree with the following statements based on the initial scenario with the chatbot.

	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
I am likely to purchase the products from this company	1	2	3	4	5	6	7
I would consider buying the product from this company if I need products of this kind	1	2	3	4	5	6	7

5. Please indicate how much you agree or disagree with the following statements based on the initial scenario with the chatbot.

	Strongly disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Strongly agree
I would recommend this brand to those who ask for my advice	1	2	3	4	5	6	7
I say positive things about this brand to other people	1	2	3	4	5	6	7
I consider this company as my first choice when I want to buy such products	1	2	3	4	5	6	7

6.

Please indicate how confident you are regarding the following statement based on the initial scenario with the chatbot.

	Not at all confident	Not confident	Slightly not confident	Neutral	Slightly confident	Confident	Very Confident
How confident are you that the product will perform as described?	1	2	3	4	5	6	7

Please indicate how certain you are about the following statement based on the initial scenario with the chatbot.

	Very uncertain	Uncertain	Slightly uncertain	Neutral	Slightly certain	Certain	Very Certain
How certain are you are the product will work satisfactorily?	1	2	3	4	5	6	7

The End

Appendix 3 – SPSS outputs for raw data analysis for Study 1

Regression Analysis for Study 1(Quality of Chatbots – Purchase Intentions)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.811[a]	.658	.657	.89761	.658	372.136	1	193	.000

a. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	299.832	1	299.832	372.136	.000[b]
	Residual	155.501	193	.806		
	Total	455.333	194			

a. Dependent Variable: PurInt

b. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.655	.193		8.569	.000
	How would you rate the quality of the chatbot? - Very low quality: Very high quality	.650	.034	.811	19.291	.000

a. Dependent Variable: PurInt

The results suggest a ***significant positive relationship*** between the quality of chatbots and purchase intentions.

Regression Analysis for Study 1 (Quality of Chatbots – Customer Loyalty)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.792[a]	.627	.625	.95349	.627	324.000	1	193	.000

a. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	294.566	1	294.566	324.000	.000[b]
	Residual	175.466	193	.909		
	Total	470.032	194			

a. Dependent Variable: CusLoy

b. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.635	.205		7.972	.000
	How would you rate the quality of the chatbot? - Very low quality: Very high quality	.645	.036	.792	18.000	.000

a. Dependent Variable: CusLoy

The results suggest a ***significant positive relationship*** between the quality of chatbots and Customer Loyalty.

Appendix 4 – SPSS outputs for raw data analysis for Study 2

Regression Analysis for Study 2 (Quality of Chatbots – Purchase Intentions)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.833[a]	.694	.692	.99094	.694	435.477	1	192	.000

a. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	427.623	1	427.623	435.477	.000[b]
	Residual	188.537	192	.982		
	Total	616.160	193			

a. Dependent Variable: PurchaseIntentions

b. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.334	.176		7.565	.000
	How would you rate the quality of the chatbot? - Very low quality: Very high quality	.701	.034	.833	20.868	.000

a. Dependent Variable: PurInt

The results suggest a ***significant positive relationship*** between the quality of chatbots and purchase intentions.

Regression Analysis for Study 2 (Quality of Chatbots – Customer Loyalty)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.879[a]	.773	.772	.82235	.773	654.337	1	192	.000

a. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	442.502	1	442.502	654.337	.000[b]
	Residual	129.842	192	.676		
	Total	572.344	193			

a. Dependent Variable: Customer Loyalty

b. Predictors: (Constant), How would you rate the quality of the chatbot? - Very low quality: Very high quality

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.163	.146		7.944	.000
	How would you rate the quality of the chatbot? - Very low quality: Very high quality	.713	.028	.879	25.580	.000

a. Dependent Variable: CusLoy

The results suggest a ***significant positive relationship*** between the quality of chatbots and Customer Loyalty.

Moderation Analysis was done using Hayes' Process Macro v3.5 (Quality – risk – Purchase Intentions)

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : PurInt
    X  : Rating
    W  : PerRisk

Sample
Size:  194

**************************************************************************
OUTCOME VARIABLE:
 PurInt

Model Summary
          R       R-sq        MSE          F        df1        df2
p
      .8912      .7942      .6675   244.3486     3.0000
190.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .2416      .3187      .7581      .4493     -.3871      .8704
Rating        .3837      .0983     3.9040      .0001      .1899      .5776
PerRisk       .6229      .0960     6.4851      .0000      .4334      .8123
Int_1        -.0116      .0196     -.5900      .5559     -.0503      .0272

Product terms key:
 Int_1    :        Rating   x        PerRisk

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0004      .3481     1.0000   190.0000      .5559
```

(The lack of significance suggests that the interaction between Chatbot quality and Purchase Intentions is not moderated by perceived risk)

```
---------------
    Focal predict: Rating   (X)
          Mod var: PerRisk  (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Rating     PerRisk    PurInt     .
BEGIN DATA.
     2.6803     3.0046     3.0483
     4.8041     3.0046     3.7894
     6.9280     3.0046     4.5304
     2.6803     4.6701     4.0340
     4.8041     4.6701     4.7341
     6.9280     4.6701     5.4342
```

```
     2.6803     6.3356     5.0197
     4.8041     6.3356     5.6788
     6.9280     6.3356     6.3379
END DATA.
GRAPH/SCATTERPLOT=
 Rating   WITH     PurInt   BY       PerRisk  .

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Moderation Analysis was done using Hayes' Process Macro v3.5 (Quality – risk – Customer loyalty)

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 3.5 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2018). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : CusLoy
    X  : Rating
    W  : PerRisk

Sample
Size:  194

**************************************************************************
OUTCOME VARIABLE:
 CusLoy

Model Summary
          R       R-sq        MSE          F        df1        df2
p
      .9332      .8709      .3890   427.0901     3.0000
190.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.0274      .2433     -.1126      .9105     -.5074      .4526
Rating        .4634      .0750     6.1751      .0000      .3153      .6114
PerRisk       .6333      .0733     8.6370      .0000      .4886      .7779
Int_1        -.0225      .0150    -1.4993      .1354     -.0521      .0071

Product terms key:
 Int_1    :        Rating   x        PerRisk

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
```

X*W .0015 2.2480 1.0000 190.0000 .1354**(The lack of significancesuggests that the interaction between Chatbot quality and Customer Loyalty is not moderated by perceivedrisk)**

```
---------------
    Focal predict: Rating   (X)
          Mod var: PerRisk  (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Rating     PerRisk    CusLoy     .
BEGIN DATA.
     2.6803     3.0046     2.9362
     4.8041     3.0046     3.7769
     6.9280     3.0046     4.6175
     2.6803     4.6701     3.8906
     4.8041     4.6701     4.6518
     6.9280     4.6701     5.4129
     2.6803     6.3356     4.8450
     4.8041     6.3356     5.5266
     6.9280     6.3356     6.2083
END DATA.
GRAPH/SCATTERPLOT=
 Rating   WITH     CusLoy   BY       PerRisk  .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Appendix 5 – Ethics Approval

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

24 June 2021

Patrick van Esch
Faculty of Business Economics and Law

Dear Patrick

Re Ethics Application: **21/162 The moderating role of perceived risk between AI chatbots, purchase intentions and customer loyalty in customer service**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 24 June 2024.

Non-Standard Conditions of Approval

1. Remove the 'how will these discomforts and risks be alleviated' and 'compensation' sections from the Information Sheet;
2. Remove the bullet points under 'consent' at the end of the Information Sheet - the statement about completion equalling consent is adequate for an anonymous survey;
3. Revise questions 2.9 and 2.21 so that they will make sense to the participant.

Non-standard conditions must be completed before commencing your study. Non-standard conditions do not need to be submitted to or reviewed by AUTEC before commencing your study.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard and that all the dates on the documents are updated.

AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: Jiaming Yu