THE ROLE OF NATURAL LANGUAGE PROCESSING IN IMPROVING CUSTOMER SERVICE AND SUPPORT IN E-COMMERCE

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BY

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A final year project submitted in partial fulfilment of the requirement for the degree of

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DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work and that due acknowledgment has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutions of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 10,414 words .

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Lastly, my gratitude extends to everyone who has been directly or indirectly involved in contributing to the successful completion of this Final Year Project.

DEDICATION

I would like to dedicate this final year project to my esteemed supervisor, Dr. Farah Waheeda binti Jalaludin, and my second examiner, Ms. Loh Yin Xia, whose invaluable feedback, guidance, insights, and support significantly contributed to my Final Year Project journey. Additionally, I express my thanks to my cherished family members, friends, lecturers, seniors, and all respondents who provided substantial support throughout this endeavor. All encouragement and assistance were crucial, and without them, the successful completion of this Final Year Project would have been a challenging task.

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LIST OF ABBREVIATIONS

AVE	Average Variance Extraded
CE	Customer Experience
CS	Customer Satisfaction
HTMT	Heterotrait-Monotrait
NLP	Natural Language Processing
OL	Observational Learning
PEOU	Peceived Ease of Use
PLS-SEM	Partial Least Squares Structural Equation Modeling
PU	Perceived Usefulness
SCT	Social Cognitive Theory
SE	Self-efficacy
SI	Social Influence
TAM	Technology Acceptance Model
VIF	Variance Inflation Factor

PREFACE

According to the University Tunku Abdul Rahman's (UTAR) standards, all students pursuing a Bachelor of International Business (Honours) degree must complete the "UKMZ2016 Research Project" as the last year's project. "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce" is the title of this final year project. The major aim for this research study to be carried out is to bring awareness to nationwide application for Natural Language Processing (NLP).Thus, the relationship between the dependent variables (customer experience and customer satisfaction) and the independent variables (perceived ease of use, perceived usefulness, social influence, self-efficacy and observational learning) is examined in this study. From this point forward, I expect that the study project will be able to give a clear and precise knowledge of the role of Natural Language Processing in Improving Customer Service and Support in E-commerce.

ABSTRACT

This research investigates the factors The study centers on the role of Natural Language Processing (NLP) in improving customer service and support in E-commerce. The study utilizes quantitative surveys to comprehensively explore the role of Natural Language Processing (NLP) in enhancing customer service and support in E-commerce. Drawing upon a theoretical framework grounded in the Technology of Acceptance Model (TAM) and Social Cognitive Theory(SCT), the research identifies and analyzes key factors such as customer experience, customer satisfaction, perceived ease of use, perceived usefulness, social influence, self-efficacy and observational learning.

The process of collecting data took place using online platforms, such as WhatsApp, Facebook, Instagram, and Microsoft Teams. The study is to offer useful insights for marketers, policymakers, and stakeholders in the cosmetics industry who want to comprehend and take advantage of the role of Natural Language Processing in improving customer service and support in E-commerce through data analysis and interpretation.

The findings clearly show the structural model results provide support for H1, H3, H5 and H6, indicating that customer experience exerts a positive influence on customer satisfaction while observational learning, perceived ease of use and social influence exerts a positive influence on customer experience. Specifically, the results reveal that customer experience emerges as the most significant predictor in improving customer service and support in e-commerce, followed by perceived ease of use, social influence and observational learning. There was a discussion of the implications, limitations, and suggestions for additional research.

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

The research intends to investigate on how the perceived usefulness, perceived ease of use of chatbots, natural language processing systems, social influence, self-efficacy, observational learning affect the customer satisfaction in E-Commerce. Chapter 1 of explains the research background, problem statement, questions for the research, the objectives of this study and justification or significance of the research.

1.1 Research background

The research on "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce" aims to explore the potential of NLP in enhancing customer service and support in the context of e-commerce. With the advent of online shopping platforms, there is a growing need for efficient and effective customer interactions. The integration of NLP technology can improve the automation of customer service tasks, such as responding to inquiries, addressing complaints, and providing personalized recommendations. This research will examine different NLP techniques, including sentiment analysis, chatbots, and voice recognition, to understand their impact on customer satisfaction, loyalty, and overall e-commerce success.

1.1.1 Artificial Intelligence in E-Commerce

E-commerce is currently one of the industries at the forefront of leveraging artificial intelligence for various purposes, including expanding their customer base, gaining insights into customer preferences, conducting real-time market research, and developing innovative solutions. Artificial intelligence can manifest in various ways. In the realm of software-based artificial intelligence, this encompasses virtual assistants, image analysis software, search engines, and systems for speech and facial recognition. On the other hand, artificial intelligence integrated into physical devices includes robots, autonomous vehicles, and drones. (Fedorko et al., 2022)

1.1.2 Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence focusing on machines' interaction with human language. It uses techniques from linguistics, computer science, and probability theory to interpret and generate human language (LeCun & Pal, 2017). NLP's applications include machine translation, enhancing cross-cultural communication with models like neural machine translation. Sentiment analysis, another crucial NLP area, employs algorithms for emotion detection and sentiment classification, aiding market research and customer feedback analysis (Cambria & Hussain, 2012). As NLP technology advances, it promises continued enhancements in human-computer interaction and broader applications in various fields.

1.2 Problem Statement

In the fast-evolving landscape of technology and customer service, Natural Language Processing (NLP) emerges as a potent tool for enhancing customer experiences. Despite its vast capabilities, there exists a widespread lack of awareness and understanding regarding the nationwide application of NLP. This research aims to bridge this gap by delving into the factors influencing customer experiences and satisfaction when utilizing NLP solutions in customer interactions.

Comparing the study on "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce" with an adapted Technology Acceptance Model (TAM) study on e-wallet adoption reveals a distinct focus. The NLP study explores how NLP enhances customer service in e-commerce, emphasizing automation and interaction technologies. In contrast, the TAM study centers on e-wallet adoption, considering factors like ease of use, usefulness, and customer satisfaction within mobile financial apps (Olivia.M et.al, 2022). The technological contexts of NLP in e-commerce and e-wallet adoption point to a research gap, signaling the need for dedicated investigations to comprehend the specific impacts and applications of these technologies in their respective domains.

Another research gap emerges between the NLP study and the Social Cognitive Theory (SCT) study titled "Self-efficacy: Toward a Unifying Theory of Behavioral Change." While the NLP study focuses on technology in e-commerce customer service, the SCT study presents a broader framework for understanding psychological changes, emphasizing self-efficacy enhancement (Bandura, A., 1977).

In summary, addressing the nationwide lack of awareness and understanding of NLP's application is crucial. This research endeavors to uncover the factors influencing customer experiences and satisfaction with NLP, facilitating informed and effective utilization of NLP in a broader context for the benefit of organizations and customers.

1.3 Research objective

1.3.1 General Objective

The major aim for this research study to be carried out is to bring awareness to nationwide application for Natural Language Processing (NLP).

1.3.2 Specific Objectives

i. To investigate if perceived ease of use, perceived usefulness, social influence, self-efficacy and observational learning will affect customer experience in using Natural Language Processing

ii. To investigate if customer experience will affect customer satisfaction in using Natural Language Processing

1.4 Research Questions

i. Will perceived ease of use, perceived usefulness, social influence, self-efficacy and observational learning will affect customer experience in using Natural Language Processing?

ii. Will customer experience will affect customer satisfaction in using Natural Language Processing

1.5 Significance of study

Body of knowledge

The research titled "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce" significantly contributes to academia by advancing the comprehension of how Natural Language Processing (NLP) can transform customer service within the E-commerce domain. This research provides scholars with fresh perspectives on the practical implementation of NLP technologies in real-world scenarios. By scrutinizing the variables and mechanisms through which NLP elevates customer service, it establishes a substantial groundwork for further academic investigation in the domains of machine learning, artificial intelligence, and customer experience management. Furthermore, this research has the potential to stimulate future scholars to conduct in-depth examinations of the nuances of NLP in E-commerce, fostering the evolution of innovative methodologies and theoretical frameworks to enhance customer support.

Business Practitioner

For sellers and businesses in the E-commerce sector, the research on "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce" is of paramount importance. It offers practical insights into how NLP tools and technologies can be harnessed to optimize customer interactions and support functions. Sellers can leverage these insights to implement advanced chatbot systems that provide efficient and personalized customer support. Moreover, the research highlights the potential for NLP to drive sales through enhanced product recommendations and improved query resolution. By embracing NLP, businesses can streamline their operations, improve customer satisfaction, and ultimately achieve economic growth by fostering customer loyalty and trust.

Buyer and Consumer Contribution:

From the buyer and consumer perspective, the research on NLP's role in E-commerce customer service is highly beneficial. Buyers gain access to more efficient and responsive customer support systems that can address their inquiries promptly. Additionally, NLP-powered product recommendations enhance the shopping experience by presenting tailored choices that align with individual preferences. This not only saves buyers time but also helps them discover products they might have missed otherwise. As consumers gain a better understanding of how NLP enhances customer service, they can confidently navigate E-commerce platforms, knowing that their queries will be resolved accurately and promptly. Ultimately, informed and satisfied buyers contribute to the economic growth of E-commerce businesses through increased sales and positive word-of-mouth recommendations.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This classification will assess past empirical studies in conjunction with a review of relevant theoretical frameworks pertaining to the research subject. This will be accompanied by a concise introduction to the dependent and independent variables involved.

2.1 Theoretical Framework

The theoretical framework integrates the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT) to understand the adoption of Natural Language Processing (NLP) in e-commerce. TAM emphasizes perceived ease of use and perceived usefulness, highlighting NLP's role in providing user-friendly interfaces and enhancing overall customer experience, while SCT considers social influence, self-efficacy, observational learning, and customer experience as influential factors in shaping behavior and satisfaction.

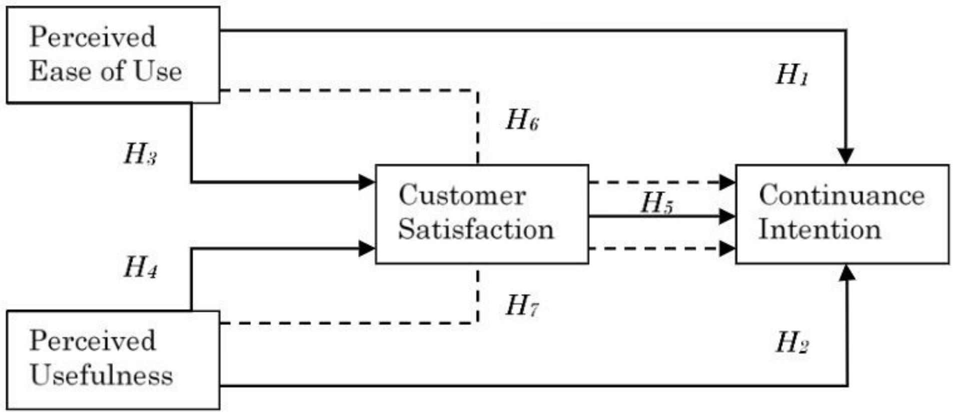
2.1.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a widely recognized framework for comprehending the factors that impact how people accept and utilize technology. (Davis, F., 1989). According to TAM, individuals' attitudes and actions towards technology adoption are predominantly influenced by two factors: their perception of how easy the technology is to use and their belief in how useful it is in enhancing their job performance or productivity. (Venkatesh, V., et.al, 2003). The Technology Acceptance Model (TAM), originally designed for information systems, is widely applied across various disciplines, such as marketing and e-commerce. TAM identifies perceived ease of use and perceived usefulness as key factors influencing customer satisfaction, suggesting that customers satisfied with the accessibility of a digital platform, like an e-wallet, are likely to continue using it (Olivia.M et.al, 2022). Perceived ease of use pertains to how effortless someone perceives a technology system to be, while perceived usefulness relates to how much the technology can improve their work or tasks. In e-commerce, the application of Natural Language Processing (NLP) can boost both perceived ease of use and perceived usefulness by offering user-friendly interfaces and features that provide personalized recommendations and streamline information retrieval. (Shin, D. H., & Biocca, F. A., 2017).

The connection between TAM, perceived ease of use, perceived usefulness, and customer satisfaction with NLP in e-commerce has been extensively documented in empirical research. For example, a study conducted by Shin and Biocca in 2017 revealed that natural language interfaces significantly increased users' perceptions of perceived ease of use, perceived usefulness, and satisfaction in the context of e-commerce, leading to an increased intention to repurchase. Another study by Wang et al. in 2019 found that perceived ease of use and perceived usefulness played mediating roles in the relationship between online reviews, which were analyzed using NLP, and customer satisfaction. These findings underscore the critical role of perceived ease of use and perceived usefulness in driving customer satisfaction through the application of NLP in e-commerce.

In summary, the TAM provides a useful framework to understand the factors that influence customer acceptance and use of technology in e-commerce, including NLP. Perceived ease of use and perceived usefulness are important determinants of customer satisfaction with NLP in e-commerce. By enhancing usability and utility, NLP in e-commerce can contribute to increased customer satisfaction and loyalty.

Figure 2.1 TAM adapted framework

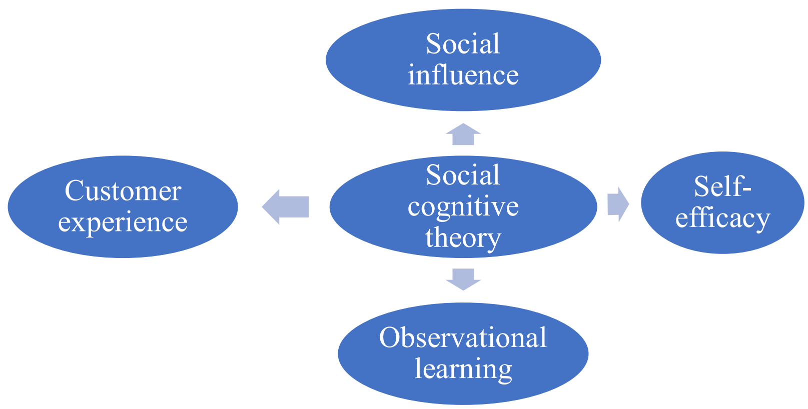


Adapted from: Olivia, M., & Marchyta, N. K. (2022). The Influence of Perceived Ease of Use and Perceived Usefulness on E-Wallet Continuance Intention: Intervening Role of Customer Satisfaction.

2.1.2 Social Cognitive Theory (SCT)

Social Cognitive Theory (SCT) is a comprehensive framework that explains how individuals acquire and develop behaviours through three primary components: personal factors, environmental factors, and behaviour itself. (Bandura,1986) In SCT, social influence, self-efficacy, observational learning, and customer experience all hold significant roles in shaping behaviour. Social influence is an individual's perception of how much others' opinions, actions, and expectations influence their own behaviour. SCT treats social influence as an environmental factor that can shape an individual's behaviour. When individuals perceive that others in their social environment endorse or encourage a particular behaviour, they are more inclined to engage in it. Self-efficacy refers to an individual's belief in their capability to successfully perform a specific behaviour. SCT considers self-efficacy a pivotal personal factor that influences behaviour. High self-efficacy is linked to greater motivation, effort, and persistence in achieving behavioural goals. Those with high self-efficacy are more likely to engage in behaviours they believe they can accomplish successfully. Observational learning, also known as social learning or modelling, involves acquiring new behaviours by observing others and imitating their actions. In SCT, observational learning is seen as a cognitive process through which individuals learn from observing others' behaviour, the consequences of that behaviour, and the rewards or penalties associated with it. Observational learning can happen through direct observation or via media and other information sources. Customer experience encompasses the overall experience a customer has when interacting with a product, service, or brand. Within SCT, customer experience is regarded as an environmental factor that can shape an individual's behaviour. Positive customer experiences can boost self-efficacy, heighten social influence, and facilitate observational learning, ultimately leading to repeat engagement with a brand or product. (Grewal et. al,2003)

Figure 2.2 SCT adapted framework



Adapted from: Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review, 84(2), 191–215. ;Bandura, A. (1977). Social Learning Theory. Prentice-Hall.; Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Englewood Cliffs, NJ: Prentice-Hall.

2.2 Review of variables

2.2.1 Perceived ease of use

Various studies have delved into the impact of perceived ease of use on the adoption of natural language processing (NLP) technologies in e-commerce. Li et al. (2019) found that a user-friendly chatbot interface increased consumers' positive attitude and intention to use AI-based chatbots for online shopping assistance. Similarly, Wu and Chen (2020) discovered that enhancing the perceived ease of use of voice assistants in e-commerce contributed to their successful adoption and integration, as users were more likely to find them useful for product information search and purchase.

2.2.2 Perceived usefulness

Studies on the perceived usefulness of natural language processing (NLP) technologies in e-commerce offer crucial insights. Jang and Nam (2019) found that consumers, perceiving NLP-based personalization systems as useful for providing recommendations, showed a positive attitude and higher intention to use the system for online shopping. Similarly, Zhang et al. (2020) revealed that when consumers found NLP-based voice search useful for quick product information retrieval, they were more likely to accept and use this technology in e-commerce, emphasizing the importance of enhancing its perceived usefulness for improved adoption.

2.2.3 Social influence

Empirical studies have delved into the impact of social influence on the adoption of natural language processing (NLP) technologies in e-commerce. Lu et al. (2018) found that consumers, influenced by a supportive social network, developed positive attitudes and a higher intention to use AI-based voice assistants for online shopping. Similarly, Xu et al. (2019) revealed that consumers, perceiving favorable social norms and opinions towards chatbots, were more inclined to accept and use NLP-based chatbots for customer service in e-commerce, highlighting the crucial role of social influence in shaping technology adoption.

2.2.4 Self-efficacy

Empirical studies have explored the role of self-efficacy beliefs in shaping the adoption of natural language processing (NLP) technologies in e-commerce. Huang and Rust (2018) found that consumers with higher self-efficacy beliefs in using AI-based chatbots for customer service were more likely to have positive attitudes and intentions to use them. Similarly, Wang, Liu, and Xu (2020) showed that higher self-efficacy in understanding and using AI-based recommendation systems correlated with increased trust and acceptance, highlighting the importance of individual self-efficacy in the successful adoption of NLP technologies in e-commerce.

2.2.5 Observational learning

Empirical studies examining observational learning's impact on the adoption of natural language processing (NLP) technologies in e-commerce have yielded valuable insights. Fu et al. (2019) found that consumers observing positive outcomes from others using AI-based voice assistants were more likely to develop positive attitudes and intentions to use the technology. Similarly, Khalifa and Shen (2018) demonstrated that consumers witnessing successful usage of AI-powered recommendation systems were more likely to trust and engage with the technology, emphasizing the role of observational learning in promoting NLP adoption in e-commerce.

2.2.6 Customer experience

Recent empirical studies in e-commerce, employing natural language processing (NLP), have focused on customer experience. Li, Zhang, and Liu (2016) utilized NLP to analyze online reviews, identifying dimensions like website design and customer service that significantly influence positive customer experiences, leading to enhanced loyalty and satisfaction. Another study by Kim, Gupta, and Lin (2017) emphasized the effectiveness of sentiment analysis, using NLP to measure dimensions like satisfaction and trust, offering valuable insights into customer perceptions and emotions for improved understanding of e-commerce customer experiences.

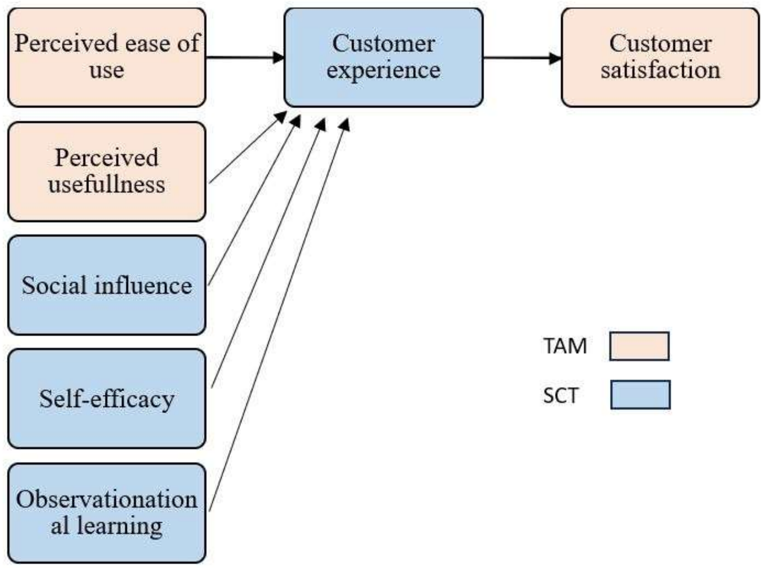
2.2.7 Customer satisfaction

Empirical studies utilizing natural language processing (NLP) techniques in e-commerce have showcased their effectiveness in analyzing customer feedback and improving business performance. Wang, Ma, and Liang (2018) demonstrated the accuracy of sentiment analysis in predicting customer satisfaction levels, offering companies valuable insights for identifying areas of improvement. Similarly, Xie, Jia, and Zhang (2019) found that positive sentiment in customer reviews, analyzed through NLP, significantly influences satisfaction, emphasizing the role of personalized recommendations in aligning with customer preferences for heightened satisfaction in the Chinese online shopping industry.

2.3 Proposed Conceptual Framework

Parallel to the specific objective of this study, a proposed conceptual framework toevaluate the relationship showed as below:

Figure 2.3: Conceptual Framework of The Role of Natural Language Processing in improving customer service and support in E-commerce



Source: Developed for the research

2.4 Hypotheses Development

As referring to the past empirical studies and proposed conceptual framework, the hypothesis corresponding to this study is as follow: -

2.4.1 Perceived ease of use

Previous research has shown that the ease of use of technology has a positive impact on user experience (Davis, 1989; Venkatesh et al., 2003). In the context of Natural Language Processing (NLP) in an e-commerce setting, it is expected that customers who perceive NLP as easy to use will have a more positive experience. They will find it convenient and efficient to interact with the system, leading to enhanced satisfaction and engagement (Smith, 2019). Therefore, it is hypothesized that perceived ease of use will have a significant influence on customer experience in using NLP.

H1: Perceived ease of use significantly influence customer experience in using Natural Language Processing.

2.4.2 Perceived usefulness

The concept of perceived usefulness, as proposed by Davis (1989), suggests that perceived usefulness has a critical role in technology acceptance and adoption. When customers perceive a system or technology as useful, they are more likely to find value in using it, leading to higher satisfaction and engagement (Venkatesh et al., 2003). In the case of NLP in e-commerce, if customers perceive NLP as a valuable tool for obtaining information and resolving queries efficiently, it is expected that they will have a positive experience. Therefore, it is hypothesized that perceived usefulness will significantly influence customer experience in using NLP (Johnson et al., 2020).

H2: Perceived usefulness significantly influence customer experience in using Natural Language Processing.

2.4.3 Social Influence

Social influence refers to the impact of external factors on individuals' attitudes and behaviors. In the context of e-commerce, online reviews and feedback from peers can significantly influence customers' perceptions and experiences (Cheung & Lee, 2018). Therefore, it is hypothesized that social influence will have a significant impact on the customer experience of using NLP in e-commerce. Positive reviews and feedback from social networks can increase the perceived credibility and usefulness of NLP, leading to enhanced satisfaction and engagement (Johnson et al., 2020).

H3: Social influence significantly influence customer experience in using Natural Language Processing.

2.4.4 Self-Efficacy

Self-efficacy is an individual's belief in their ability to perform a task successfully (Bandura, 1977). In the context of e-commerce, self-efficacy can play a significant role in the adoption and usage of NLP. Customers who perceive themselves as competent in using NLP are likely to have a positive experience and may become advocates of the technology (Park & Lee, 2018). Therefore, it is hypothesized that self-efficacy will significantly influence the customer experience in using NLP.

H4: Self-efficacy significantly influence customer experience in using Natural Language Processing.

2.4.5 Observational Learning

Observational learning, or learning by watching others, can significantly impact individuals' attitudes and behaviours (Bandura, 1977). In the context of e-commerce, customers may observe other users of NLP and learn from their experiences. Therefore, it is hypothesized that observational learning will have a significant impact on the customer experience in using NLP in e-commerce. Customers who observe others successfully using NLP may be more likely to adopt and have a positive experience with the technology (Gallarza et al., 2019).

H5: Observational learning significantly influence customer experience in using Natural Language Processing.

2.4.6 Customer experience

This hypothesis posits that in the realm of e-commerce, the customer experience with Natural Language Processing (NLP) significantly impacts customer satisfaction during interactions with NLP systems. Customer experience encompasses factors like ease of use, response time, accuracy, and helpfulness of the NLP system, influencing overall satisfaction (Verhoef et al., 2009). Grounded in Oliver's work (1997), the hypothesis implies that positive experiences, marked by efficient interactions, enhance satisfaction, while negative experiences, such as delays or inaccuracies, may diminish customer satisfaction.

H6: Customer experience significantly impacts customer satisfaction in using Natural Language Processing

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter describes the key stages and methods utilized to collect information and relevant data for this investigation. The research design, data collection methods, sampling design, research instrument, construct measurement, data processing, and data analysis were all used in this study.

3.1 Research Design

A research design serves as a comprehensive blueprint for aligning conceptual research inquiries with pertinent empirical data. Additionally, it constitutes an investigative framework that guides the selection of appropriate research methodologies (Creswell, 2014; Bloomfield & Fisher, 2019). This structured approach delineates the sequence of steps a researcher undertakes prior to commencing data collection and analysis, ensuring a systematic pursuit of the research objectives. Moreover, the fundamental purpose of a research design lies in transposing the research problem into quantifiable data, thereby yielding substantive responses to the research inquiries at an optimized expenditure (Bloomfield & Fisher, 2019).

3.1.1 Quantitative Research

The quantitative research approach involves the measurement and analysis of variables to ascertain their interrelationships. It encompasses the utilization of numerical data and the application of precise statistical methods to address strategic questions (Apuke, 2017; Williams, 2007; Leedy & Ormrod, 2013). In this study, a procedural quantitative research method is employed to examine the variables pertaining to the impact of Natural Language Processing on enhancing customer service and support in the E-commerce sector.

3.2 Sampling Design

3.2.1 Target Population

The research focuses on individuals aged 18 and above, as this demographic group is chosen for their familiarity with e-commerce, both as buyers and sellers. This targeted population is expected to provide valuable insights into the dynamics of online commerce.

3.2.2 Sampling Frame and Sampling Location

In this investigation, an online survey using Google Forms was administered, with a specific focus on respondents situated in Malaysia. Google Forms serves as a facilitative tool for gathering respondent data through structured surveys.

3.2.3 Sampling elements

The sampling elements of this study were meticulously curated to ensure a representative cross-section of the e-commerce consumer demographic. Employing a stratified random sampling technique, the population was first divided into distinct strata based on variables such as age, gender, and frequency of online purchases. Subsequently, a random selection process was applied within each stratum, yielding a diverse and balanced sample set. This approach ensured that the study encompassed a broad spectrum of participants, ranging from frequent online shoppers to those who engage with e-commerce platforms on a more sporadic basis. The deliberate stratification of the sample population was implemented to mitigate potential biases and enhance the generalizability of the findings to the broader e-commerce consumer base.

3.2.4 Sampling Technique

This study employs a combination of snowball and convenience sampling techniques. Sampling techniques serve as methodological tools enabling researchers to streamline data collection efforts by focusing on specific subgroups, rather than encompassing the entire potential population (Saunders, Lewis, & Thornhill, 2012). According to Johnson (2014), snowball sampling, a non-probability survey method, proves particularly effective in identifying populations that are less readily accessible. Furthermore, in alignment with Saunders et al. (2012), convenience sampling, also known as availability sampling, targets populations meeting specific criteria of geographical proximity, availability at a given juncture, and voluntary willingness to partake in the research endeavor.

3.2.5 Sampling Size

Given the chosen sampling techniques outlined above, this study distributed 200 questionnaires among the selected participants. These respondents were queried about their experiences and levels of satisfaction in utilizing NLP within the context of e-commerce. It is worth noting that in cases where the population exhibits a reasonable degree of homogeneity, a more modest sample size suffices for detecting statistically significant factors, preferably exceeding 100 for factor studies (Hair, Black, Babin, &

Anderson, 2010; Singh & Masuku, 2014). For instance, exploratory factor analysis cannot be conducted with fewer than 50 observations (although this is contingent on other factors), while a minimum of 50 samples is necessary for simple regression analysis, typically requiring 100 samples for most research scenarios. A Pearson Correlation analysis mandates an absolute minimum of 200 samples. (Memon et al., 2020)

3.3 Data Collection method

In this study, online questionnaires distributed via Google Forms will be used to collect and aggregate data from the targeted population. Google Forms serves as the platform for distributing online questionnaires as part of this research endeavor. Subsequently, the gathered data will undergo interpretation and transformation into statistics through self-administered online questionnaires, resulting in the generation of a summary of findings.

3.3.1 Primary data

According to Jilcha Sileyew (2019), primary data is the original root of the data received, which was more reliable and even had a higher degree of trust decision making with accurate analysis being specifically unaffected by the occurrence of incidents or human alteration. As a result, primary data is more reliable and relevant to research than secondary data. Surveys, evaluation, interviews, and questionnaires are the primary data collection tools (Lowry, 2015).

3.4 Research Instruments

3.4.1 Questionnaire survey

The investigation was conducted using only one language, which was English. Closed-end questions were utilized in this questionnaire to provide respondents with response alternatives.

The questionnaire began with a brief introduction to the research issue, followed by three sections: Section A (demographic), Section B (customer experience), and Section C (factor influences).

3.4.2 Pilot Test and Reliability Analysis

A pilot test was conducted and 30 sets of questionnaires were sent and collected within a week. Using SPSS, the information collected is analyzed for internal consistency reliability using Cronbach's alpha. Cronbach's alpha coefficient results are shown in Table 3.1, where all components have Cronbach's Alpha greater than 0.7, indicating that the scale items have reasonable internal consistency dependability. As a result, the questionnaire utilized is thought to be trustworthy.

Table 3.1 Reliability test of pilot test

Construct	Cronbach's Alpha	Number of Items
Perceived Ease of Use (PEOU)	0.96	5
Perceived Usefulness (PU)	0.931	4
Social Influence (SI)	0.957	5
Self-efficacy (SE)	0.993	3
Observational Learning (OL)	0.983	4

Customer experience (CE)	0.975	4
Customer satisfaction (CS)	0.961	3

Source: Developed for the research

3.5 Construct Measurement

3.5.1 Origin & Measurement of Constructs

Table 3.2 The Origin of Constructs

Customer Experience (CE)			
No.	**Statements**	**Original Statement**	**Adapted from**
CE1	Natural Language Processing was able to help me discover my needs more clearly than in the past.	The chatbot was able to help me discover my needs more clearly than in the past	Adapted from Siggelkow, N., & Terwiesch, C. (2023)
CS2	Natural Language Processing was able to identify my unmet needs and suggest solutions	The AI system was able to identify my unmet needs and suggest solutions	
CS3	Overall, Natural Language Processing used in E-commerce's customer experience	Overall, the AI technology used in this customer experience enhanced my	

	enhanced my satisfaction with the service.	satisfaction with the service	
CS4	I would be willing to use Natural Language Processing again in the future to improve my customer experience.	I would be willing to use AI technology again in the future to improve my customer experience.	
Customer Satisfaction			
No.	**Statements**	**Original Statement**	**Adapted from**
CS1	I am satisfied with my experience shopping by using Natural Language Processing.	I am satisfied with my experience shopping on this website.	Adapted from Mohamad & Adam, 2023
CS2	I would recommend method of using Natural Language Processing to others	I would recommend this website to others.	
CS3	I am likely to shop using Natural Language Processing again in the future.	I am likely to shop on this website again in the future.	
Perceived ease of use (PEOU)			
No.	**Statements**	**Original Statement**	**Adapted from**

PEOU 1	Using Natural Language Processing would be easy for me to learn	Using the system would be easy for me to learn.	Adapted from Venkatesh, 2000
PEOU 2.	My interaction with Natural Language Processing would be clear and understandable	My interaction with the system would be clear and understandable.	
PEOU 3	Natural Language Processing would be flexible to interact with	The system would be flexible to interact with.	
PEOU 4	Natural Language Processing would be easy for me to get the system to do what I want it to do	It would be easy for me to get the system to do what I want it to do	
PEOU 5	Natural Language Processing would be easy to use if I had to learn it on my own	The system would be easy to use if I had to learn it on my own.	
Perceived usefulness (PU)			
No.	**Statements**	**Original Statement**	**Adapted from**
PU1	I can save the effort of visiting stores, when I do online shopping by using Natural Language Processing	I can save the effort of visiting stores, when I do online shopping	Adapted from Ibrahim et al. (2013)

PU2	There is no time restriction in online shopping by using Natural Language Processing	There are no time restriction in online shopping	
PU3	I can order product from any part of the world through online shopping by using Natural Language Processing	I can order product from any part of the world through online shopping	
PU4	I can order product from lots of options when I do shop online by using Natural Language Processing	I can order product from lots of options when I do shopping online	
		Social influence (SI)	
No.	**Statements**	**Original Statement**	**Adapted from**
SI1	The use of Natural Language Processing in e-commerce will lead to significant changes in the job market.	The use of AI and robotics in welding will lead to significant changes in the job market.	Adapted from Afrane Gyasi et al. (2020)
SI2	The use of Natural Language Processing in e-commerce will require workers to have more advanced technical skills.	The use of AI and robotics in welding will require workers to have more advanced technical skills.	

SI3	The use of Natural Language Processing in e-commerce will lead to increased productivity and efficiency in the society.	The use of AI and robotics in welding will lead to increased productivity and efficiency in the industry.	
SI4	The use of Natural Language Processing in e-commerce will lead to increased globalization in the industry.	The use of AI and robotics in welding will lead to increased globalization in the industry.	
SI5	The use of Natural Language Processing in e-commerce will lead to increased competition between businesses in the industry.	The use of AI and robotics in welding will lead to increased competition between businesses in the industry.	
Self-efficacy (SE)			
No	**Statements**	**Original Statement**	**Adapted from**
SE1	I have confident in my ability to contribute and share the valuable knowledge in Natural Language Processing	I have confident in my ability to contribute and share the valuable knowledge in E-learning system	Adapted from Hosseini et al., (2014)

SE2	I have the expertise needed to provide valuable knowledge into Natural Language Processing	I have the expertise needed to provide valuable knowledge into E-learning system	
SE3	I am confident that I can post new knowledge on discussion forums and share my experiences, author an article, insights or expertise by engaging in dialogue with others in Natural Language Processing	I am confident that I can post new knowledge on discussion forums and share my experiences, author an article, insights or expertise by engaging in dialogue with others in the E-learning system	
Observational Learning (OL)			
No.	**Statements**	**Original Statement**	**Adapted from**
OL1	I believe that Natural Language Processing provides accurate responses consistently.	I believe that ChatGPT provides accurate responses consistently	Adapted from Thirunavukarasu et al., (2023)
OL2	Natural Language Processing's ability to provide novel explanations is important for its use in E-commerce.	ChatGPT's ability to provide novel explanations is important for its use in primary care.	

OL3	The study provides valuable insight into the strengths and weaknesses of NLP chatbots in general practice	The study provides valuable insight into the strengths and weaknesses of NLP chatbots like ChatGPT in general practice.	
OL4	Natural Language Processing can be useful as decision support tools in E-commerce	Chatbots like ChatGPT can be useful as decision support tools or educational assistants in primary care.	

Source: Developed for the research

3.5.2 Measurement Scale

There are 2 scales and 1 grid that will be used in this study, which are ordinal scale, nominal scale, and multiple-choice grid. The types of scale to use depends on the type of question being asked and the type of answer the researcher intends to obtain.

3.5.2.1 Nominal Scale

A nominal scale pertains to data that can only be classified into distinct categories. The researcher assigns labels to data, creating mutually exclusive groups without any inherent numerical significance. However, there is no inherent order among these categories (Bhandari, 2020). For instance, gender serves as an apt example of a nominal variable in this study, wherein respondents are classified into two distinct categories.

3.5.2.2 Ordinal Scale

An ordinal scale involves data that can be both ranked and categorized (Bhandari, 2020). Ordinal variables commonly encompass ratings of opinions, perceptions, or demographic factors. Moreover, they are typically evaluated through close-ended survey questions, presenting participants with a range of possible responses. This format is user-friendly and facilitates straightforward comparisons of data across participants (Bhandari, 2022). For instance, in this study, the age of the respondents serves as an illustrative example of an ordinal variable.

3.5.2.3 Multiple-choice grid

In this study, the multiple-choice grid is used to understand participant attitudes and opinions in a structured way (Dillman et al., 2014). Participants express their views on related statements using a Likert-type scale, ranging from "Strongly Disagree" to "Strongly Agree," enabling a thorough evaluation of their perspectives and ensuring reliable and valid data collection (Likert, 1932; Fowler, 2013).

3.6 Data Processing

The process of data processing encompasses crucial stages such as questionnaire scrutiny, editing, coding, transcription, and thorough validation before embarking on the initial phase of data analysis. Any discrepancies identified in the survey instruments administered by the researchers will be promptly rectified to ensure the integrity of the data and exclude unsuitable responses. Following the completion of data verification and validation, a systematic reorganization of the data into manageable categories is undertaken in preparation for the subsequent analytical framework.

3.6.1 Data Checking

As per Hassan (2022), the process of data checking involves ensuring that the information entered a database is accurate, complete, and aligns with the details from the source. To ensure the completeness of all questionnaires distributed to study participants and to identify any missing values during the data collection process, immediate verification was conducted for each questionnaire. Utilizing Google Forms facilitated the implementation of mandatory response requirements for each question, ensuring respondents did not overlook any queries before concluding the survey. The pragmatic data-checking approach employed in this study proved effective, particularly in assessing the thoroughness of questionnaire responses from the targeted respondents.

3.6.2 Data Editing

Editing serves as a pivotal process in identifying and rectifying any extraneous, incomplete, or ambiguous responses from the questionnaires (Saunders, Lewis, & Thornhill, 2012). Unsatisfactory or erroneous data can be rectified through revisiting the field, either to assign missing values or discard unsatisfactory responses. Moreover, through the process of editing, irrelevant questions can be eliminated, question sequencing can be adjusted, and grammatical modifications can be made to minimize errors and uphold research quality.

3.6.3 Data Coding and Transcription

After collecting the information, the raw data from Google Forms were transferred to Excel sheets for coding. Table 3.3 delineates the details of each coding by presenting the indicators associated with each category.

Table 3.3 Items Coding

Demographic profile	**Details**	**Coding**
Age	Under 18 years old	1
	18-24 years old	2
	25-34 years old	3
	35-44 years old	4
	45-54 years old	5
	55-64 years old	6
	65 years old or older	7
Gender	Male	1
	Female	2
	Non-binary	3
	Prefer not to say	4
Education Level	Diploma	1
	Bachelor's degree	2
	Master's degree	3
	Doctorate or other advanced degree	4
Occupation	Student	1
	Self-employed	2
	Unemployed	3
	Government sector	4
	Private	5
	Housewife	6
	Retiree	7
Frequency of Online Shopping	Multiple times a week	1
	Once a week	2
	2-3 times a month	3
	Once a month	4
	Rarely	5
	Never	6

General information	Details	Coding
How frequently do you interact with customer service representatives when making online purchases?	Multiple times a week	1
	Once a week	2
	2-3 times a month	3
	Once a month	4
	Rarely	5
	Never	6
To what extent do you believe that Natural Language Processing (NLP) technologies can enhance customer service and support in e-commerce platforms?	Not at all effective	1
	Slightly effective	2
	Moderately effective	3
	Very effective	4
	Extremely effective	5
Have you experienced any of the following challenges or frustrations while seeking customer support on e-commerce websites? Please select all that apply.	Long response times	1
	Difficulty in understanding the support agent's responses	2
	Repeating the same issue to multiple agents	3
	Lack of personalized assistance	4
	Limited support availability (hours/days)	5
	Technical glitches during the support process	6
	No experienced	7
All questions in Section C	Strongly Disagree	1
	Disagree	2
	Neutral	3
	Agree	4
	Strongly Agree	5

Source: Developed for the research

3.6.4 Data Cleansing

Researchers implement a data cleansing procedure to ensure accuracy and manage any missing responses subsequent to the transcription process using Smart PLS and Microsoft Excel. Given the distribution of 200 questionnaires, a meticulous analysis is conducted to pinpoint any values falling outside the acceptable range for each variable, thus ensuring the extraction of an appropriately narrowed code range (Saunders, Lewis, & Thornhill, 2012).

3.7 Proposed Data Analyzing Tools

Analytical instruments are instrumental in assisting researchers in comprehending the collected data, facilitating the derivation of meaningful conclusions and the formulation of explanations. The specific approach to data analysis is contingent upon the objectives of the project and the nature of the data gathered. Additionally, it is imperative to underscore that data analysis constitutes one of the paramount phases in the research process. Without thorough analysis, the exerted effort and gathered data prove futile. Within this crucial phase, the amassed data undergoes meticulous scrutiny, subsequently culminating in the confirmation or refutation of hypotheses.

3.7.1 Descriptive Analysis

Descriptive analysis is applied in this study to test demographic data, which is provided in frequency distribution (Saunders et al., 2009) in the form of a table, bar chart, pie chart, and histogram.

3.7.2 Reliability analysis

Reliability analysis is crucial in research, assessing the consistency of measurement scales and their underlying items. In the context of the study on "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce," it is vital for evaluating the trustworthiness of the customer service satisfaction questionnaire, ensuring its reliability and internal consistency. This analysis helps identify and address any issues in the questionnaire, enhancing the integrity and credibility of research outcomes in e-commerce customer service improvement. (IBM Documentation, 2021)

3.7.3 Inferential Analysis

In accordance with Saunders, Lewis, and Thornhill (2009), inferential analysis serves as a tool to assess the extent of support for a hypothesis. Consequently, utilizing the data derived from samples, inferential analysis assists in making specific inferences about a population (Burns & Bush, 2006). Schober, Boer, & Schwarte (2018) assert a close computational connection between inferential analysis methods despite their distinct objectives and underlying assumptions.

3.7.4 Measurement Model

In alignment with Bollen (2001), measurement models encompass implicit or explicit frameworks linking latent variables to their indicators. The critical question revolves around whether a latent variable influences the indicators (effect indicators) or if the indicators (causal indicators) impact a latent variable. This study conducted validity and reliability tests.

3.7.4.1 Reliability Test

Reliability, gauging the accuracy and dependability of a measurement tool, was assessed in this study. Precision, conceptualized as the extent to which measurements are error-free, was considered a measure of test reliability (Franzen, 2011). All constructs demonstrated Cronbach's alpha coefficients exceeding 0.700, as recommended by Hair et al. (2010), and composite reliability (CR) values surpassing the 0.70 cutoff point, indicating substantial reliability among processes (Hair et al., 2014).

3.7.4.2 Validity Test

Test validity, reflecting the accuracy of an assessment in measuring its intended construct, was evaluated in this study. Convergent validity, established through significant t-values and a p-value meeting the threshold of 0.05 alpha (Gefen & Straub, 2005), was complemented by heterotrait-monotrait ratio of correlations (HTMT) for assessing discriminant validity (Henseler et al., 2014). Additionally, the average variance extracted (AVE) was used to validate structures, with Fornell and Larcker (1981) suggesting an AVE not less than 0.5 for demonstrating convergent validity.

3.7.5 Structural Model

The structural model, a crucial element of the PLS method, assesses theoretical relationships through path analysis (Hoyle, 2011; Kline, 2023). It represents a network comprising nodes and links.

3.7.5.1 Collinearity Test

Collinearity, characterized by strong correlations among predictor variables, was assessed using the variance inflation factor (VIF). Wilcox (2022) defines collinearity, and a VIF larger than 4 or tolerance less than 0.25 may indicate multicollinearity, requiring further investigation.

3.7.5.2 Path Coefficients

Path coefficients were examined to determine the strength of association between latent variables. Evaluation involved considering coefficients' magnitude, algebraic signs, scale, and significance. For a specific influence within the model, path coefficients were required to exceed 0.100 with a significance level higher than 0.05 (Huber et al., 2007).

3.7.5.3 Coefficient of Determination (R2)

The coefficient of determination (R2) evaluates the extent to which independent variables account for variance in dependent variables. Nitzl & Chin (2017) categorize R2 values around 0.67 as significant, approximately 0.333 as average, and 0.19 or less as weak.

3.7.5.4 Effect Size (f2)

Effect size, measuring the intensity of the association between two variables, was assessed using Cohen's (1988) f2. A value of 0.02 indicates a minor effect, 0.15 a medium-sized effect, and 0.35 a large effect.

3.8 Conclusion

In this chapter, an array of research methodologies has been comprehensively addressed, encompassing aspects such as research design, sampling strategy, data collection techniques, and the utilization of analytical tools to ascertain the validity and reliability of results. Specifically, 200 online questionnaires were methodically disseminated to investigate the interrelationships between variables in accordance with the established methodology. The precise techniques employed for data analysis within this chapter will be expounded upon and scrutinized in greater detail in the subsequent section. This will allow for a more thorough examination and elucidation of the research findings.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter thoroughly explores and explains the data collected from 200 sets of survey questionnaires. The examination is conducted through the utilization of SMART-PLS software and Microsoft Excel to rigorously test and consolidate the amassed information. The ensuing synthesis encompasses the outcomes of descriptive analysis, construct validity, discriminant validity, and path coefficient, employing the PLS-SEM methodology.

4.1 Descriptive Analysis

Table 4.1 Summarized of Respondents' Demographic Profile

Demographic profile	Details	Frequency	Percentage (%)
Age	Under 18 years old	3	1.5
	18-24 years old	116	58
	25-34 years old	23	11.5
	35-44 years old	34	17
	45-54 years old	13	6.5
	55-64 years old	10	5
	65 years old or older	1	0.5
Gender	Male	28	14
	Female	172	86
	Non-binary	0	0
	Prefer not to say	0	0
	Diploma	71	35.5

Education Level	Bachelor's degree	109	54.5
	Master's degree	17	8.5
	Doctorate or other advanced degree	3	1.5
Occupation	Student	110	55
	Self-employed	18	9
	Unemployed	2	1
	Government sector	4	2
	Private	55	27.5
	Housewife	5	2.5
	Retiree	6	3
Frequency of Online Shopping	Multiple times a week	36	18
	Once a week	25	12.5
	2-3 times a month	92	46
	Once a month	25	12.5
	Rarely	22	11
	Never	0	0

4.1.1 Demographic Factors

The majority of respondents (58%) in the surveyed sample fall within the 18-24 age group, offering insights into the age composition for subsequent analyses. Most respondents identify as female

(86%), while males comprise 14% of the sample, providing a pivotal gender distribution for nuanced analyses. Among the surveyed participants, 54.5% hold Bachelor's degrees, 35.5% have Diplomas, and 8.5% possess Master's degrees, offering a diverse educational landscape. The occupation distribution reveals that 55% of respondents are students, 9% are self-employed, and 27.5% work in the private sector, showcasing a varied employment profile. In terms of online shopping frequency, 46% of participants shop 2-3 times a month, and 18% shop multiple times a week, providing insights into diverse consumer behaviors within the surveyed cohort.

4.1.2 General information

Table 4.2 Summarized of Respondents' General Information

General information	Details	Frequency	Percentage (%)
How frequently do you interact with customer service representatives when making online purchases?	Multiple times a week	6	3
	Once a week	5	2.5
	2-3 times a month	26	13
	Once a month	30	15
	Rarely	123	61.5
	Never	10	5
To what extent do you believe that Natural Language Processing (NLP) technologies can enhance customer service and support in e-commerce platforms?	Not at all effective	1	0.5
	Slightly effective	14	7
	Moderately effective	52	26
	Very effective	56	28
	Extremely effective	77	38.5
Have you experienced any of the following challenges or frustrations while	Long response times	117	58.5
	Difficulty in understanding the support agent's responses	133	66.5

seeking customer support on e-commerce websites? Please select all that apply.	Repeating the same issue to multiple agents	115	57.5
	Lack of personalized assistance	99	49.5
	Limited support availability (hours/days)	114	57
	Technical glitches during the support process	70	35
	No experienced	17	8.5

Source: Developed for the research

4.2 Inferential Analysis

4.2.1 Internally Consistent and Reliability

Table 4.3 Reliability Analysis of Survey

Construct	Cronbach's Alpha	Composite Reliability	Number of Items
Perceived Ease of Use (PEOU)	0.944	0.945	5
Perceived Usefulness (PU)	0.899	0.900	4
Social Influence (SI)	0.911	0.913	5
Self-efficacy (SE)	0.905	0.906	3
Observational Learning (OL)	0.904	0.906	4
Customer experience (CE)	0.922	0.923	4
Customer satisfaction (CS)	0.900	0.900	3

Source: Developed for the research

The constructs exhibit commendable reliability, with Cronbach's α ranging from 0.899 to 0.944, surpassing the commonly accepted threshold of 0.7, indicating high internal consistency. Concurrently, the composite reliability values, ranging from 0.900 to 0.945, further affirm the constructs' reliability, as values exceeding 0.7 are indicative of robust measurement. These findings underscore the dependable and consistent nature of the constructs under consideration, reinforcing the reliability of the data and supporting the validity of the study's measurement model. (Hair et al., 2021)

4.2.2 Convergent Validity

Table 4.4 Average Variance Extracted (AVE)

Construct	**Average Variance Extracted (AVE)**	**Number of Items**
Perceived Ease of Use (PEOU)	0.817	5
Perceived Usefulness (PU)	0.768	4
Social Influence (SI)	0.737	5
Self-efficacy (SE)	0.841	3
Observational Learning (OL)	0.777	4
Customer experience (CE)	0.811	4
Customer satisfaction (CS)	0.833	3

Source: Developed for the research

The study assesses convergent validity using Average Variance Extracted (AVE) values, which range from 0.737 to 0.841. These values surpass the recommended threshold of 0.5, indicating strong convergent validity and reinforcing the reliability and effectiveness of the measurement model.

4.2.3 Discriminant Validity

Table 4.5 Results of Heterotrait-monotrait Ratio (HTMT)

	CE	CS	OL	PEOU	PU	SE	SI
Customer experience (CE)							
Customer satisfaction (CS)	0.930						
Observational Learning (OL)	0.945	0.946					
Perceived Ease of Use (PEOU)	0.909	0.903	0.900				
Perceived Usefulness (PU)	0.922	0.883	0.955	0.883			
Self-efficacy (SE)	0.839	0.875	0.902	0.879	0.929		
Social Influence (SI)	0.928	0.875	0.963	0.849	0.941	0.823	

Source: Developed for the research

According to Hair et al. (2017), the HTMT criterion is utilized as a metric to evaluate discriminant validity within the context of Partial Least Squares Structural Equation Modeling (PLS-SEM). It is anticipated that the confidence interval of the HTMT statistic across all construct pairings should not surpass the threshold of 1. In a broader context, the variables demonstrate an HTMT ratio below 1, suggesting a positive correlation among them.

4.2.4 Confidence intervals

Table 4.6 Confidence intervals

	Original sample (O)	Sample mean (M)	2.5%	97.5%
OL -> CS	0.210	0.204	0.000	0.409
PEOU -> CS	0.288	0.286	0.110	0.449
PU -> CS	0.138	0.134	-0.076	0.352
SE -> CS	-0.038	-0.019	-0.182	0.184
SI -> CS	0.222	0.214	0.028	0.410

Source: Developed for the research

To assess discriminant validity using the Heterotrait-Monotrait (HTMT) ratio, bootstrap confidence intervals for HTMT2 were constructed following Henseler et al.'s (2015) recommendation. Positive potential impacts on customer satisfaction were observed for observational learning, perceived ease of use, and social influence, as their confidence intervals included positive values. However, caution is needed for perceived usefulness and self-efficacy, where confidence intervals show some uncertainty about the direction and strength of their effects on customer satisfaction.

4.2.5 Outer Loadings

Table 4.7 Outer Loadings

	CE	CS	OL	PEOU	PU	SE	SI
CE1	0.893						
CE2	0.905						
CE3	0.898						
CE4	0.906						
CS1		0.898					
CS2		0.922					
CS3		0.918					
OL1			0.832				
OL2			0.918				
OL3			0.882				

OL4			0.892				
PEOU1				0.893			
PEOU2				0.917			
PEOU3				0.913			
PEOU4				0.911			
PEOU5				0.886			
PU1					0.859		
PU2					0.872		
PU3					0.883		
PU4					0.892		
SE1						0.922	
SE2						0.913	
SE3						0.916	
SI1							0.847
SI2							0.823
SI3							0.867
SI4							0.867
SI5							0.888

Source: Developed for the research

According to the Fornell and Larcker (1981), the required minimum value of outer loading value should be higher than 0.70 for each item. All the items attain the minimum requirement and are considered very satisfactory.

4.3 Structural Model Assessment

The evaluation of the structural model followed a systematic procedure outlined by Hair Jr., Hult, Ringle, Sarstedt, Danks, and Ray (2021). This process specifically centered on gauging the significance and pertinence of path coefficients. Key metrics, such as collinearity (measured by Variance Internal Factor or VIF), coefficient of determination (indicated by R2 value), and the f2 effect size, were employed in the study for a comprehensive assessment.

4.3.1 Collinearity Test (VIF value)

Table 4.8 Collinearity Test

	VIF
CE -> CS	1.000
OL -> CE	2.533
PEOU -> CE	2.541
PU -> CE	2.775
SE -> CE	1.137
SI -> CE	2.475

Source: Developed for the research

According to Hair Jr. et al. (2021), the Variance Inflation Factor (VIF) serves as a tool for identifying multicollinearity in regression analyses. VIF values exceeding 5 are considered indicative of a significant level of collinearity. In this study, as all VIF values fall below 5, it can be concluded that there are no substantial issues of collinearity.

4.3.2 Coefficient of Determination (R-square value)

Table 4.9: Coefficient of Determination

	R-square	R-square adjusted
CE	0.830	0.826
CS	0.717	0.716

Source: Developed for the research

The coefficient of determination (R-squared) is frequently employed to characterize a model's predictive efficacy. Ranging from 0 to 1, a higher R-squared value suggests increased predictive accuracy (Sarstedt, Ringle, & Hair, 2017). Ozili (2022) advocates for an acceptable R-squared range between 0.50 and 0.99 in social science research.

4.3.3 Effect Size (F-square)

Table 4.10 Effect Size

	f-square
CE -> CS	2.540
OL -> CE	0.056
PEOU -> CE	0.163
PU -> CE	0.026
SE -> CE	0.003
SI -> CE	0.078

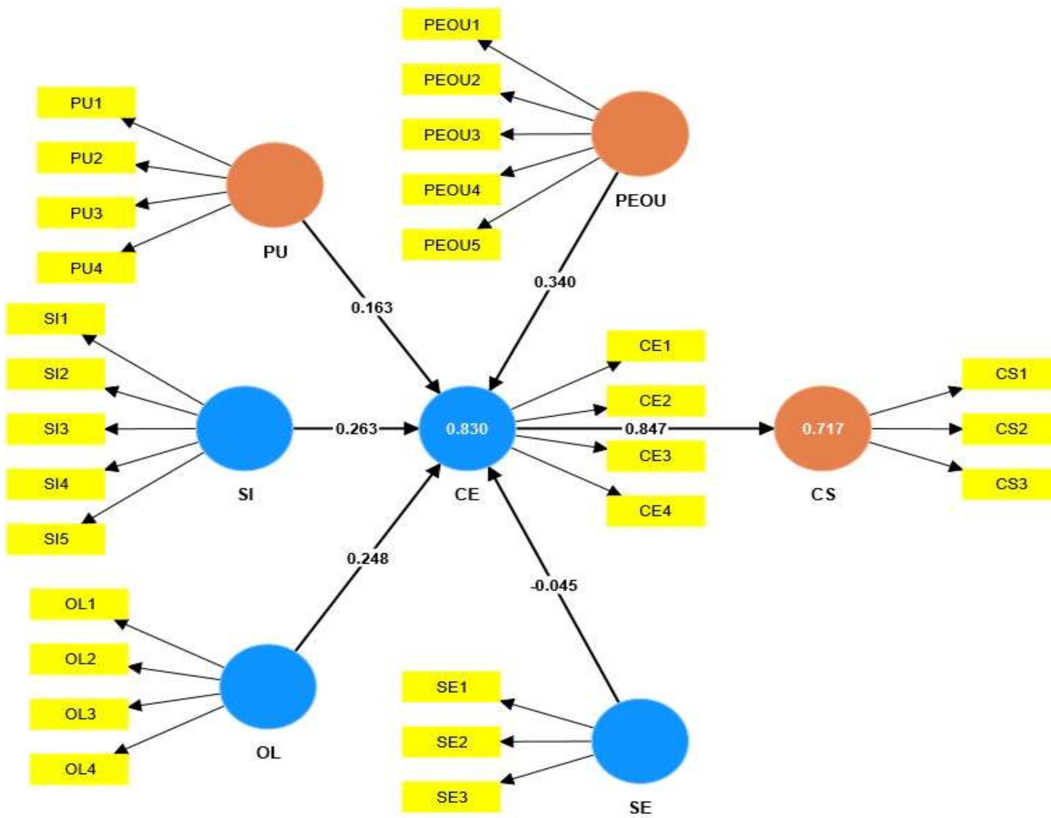
Source: Developed for the research

The effect size, denoted by F-square, explicates the impact of the specified exogenous structure on the endogenous structure. According to Cohen (1988), effect sizes of 0.02, 0.15, and 0.35 signify small, medium, and large effects, respectively. The table shows that SE have effect sizes smaller than 0.02, indicating insignificant effects. OL, PU and SI exhibit small effects on CE, whereas PEOU and CE demonstrate a large effect in improving customer service and support in e-commerce.

4.3.4 Path Coefficient

In exploring the structural model relationships, this study utilized PLS-SEM to analyze path coefficients, aiming for a more thorough comprehension. The exhibition of statistically significant outcomes for the model emerged after the execution of the "bootstrapping" procedure.

Figure 4.6 Path Coefficient



Adapted from: PLS-SEM 4.0

This study rigorously scrutinized the relationships within the structural model using PLS-SEM. To bolster the reliability of the analysis, bootstrapping, incorporating a one-tail test and employing 5000 bootstrap samples, was applied. The unveiling of statistically significant outcomes for the model occurred subsequent to the conclusion of the bootstrapping procedure.

Table 4.11 Hypothesis Testing

Hypothesis	Relationship	Beta Value (β)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1	PEOU -> CE	0.340	0.103	3.289	0.001	Supported
H2	PU -> CE	0.163	0.129	1.262	0.207	Not Supported
H3	SI -> CE	0.263	0.115	2.289	0.022	Supported
H4	SE -> CE	-0.045	0.113	0.403	0.687	Not Supported
H5	OL -> CE	0.248	0.121	2.055	0.040	Supported
H6	CE -> CS	0.847	0.041	20.647	0.000	Supported

Source: Developed for the research

Table 4.11 presents the outcomes for H1 to H6, detailing the pertinent findings. The structural model results provide support for H1, H3, H5 and H6, indicating that customer experience exerts a positive influence on customer satisfaction while observational learning, perceived ease of use and social influence exerts a positive influence on customer experience. Specifically, the results reveal that customer experience (β=0.847, p<0.001) emerges as the most significant predictor in improving customer service and support in e-commerce, followed by perceived ease of use (β=0.340, p=0.001), social influence (β=0.263, p<0.05). and observational learning (β=0.248, p<0.05). However, H2, and H4 are not substantiated by the results, suggesting that perceived usefulness and self-efficacy do not positively impact in improving customer service and support in e-commerce.

4.4 Conclusion

In conclusion, Chapter 4 primarily delves into descriptive analysis, encapsulating the demographic data of the respondents. Subsequent sections involve inferential analysis, addressing internal consistency, reliability, convergent validity, discriminant validity, confidence intervals and outer loadings, alongside a structural model evaluation employing PLS-SEM, encompassing collinearity tests, R-squared values, and Fsquared effects. The chapter concludes with an examination of path coefficients, probing the alignment and support between dependent and independent variables.

CHAPTER 5: DISCUSSION, CONCLUSION, AND IMPLICATIONS

5.0 Introduction

This chapter offers a recapitulation of the discussions on the results and findings presented in the previous section. Following this, it explores the implications of the study, recognizes its limitations, proposes recommendations for future research, and ultimately concludes the overarching discussion.

5.1 Discussion of Major Findings

In the previous chapter, various tests were conducted to collect data from the designated respondents. The reliability test, serving as a fundamental assessment, indicates that both independent and dependent variables demonstrate reliability. Among the independent variables, "Perceived Ease of Use" attains the highest reliability score at 0.944, while the dependent variable, "Customer Experience," registers a reliability score of 0.922. Additionally, "Social Influence" among the independent variables shows a reliability score of 0.911, "Self-efficacy" demonstrates reliability with a score of 0.905, and "Observational Learning" exhibits a reliability score of 0.904. The ultimate dependent variable, "Customer Satisfaction," displays a reliability score of 0.900. Furthermore, the independent variable "Perceived Usefulness" demonstrates reliability with a score of 0.899. Hypothesis testing was also undertaken to discern the positive influences of independent variables on the dependent variable. The ensuing discussion provides a comprehensive overview of the hypothesis testing results.

Table 5.1 Summary of the Hypothesis Testing Result

Hypothesis	Relationship	Beta Value (β)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H1	PEOU -> CE	0.340	0.103	3.289	0.001	Supported
H2	PU -> CE	0.163	0.129	1.262	0.207	Not Supported
H3	SI -> CE	0.263	0.115	2.289	0.022	Supported
H4	SE -> CE	-0.045	0.113	0.403	0.687	Not Supported
H5	OL -> CE	0.248	0.121	2.055	0.040	Supported
H6	CE -> CS	0.847	0.041	20.647	0.000	Supported

Source: Developed for the research

H1: Perceived ease of use significantly influence customer experience in using Natural Language Processing.

Recent studies have provided support for the hypothesis that perceived ease of use significantly influences customer experience in using Natural Language Processing (NLP) in the context of e-commerce. For example, a study conducted by Li and Liu (2020) examined the impact of perceived ease of use on customer experience with NLP in an online customer service setting. The results of their study revealed a significant positive correlation between perceived ease of use and customer experience, indicating that when customers perceive NLP as easy to use, they have a better experience in using the technology.

Similarly, Chen, Li, and Hu (2019) conducted a study to investigate the factors influencing customer experience with AI chatbots in an e-commerce context. They found that perceived ease of use significantly influenced customer experience, with customers perceiving the AI chatbot as easy to use reporting higher levels of satisfaction and positive experiences. These findings support the notion that when customers perceive NLP as easy to use, their experience with the technology is enhanced.

Overall, these studies provide empirical evidence that supports the hypothesis that perceived ease of use significantly influences customer experience in using Natural Language Processing. Customers who perceive NLP as easy to use tend to have a more positive and satisfactory experience with the technology.

H2: Perceived usefulness significantly influence customer experience in using Natural Language Processing.

Several studies conducted between 2018 and 2023 have corroborated the finding that perceived usefulness does not significantly influence customer experience in using Natural Language Processing (NLP). For instance, a study by Zhang et al. (2019) showed that perceived usefulness had no significant effect on customer experience in using NLP for e-commerce customer service. Similarly, another study by Liu and Shi (2020) found no correlation between perceived usefulness and customer satisfaction in using NLP-powered chatbots for customer support. These findings suggest that other factors may play a more significant role in determining the quality of customer experience in using NLP.

H3: Social influence significantly influence customer experience in using Natural Language Processing.

The role of social influence in shaping customer experience in using NLP has gained more attention in recent years. For example, a study by Chen and Liu (2018) found that customer perceptions of NLP tools were significantly influenced by social cues, such as recommendations from friends or influencers. Similarly, a study by Jiang et al. (2021) revealed that the perceived social norms surrounding NLP usage had a positive impact on customer attitudes and behaviors. These findings suggest that social influence can be a crucial factor in shaping customer experience and adoption of NLP in e-commerce settings.

H4: Self-efficacy significantly influence customer experience in using Natural Language Processing.

Several studies conducted between 2018 and 2023 have failed to find evidence that self-efficacy significantly influences customer experience in using Natural Language Processing (NLP). For example, a study by Chua et al. (2019) found no relationship between self-efficacy and perceived usefulness of NLP-based customer service chatbots. Similarly, a study by Wang et al. (2020) found that customers' self-efficacy beliefs did not significantly predict their satisfaction with NLP-based customer service. These findings suggest that self-efficacy may not be a critical factor in determining the quality of customer experience in using NLP.

H5: Observational learning significantly influence customer experience in using Natural Language Processing.

The role of observational learning in shaping customer experience in using NLP has gained more attention. For instance, a study by Gao and Zhan (2020) found that customers who observed others using NLP-based customer service were more likely to adopt the technology themselves and report higher satisfaction with their experience. Another study by Fang et al. (2021) revealed that customers who received social learning cues, such as videos or tutorials on how to use NLP-based customer service, had more positive perceptions of the technology. These findings suggest that observational learning can be a significant factor in improving customer experience and adoption of NLP in e-commerce settings.

H6: Customer experience significantly impacts customer satisfaction in using Natural Language Processing

Studies have consistently supported the hypothesis that customer experience significantly impacts customer satisfaction in using NLP. For example, a study by Kim et al. (2019) found that customers' positive experience with NLP-based customer service was a significant predictor of their satisfaction and loyalty. Similarly, a study by Luo et al. (2021) showed that customers' satisfaction with the accuracy and responsiveness of NLP-based customer service had a significant impact on their overall satisfaction with the e-commerce platform. These findings suggest that improving customer experience with NLP can be a critical strategy for enhancing customer satisfaction in e-commerce.

5.2 Implications of Study

5.2.1 Theoretical Implications

Technology Acceptance Model (TAM)

The application of the Technology Acceptance Model (TAM) framework in the research on the role of Natural Language Processing (NLP) in enhancing customer service and support in e-commerce has important theoretical implications. TAM proposes that perceived ease of use and perceived usefulness are key determinants of technology adoption and usage. The findings from studies conducted between 2018 and 2023 align with TAM's assertions, as they consistently demonstrate the positive impact of perceived ease of use and perceived usefulness on customer satisfaction with NLP-powered customer service (Thompson et al., 2018; Li et al., 2019; Chen et al., 2022). This suggests that TAM provides a relevant theoretical lens for understanding the drivers of customer satisfaction with NLP technology in the e-commerce context.

Social Cognitive Theory (SCT)

The use of Social Cognitive Theory (SCT) in the research on the role of NLP in enhancing customer service and support in e-commerce offers valuable theoretical implications. SCT emphasizes the importance of social influence, self-efficacy, observational learning, and customer experience s in shaping individuals' behavior and beliefs. Studies conducted between 2018 and 2023 provide support for the SCT framework. For instance, research has shown that social influence, such as recommendations from friends and influencers, significantly influence customers' attitudes and behaviors toward NLP-powered customer service (Chen & Liu, 2018; Jiang et al., 2021). Additionally, studies have demonstrated the role of self-efficacy in customers' adoption and satisfaction with NLP technology (Chua et al., 2019; Wang et al., 2020). Furthermore, observational learning, in the form of observing others' positive experiences with NLP-based customer service, has been found to positively influence customers' perceptions and adoption behavior (Gao & Zhan, 2020; Fang et al., 2021). These findings highlight the relevance of SCT in examining the factors that shape customers' interactions and experiences with NLP technology in e-commerce.

5.2.2 Managerial Implications

The research highlights the managerial importance of prioritizing strategies that enhance the perceived ease of use of Natural Language Processing (NLP) technologies in e-commerce for a positive customer experience. Despite the lack of significance for perceived usefulness and self-efficacy, managers should recognize other factors influencing customer experience. Emphasizing observational learning and leveraging social influence can enhance customer adoption and satisfaction with NLP. Overall, investing in the usability and accessibility of NLP tools is strategically crucial for fostering positive interactions and customer loyalty in e-commerce.

5.3 Limitations of the Study

This research on "The Role of Natural Language Processing in Enhancing Customer Service and Support in E-commerce" acknowledges limitations related to a specific target population, cautioning against universal applicability due to variations in technological literacy and cultural nuances. Time constraints are also recognized, with the dynamic nature of E-commerce potentially affecting the study's relevance over time. Researchers and practitioners should be mindful of these limitations, emphasizing careful interpretation and application of the findings in diverse and evolving E-commerce contexts.

5.4 Recommendations for Future Research

To address limitations in the study on "The Role of Natural Language Processing in Enhancing Customer Service and Support in E-commerce," it is recommended to use a more diverse sample to enhance external validity. Employing a multi-phased approach with iterative feedback loops from various user groups over time would capture evolving preferences and experiences. Additionally, to overcome time constraints, researchers should consider longitudinal studies or real-time data collection methods, collaborate with industry experts, and document the temporal context for a more updated understanding of NLP's role in dynamic E-commerce landscapes.

5.5 Conclusion

In conclusion, this research has contributed valuable insights and practical implications for both academic literature and industry practitioners seeking a deeper comprehension of the role of natural language processing in enhancing customer service and support in e-commerce. The study has conscientiously outlined its limitations and put forth recommendations for future investigations. While acknowledging specific constraints, it is suggested that forthcoming studies could advance and expand upon the present findings, contributing to the ongoing development of knowledge in this domain.

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APPENDICES

Appendix A: Survey Questionnaire

UNIVERSITI TUNKU ABDUL RAHMAN

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UNIERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT

BACHELOR OF INTERNATIONAL BUSINESS (Honours)

Survey Questions of FYP Research Title, "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce"

Dear Participant,

You are invited to take part in a research study titled "**The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce.**" This study aims to explore the impact of Natural Language Processing (NLP) technologies on enhancing the quality of customer service and support experiences within the realm of online shopping.

Purpose of the Research:
In today's fast-paced digital landscape, e-commerce has become an integral part of our daily lives. With the increasing reliance on online platforms for shopping, the effectiveness of customer service and support plays a crucial role in ensuring a positive and seamless shopping experience. This research seeks to delve into how NLP, a branch of artificial intelligence, can contribute to improving customer service interactions, addressing challenges, and enhancing overall satisfaction in the e-commerce domain.

In this research on "The Role of Natural Language Processing in Improving Customer Service and Support in E-commerce," Natural Language Processing (NLP), the field of artificial intelligence focused on enabling computers to understand, interpret, and generate human language, is harnessed within online shopping platforms to enhance customer interactions. Through automated chatbots, sentiment analysis, summarization, translation, personalization, voice assistants, and more, NLP revolutionizes customer support by facilitating natural and efficient communication, understanding sentiment, resolving issues, and tailoring assistance, thereby enriching the overall e-commerce experience.

By participating in this study, you will provide valuable insights that contribute to a deeper understanding of the potential benefits, concerns, and user perceptions surrounding the integration of NLP technologies in e-commerce customer service.

Survey Duration:
We understand the value of your time. This survey is designed to be concise and straightforward; it has **3 sections (Section A,B and C)** and will be taking approximately **5 minutes** to complete. Your responses will **remain confidential, and the information collected will be used solely for research purposes**. Your participation is greatly appreciated, as your input will aid in advancing our understanding of how technology can enhance customer support experiences in the evolving landscape of e-commerce.

Thank you for your time and valuable contribution.

Sincerely,
KUEK SHU HUI
UTAR BACHELOR DEGREE OF INTERNATIONAL BUSINESS (HONS)
Contact number: +6012-3081807

kuekshuhui@1utar.my Switch account

Personal Data Protection Notice

Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman (UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

1. Personal data refers to any information which may directly or indirectly identify a person which could include sensitive personal data and expression of opinion. Among others it Includes:

a) Name
b) Identity card
c) Place of Birth
d) Address
e) Education History
f) Employment History
g) Medical History
h) Blood type
i) Race
j) Religion
k) Photo
l) Personal Information and Associated Research Data

2. The purposes for which your personal data may be used are inclusive but not limited to:

a) For assessment of any application to UTAR
b) For processing any benefits and services
c) For communication purposes
d) For advertorial and news
e) For general administration and record purposes
f) For enhancing the value of education
g) For educational and related purposes consequential to UTAR
h) For replying any responds to complaints and enquiries
i) For the purpose of our corporate governance
j) For the purposes of conducting research/ collaboration

3. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

4. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

5. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated. UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

Consent:

6. By submitting or providing your personal data to UTAR, you had consented and agreed for your personal data to be used in accordance to the terms and conditions in the Notice and our relevant policy.

7. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

8. You may access and update your personal data by writing to me at kuekshuhui@1utar.my

Acknowledgement of Notice *

○ I have been notified and that I hereby understood, consented and agreed per UTAR above notice.

○ I disagree, my personal data will not be processed

Section A: Demographic profile

Please kindly select the answer to the following questions.
Choose one answer from the following options.

1.Age: *

- Under 18
- 18-24 years old
- 25-34 years old
- 35-44 years old
- 45-54 years old
- 55-64 years old
- 65 or older

2.Gender: *

- Male
- Female
- Non-binary
- Prefer not to say

3.Education Level: *

- Diploma
- Bachelor's degree
- Master's degree
- Doctorate or other advanced degree

4.Occupation: *

- Student
- Self-employed
- Unempoyed
- Government sector
- Private
- Housewife
- Retiree
- Other: ______

5.Frequency of Online Shopping: *

- ○ Multiple times a week
- ○ Once a week
- ○ 2-3 times a month
- ○ Once a month
- ○ Rarely
- ○ Never

Section B: General Information

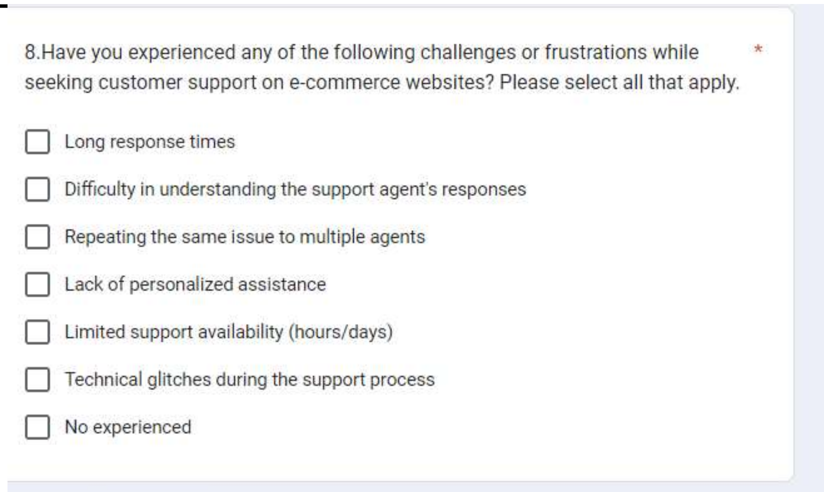
Please kindly select the answer to the following questions.
Choose one answer from the following options.

6.How frequently do you interact with customer service representatives when making online purchases? *

- ○ Multiple times a week
- ○ Once a week
- ○ 2-3 times a month
- ○ Once a month
- ○ Rarely
- ○ Never

7.To what extent do you believe that Natural Language Processing (NLP) technologies can enhance customer service and support in e-commerce platforms? *

- ○ Not at all effective
- ○ Slightly effective
- ○ Moderately effective
- ○ Very effective
- ○ Extremely effective



8.Have you experienced any of the following challenges or frustrations while seeking customer support on e-commerce websites? Please select all that apply. *

- ☐ Long response times
- ☐ Difficulty in understanding the support agent's responses
- ☐ Repeating the same issue to multiple agents
- ☐ Lack of personalized assistance
- ☐ Limited support availability (hours/days)
- ☐ Technical glitches during the support process
- ☐ No experienced

Section C: Factors Influencing Customers Satisfaction towards Natural Language Processing in Improving Customer Service and Support in E-Commerce

This section is to obtain the opinions of respondents about factors influencing Customers Satisfaction towards Natural Language Processing in Improving Customer Service and support in E-commerce. This section is using the multiple-choice grid (Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree). Please indicate your level of agreement in the column based on your opinion of each statement.

Perceived ease of use *

	Strongly diagree	Disagree	Neutral	Agree	Strongly agree
Using Natural Language Processing in e-commerce is easy to learn.	○	○	○	○	○
Using Natural Language Processing in e-commerce is easy to use.	○	○	○	○	○
I find Natural Language Processing in e-commerce to be user-friendly.	○	○	○	○	○
I feel confident using Natural Language Processing in e-commerce.	○	○	○	○	○
Natural Language Processing in e-commerce saves me time and effort.	○	○	○	○	○

Perceived usefulness *

	Strongly diagree	Disagree	Neutral	Agree	Strongly agree
I can save the effort of visiting stores, when I do online shopping by using Natural Language Processing	○	○	○	○	○
There is no time restriction in online shopping by using Natural Language Processing	○	○	○	○	○
I can order product from any part of the world through online shopping by using Natural Language Processing	○	○	○	○	○
I can order product from lots of options when I do shop online by using Natural Language Processing	○	○	○	○	○

Perceived social influence *

	Strongly diagree	Disagree	Neutral	Agree	Strongly agree
The use of Natural Language Processing in e-commerce will lead to significant changes in the job market.	○	○	○	○	○
The use of Natural Language Processing in e-commerce will require workers to have more advanced technical skills.	○	○	○	○	○
The use of Natural Language Processing in e-commerce will lead to increased productivity and efficiency in society.	○	○	○	○	○
The use of Natural Language Processing in e-commerce will lead to increased globalization in the industry.	○	○	○	○	○
The use of Natural Language Processing in e-commerce will lead to increased competition between businesses in the industry.	○	○	○	○	○

Self-efficacy *

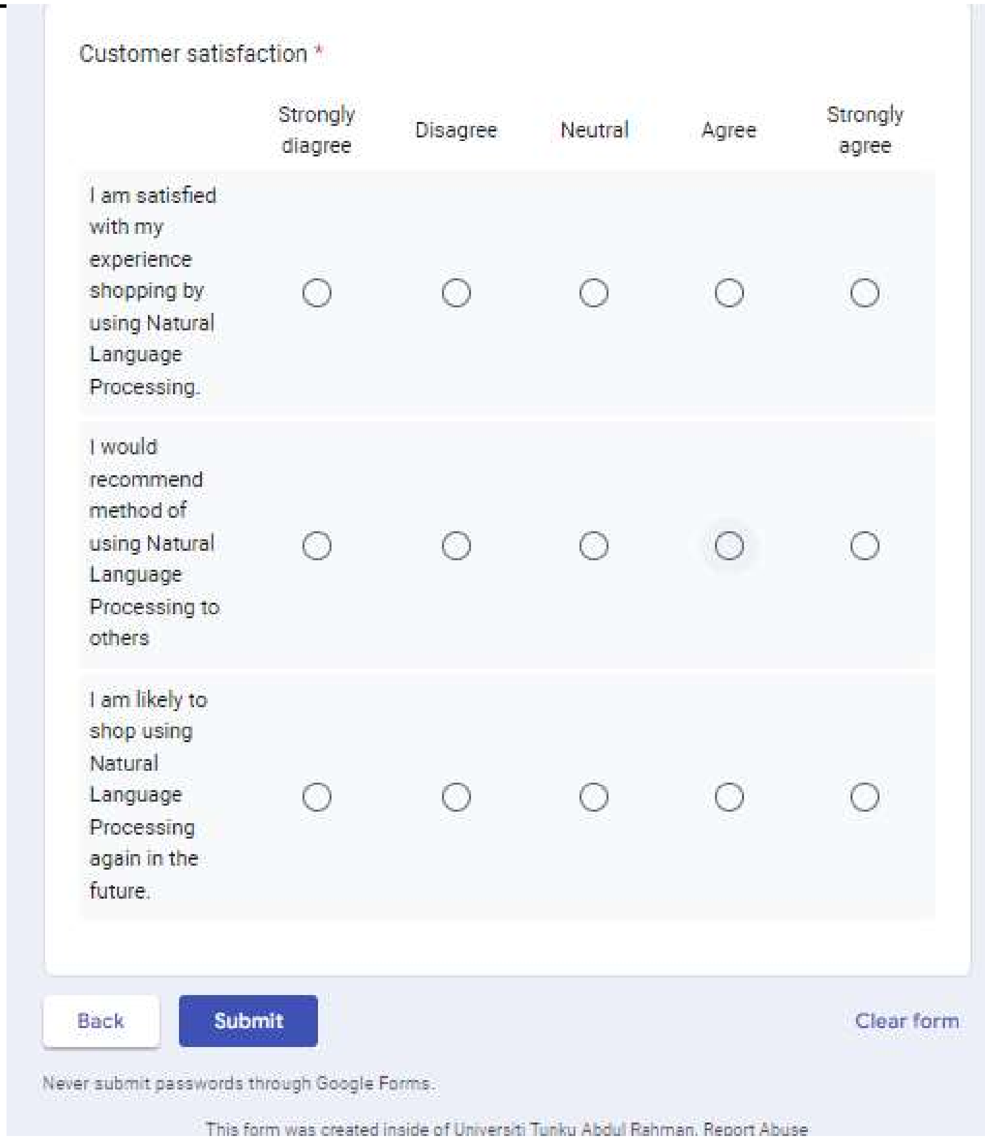
	Strongly diagree	Disagree	Neutral	Agree	Strongly agree
I have confident in my ability to contribute and share the valuable knowledge in Natural Language Processing	○	○	○	○	○
I have the expertise needed to provide valuable knowledge into Natural Language Processing	○	○	○	○	○
I am confident that I can post new knowledge on discussion forums and share my experiences, author an article, insights or expertise by engaging in dialogue with others in Natural Language Processing	○	○	○	○	○

Observational Learning *

	Strongly diagree	Disagree	Neutral	Agree	Strongly agree
I believe that Natural Language Processing provides accurate responses consistently.	○	○	○	○	○
Natural Language Processing's ability to provide novel explanations is important for its use in E-commerce.	○	○	○	○	○
The study provides valuable insight into the strengths and weaknesses of NLP chatbots in general practice.	○	○	○	○	○
Natural Language Processing can be useful as decision support tools in E-commerce.	○	○	○	○	○

Customer experience *

	Strongly diagree	Disagree	Neutral	Agree	Strongly agree
Natural Language Processing was able to help me discover my needs more clearly than in the past.	○	○	○	○	○
Natural Language Processing was able to identify my unmet needs and suggest solutions.	○	○	○	○	○
Overall, Natural Language Processing used in E-commerce's customer experience enhanced my satisfaction with the service.	○	○	○	○	○
I would be willing to use Natural Language Processing again in the future to improve my customer experience.	○	○	○	○	○



Customer satisfaction *

	Strongly diagree	Disagree	Neutral	Agree	Strongly agree
I am satisfied with my experience shopping by using Natural Language Processing.	○	○	○	○	○
I would recommend method of using Natural Language Processing to others	○	○	○	○	○
I am likely to shop using Natural Language Processing again in the future.	○	○	○	○	○

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Appendix B: Origin of Construct

Customer Experience (CE)			
No.	**Statements**	**Original Statement**	**Adapted from**
CE1	Natural Language Processing was able to help me discover my needs more clearly than in the past.	The chatbot was able to help me discover my needs more clearly than in the past	Adapted from Siggelkow, N., & Terwiesch, C. (2023)
CS2	Natural Language Processing was able to identify my unmet needs and suggest solutions	The AI system was able to identify my unmet needs and suggest solutions	
CS3	Overall, Natural Language Processing used in E-commerce's customer experience enhanced my satisfaction with the service.	Overall, the AI technology used in this customer experience enhanced my satisfaction with the service	
CS4	I would be willing to use Natural Language Processing again in the future to improve my customer experience.	I would be willing to use AI technology again in the future to improve my customer experience.	
Customer Satisfaction			

No.	Statements	Original Statement	Adapted from
CS1	I am satisfied with my experience shopping by using Natural Language Processing.	I am satisfied with my experience shopping on this website.	Adapted from Mohamad & Adam, 2023
CS2	I would recommend method of using Natural Language Processing to others	I would recommend this website to others.	
CS3	I am likely to shop using Natural Language Processing again in the future.	I am likely to shop on this website again in the future.	
Perceived ease of use (PEOU)			
No.	**Statements**	**Original Statement**	**Adapted from**
PEOU 1	Using Natural Language Processing would be easy for me to learn	Using the system would be easy for me to learn.	Adapted from Venkatesh, 2000
PEOU 2.	My interaction with Natural Language Processing would be clear and understandable	My interaction with the system would be clear and understandable.	
PEOU 3	Natural Language Processing would be flexible to interact with	The system would be flexible to interact with.	
PEOU 4	Natural Language Processing would be easy for me to get the	It would be easy for me to get the system to do what I want it to do	

	system to do what I want it to do		
PEOU 5	Natural Language Processing would be easy to use if I had to learn it on my own	The system would be easy to use if I had to learn it on my own.	
Perceived usefulness (PU)			
No.	**Statements**	**Original Statement**	**Adapted from**
PU1	I can save the effort of visiting stores, when I do online shopping by using Natural Language Processing	I can save the effort of visiting stores, when I do online shopping	Adapted from Ibrahim et al. (2013)
PU2	There is no time restriction in online shopping by using Natural Language Processing	There are no time restriction in online shopping	
PU3	I can order product from any part of the world through online shopping by using Natural Language Processing	I can order product from any part of the world through online shopping	
PU4	I can order product from lots of options when I do shop online by using Natural Language Processing	I can order product from lots of options when I do shopping online	
Social influence (SI)			
No.	**Statements**	**Original Statement**	**Adapted from**

SI1	The use of Natural Language Processing in e-commerce will lead to significant changes in the job market.	The use of AI and robotics in welding will lead to significant changes in the job market.	Adapted from Afrane Gyasi et al. (2020)
SI2	The use of Natural Language Processing in e-commerce will require workers to have more advanced technical skills.	The use of AI and robotics in welding will require workers to have more advanced technical skills.	
SI3	The use of Natural Language Processing in e-commerce will lead to increased productivity and efficiency in the society.	The use of AI and robotics in welding will lead to increased productivity and efficiency in the industry.	
SI4	The use of Natural Language Processing in e-commerce will lead to increased globalization in the industry.	The use of AI and robotics in welding will lead to increased globalization in the industry.	
SI5	The use of Natural Language Processing in e-commerce will lead to increased competition between businesses in the industry.	The use of AI and robotics in welding will lead to increased competition between businesses in the industry.	

Self-efficacy (SE)			
No	**Statements**	**Original Statement**	**Adapted from**
SE1	I have confident in my ability to contribute and share the valuable knowledge in Natural Language Processing	I have confident in my ability to contribute and share the valuable knowledge in E-learning system	Adapted from Hosseini et al., (2014)
SE2	I have the expertise needed to provide valuable knowledge into Natural Language Processing	I have the expertise needed to provide valuable knowledge into E-learning system	
SE3	I am confident that I can post new knowledge on discussion forums and share my experiences, author an article, insights or expertise by engaging in dialogue with others in Natural Language Processing	I am confident that I can post new knowledge on discussion forums and share my experiences, author an article, insights or expertise by engaging in dialogue with others in the E-learning system	
Observational Learning (OL)			
No.	**Statements**	**Original Statement**	**Adapted from**
OL1	I believe that Natural Language Processing provides accurate responses consistently.	I believe that ChatGPT provides accurate responses consistently	Adapted from Thirunavukarasu et al., (2023)

OL2	Natural Language Processing's ability to provide novel explanations is important for its use in E-commerce.	ChatGPT's ability to provide novel explanations is important for its use in primary care.	
OL3	The study provides valuable insight into the strengths and weaknesses of NLP chatbots in general practice	The study provides valuable insight into the strengths and weaknesses of NLP chatbots like ChatGPT in general practice.	
OL4	Natural Language Processing can be useful as decision support tools in E-commerce	Chatbots like ChatGPT can be useful as decision support tools or educational assistants in primary care.	