CUSTOMER ATTITUDES TOWARDS THE USE OF INTELLIGENT CONVERSATIONAL AGENTS

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A Thesis Submitted to the School of Graduate Studies in Partial Fulfilment of the Requirements for the Degree
Doctor of Philosophy in Business Administration

McMaster University

McMaster University DOCTOR OF PHILOSOPHY IN BUSINESS ADMINISTRATION (2022) Hamilton, Ontario (Information Systems)

TITLE: Customer Attitudes Towards the Use of Artificially Intelligent Conversational Agents

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SUPERVISOR: Professor Yufei Yuan

NUMBER OF PAGES: xiii, 205

Abstract

Intelligent conversational agents (ICAs) are artificial intelligence (AI)-enabled systems that can communicate with humans through text or voice using natural language. The first ICA, "Eliza," appeared in 1966 to simulate human conversation using pattern matching. Commercial ICAs appeared on the AOL and MSN platforms in 2001 and aided in developing advanced AI and Human-Computer Interaction (HCI). Since then, ICAs have progressively appeared in consumer products and services. Their success depends on the user's experience and attitude towards these services. This research examines customer attitudes towards ICAs through a theoretical framework of integrated Expectation Confirmation Theory (ECT) and Task Technology Fit Theory (TTF). By exploring user experience via an experiment that engages end-users with ICA's different functions and tasks, this study examines user perception of ICA's AI capabilities, such as Conversation Ability, Friendliness, Intelligence, Responsiveness, Task Performance, and Trust. This research investigates how customer satisfaction with ICA capabilities and perceived task technology fit influence their intention to use ICAs. A field survey of 380 Canadian end-users utilizing ICAs on the websites of five large Canadian telecom service providers enabled empirical testing of the model.

Keywords: Chatbots, Intelligent Conversational Agents (ICAs), Task Technology Fit (TTF) model, Expectation-Confirmation Theory (ECT), User Satisfaction, Behavioural Intention, Perceived Conversation Ability, Perceived Friendliness, Perceived Intelligence, Perceived Responsiveness, Perceived Task Performance, and Perceived Trust.

Dedication

I dedicate my dissertation to my family and friends. My heartfelt appreciation goes out to my family. I started my Ph.D. journey with my late parents and now complete it with my siblings, their families, relatives and friends. I was blessed to have the most loving parents in the world. My late parents, Muhammad Agha Sohail and Hashmat Ara Begum, were the source of love, encouragement, tenacity and motivation. I grew up observing them inculcating in all of us the virtue of Facta Non-Verba, and with love, serve one another, and that perseverance continues to ring in my ears and shine in front of my eyes. I feel blessed that my siblings Massarrat (Baji), Abid Bhai, Mohsin, Nazish, Masood, Talat, Nusrat, Hammad, Nudrat, Ehtehsam and Azlinda have been a beacon of light and showered unconditional affection. The love from my nephews and nieces gave me the strength to proceed in my Ph.D. journey. Ali, Zainab, Ambreen, Ahsan, Zehra, Zaeema, Hassan, Amir, Fatima and Maryam have never left my side and are very special. Excluding the beautiful felines: Munchee, Fibz (now deceased), Flavia, and Oliver is impossible; they kept me company while I was researching and writing.

I devote this effort to Chacha Mian Taqi Ali Khan, Sharib Chacha, Mrs. Afroze Haidery, Mrs. Nur, Babu Bhai, Pervaiz Bhai, Asad, N.A. Salam, Mrs. Roshan Zaidi, Sehar, Haque, Naeem, Amir, Shahzar, Nauman, Ghazanfar, Basit, Sarmad, Nadir, Asim, Sajjad Kazmi, Nayyar, Iftikhar, Attique, Kashif, Mohsin, Ch. & Imran, Ilyas, Khalil, Farhan, Samer, Asif Rao and their families. I commit this dissertation to many unnamed friends and family members who have supported me. My heart, mind and soul are etched with their names for helping me throughout my journey of doctoral studies. They have been and will always be my greatest cheerleaders. Finally, I dedicate my dissertation to the 14 infallibles, who will always make this world a beautiful place for us all.

Acknowledgements

I take this opportunity to thank my committee for supporting my endeavour. They made themselves available to answer my untimely questions. They extended unconditional help. This thesis document mirrors my research journey, which was impossible without the unconditional support of my committee, comprising Professor Dr. Yuan, Professor Dr. Wang, and Professor Dr. Archer. I am grateful for their kindness as they gave me unwavering support. My time with them has been a blessing; I received indispensable suggestions, devoted assistance and countless reviews that helped shape the final dissertation. My special thanks to Professor Dr. Wang for helping me with the SEED grant and Professor Dr. Yuan for kindly funding my research with a generous stipend.

Professor Dr. Khalid Hassanein, Professor Dr. Brian Detlor, Professor Dr. Maryam Ghasemaghaei, Professor Dr. Nicole Wagner, Professor Dr. Verma, Professor Dr. Khalid Nainar, Professor Dr. Isik Zeytinoglu, Professor Dr. Benson Honig, and Professor Dr. Mahmut Parlar cannot be equitably thanked. I appreciate the King of Kindness, Professor Dr. Baba, for providing priceless mentoring. I especially want to thank Professor Dr. Montazemi for making this journey possible. He hosted lavish feasts for his students with his beautiful family, epitomizing the rich Iranian culture known for its hospitality and generosity. Cheers to Deb, Jeanette, Alicja, and Bani for acting as pillars of rationality and sanity to resolve admin issues. Thanks to Pam at Bistro for serving tea and biscuits with a reassuring smile. Hat tip to my DSB friends Bell, Mehmet, Edo, Aydin, Mohsen, Wenting, Esraa, Ahmed, Alyaa, Emanuele, Hussain, Muhammad, Fateme, Fatma and Galini for encouraging words whenever it mattered the most. I am guilty of ignoring my family while working on this dissertation. As a result, I would like to express my heartfelt gratitude to my family, who have continued to love me and support my endeavours despite my absence.

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Acronyms

AI	:	Artificial Intelligence
AIECA	:	Artificial Intelligence-Enabled Conversational Agent
AIECS	:	Artificial Intelligence-Enabled Customer Service
AVE	:	Average Variance Extracted
BI	:	Behavioural Intention
CA	:	Conversational Agents
CI	:	Continuation Intention
CONF	:	Confirmation
CONFC	:	Confirmed Conversational Ability
CONFF	:	Confirmed Friendliness
CONFI	:	Confirmed Intelligence
CONFRESP	:	Confirmed Responsiveness
CONFTP	;	Confirmed Task Performance
CONFTT	:	Confirmed Trust
CONT	:	Context
CONV	:	Conversational Ability
CR	:	Composite Reliability
CRM	:	Customer Relationship Management
CRME	:	Customer Relationship Management Experience
CUI	:	Conversational User Interface
ECM	:	Expectation Confirmation Model
ECT	:	Expectation Confirmation Theory
EE	:	Experiment Effort
EXPT	:	Expectations
EXPTC	:	Experienced Conversational Ability
EXPTF	:	Experienced Friendliness
EXPTI	:	Experienced Intelligence
EXPTRESP	:	Experienced Responsiveness
EXPTTP	:	Experienced Task Performance
EXPTTT	:	Experienced Trust
F	:	Friendliness
FFA	:	Fit For Availability
FFC	:	Fit For Complexity
FFT	:	Fit For Timeliness
GUI	:	Graphical User Interface
HAECS	:	Human Agents Enabled Customer Service

I	:	Intelligence
ICAs	:	Artificially Intelligent Conversational Agents
ITU	:	Intention To Use
NLP	:	Natural Language Processing
NLU	:	Natural Language Understanding
PA	:	Perceived Attitude
PAIE	:	Previous Artificial Intelligence Experience
PPC	:	Perceived Conversational Ability
PDA	:	Palm Device Assistance
PPF	:	Perceived Friendliness
PPI	:	Perceived Intelligence
POAF	:	Perceived Overall Fit
PP	:	Perceived Performance
PPRESP	:	Perceived Responsiveness
PPTP	:	Perceived Task Performance
PPTT	:	Perceived Trust
R	:	Responsiveness
SATF	:	Satisfaction
TAM	:	Technology Adoption Model
TCOM	:	Task Complexity
TP	:	Task Performance
TPB	:	Theory of Planned Behaviour
TRA	:	Theory of Reasoned Action
TSBAM	:	Two-Stage Change in Beliefs and Attitude Model
TSCCM	:	Two-Stage Change in Cognition Model
TSMABC	:	Two-Stage Model of Attitude and Belief Change
TT	:	Trust
TTF	:	Task Technology Fit
UTAUT	:	Unified Theory of Acceptance and Use of Technology
VA	:	Virtual Assistant

Chapter 1: Introduction

Intelligent conversational agent (ICA) is a term used in extant literature for artificial intelligence (AI) enabled chatbots (Ling et al., 2021). Chatbots are automated programs that can interact with humans via text or voice using natural language (Fadhil and Gabrielli, 2017; Przegalinska et al., 2019; Radziwill and Benton, 2017; Sivaramakrishnan et al., 2007). Interchangeable terms include “chatbots,” “conversational agents,” “virtual assistants,” “intelligent assistants,” and “digital assistants” (Koetter et al., 2019). Customers interact with these applications to search for information, place online orders, resolve service problems, and receive advice or recommendations (Luo et al., 2019). ICAs’ capabilities have improved enormously in recent years because of advances in AI (Knijnenburg and Willemsen, 2016), particularly machine learning (ML) methods. ML is the capacity of systems to learn from problem-specific training data to automate the analytical model construction process and the resolution of related tasks. At the same time, deep learning (DL) is an artificial neural network-based machine learning concept (Janiesch et al., 2021). ICAs can facilitate real-time user interaction, provide support and assessment features (question-answer exchanges between chatbots and users), and are user-friendly. Moreover, by integrating NLP (natural language processing), ML, AI, and DL technologies, ICA can deliver effective performance (Bahja et al., 2020).

Researchers have shown keen interest in challenges faced by users related to conversational interface usage (Zue and Glass, 2000). Human-ICA interaction differs from the traditional menu or command-driven graphical user interface (GUI) (Schuetzler et al., 2018). An ICA has two distinct features: speech recognition and a dialogue system (Cowan et al., 2017). ICAs like Siri and Google Assistant work in rich and engaging content. The ICA is a virtual assistant assisting users in real-time by understanding their needs (Cowan et al., 2017). The first ICA ELIZA was introduced in 1966 and used pattern matching and substitution to simulate conversation (Weizenbaum, 1966). SmarterChild ICA was introduced commercially in 2001. It ran on AOL and MSN, allowing end-users to interact and retrieve data from databases about movie times, sports scores, stock prices, news, and weather information, resulting in a significant advance in machine intelligence and human-computer interaction (HCI) (Molnár and Zolnár, 2018). Apple introduced Siri in 2011 as a personal assistant (Soffar, 2019), while Google introduced Google Assistant at Google's developer conference in 2016 (Lynley, 2016). Google Assistant was available on over 1 billion devices by 2020 (Bronstein, 2020).

AI refines business models and impacts the maturity of AI levels in terms of strategy, organization, data, technology, and operations (Pringle and Zoller, 2018). With its DL and ML capabilities, AI provides an opportunity for improving sophistication and maturity. Three maturity levels frequently categorize chatbots. The interaction level is the first maturity level and highlights how chatbots vary in accepting text input. The intelligence level is the second maturity level that shows the chatbot’s capacity to understand and respond to users’ inputs. The integration level is the third maturity level and refers to how successfully the chatbot’s back end integrates with other websites, servers, and services (Smiers, 2017). Similarly, the AI Maturity Model comprises five levels: initial, assessing, determined, managed, and optimized, which show how the parameters of AI functions, data structure, people, and organization can be measured and improved (Alsheiabni et al., 2019).

Organizations integrate ICAs with business intelligence and big data analytics to use AI's immense promise (Reshmi and Balakrishnan, 2018). Motivated enterprises deploy ICAs to meet customer needs and improve their business to increase customer lifetime value (Kaczorowska-

Spychalska, 2019). ICAs are also increasingly used internally to streamline and expedite operations (Johannsen et al., 2021) and influence the emerging role of AI in e-commerce (Soni, 2020; Illescas-Manzano et al., 2021).

ICA continues to reshape the customer service industry, with intended benefits to customers and businesses regarding time and cost savings. AI-enabled customer relationship management (CRM), like ICAs, can help maintain customer experience effectively (Hoyer et al., 2020; Jiménez-Barreto et al., 2021). An advantage of an ICA is that it offers 24/7 help in various industries, including sales, customer service, and marketing. Businesses want to employ ICA applications when they are accessible, flexible, inexpensive, and can effectively replace human agents (Przegalinska et al., 2019; Radziwill and Benton, 2017).

ICAs have only partially succeeded in assisting businesses in communicating with customers and have often left the customers unhappy or dissatisfied with the ICA's performance (Feine et al., 2019; Suhaili et al., 2021). Although customers and end-users may trust ICA applications beyond a certain degree of similarity to humanness, they may feel “too eerie for some users,” resulting in users withdrawing from ICA use. Researchers refer to this behaviour as the customers’ "uncanny effect" (Ciechanowski et al., 2019; Skjuve et al., 2019) or "human fear of robots" (Szollosy, 2017). Chen et al. (2022) have used mixed methods to identify the AI chatbot service quality (AISQ) scale that positively influences customers’ satisfaction with perceived value and continuous use of ICAs.

Most published ICA research covers design or technical details, although more recent research has described customers' experience with ICAs. However, researchers have not investigated and compared customers' expectations about ICAs from the AI perspective with their actual experiences. My study examines the AI capabilities of ICAs, with their ability to imitate human behaviour, which is unique and distinct from the traditional human-computer interface and can thus influence human perceptions and behaviours of obtaining services from ICAs.

My study was multifaceted, extensive, and distinguishable at broader and more specific levels. Its broader area pertains to AI and AI-enabled customer services, while the more specific scope focuses on customer satisfaction with ICAs. My study advances the understanding of the theoretical foundations of customer (end-user) satisfaction by investigating if ICA-enabled customer service is as effective as traditional customer service (Melone, 1990). I did so with the help of a model that obtains additional explanatory power through reasoning elements taken from a combination of the Expectation Confirmation Theory (ECT) and Task Technology Fit (TTF) theory. By incorporating specific constructs from these theories, my study capitalizes on the cognitive dimensions inherent in both theories. The integrated theoretical framework of ECT (Oliver, 1977; 1980) and TTF (Goodhue and Thompson, 1995) explains and predicts customer attitudes towards using ICAs while examining the fit between ICA technology and the tasks assigned to it by the customer.

My research involves an experiment where the participants interacted with a commercial ICA and performed specific tasks. The participants and the ICA imitated customer service encounters while interacting with the ICA service providers. This interaction allowed me to measure customer perceptions of specific ICA capabilities before and after interacting with the ICA technology.

The self-developed experiment formed a critical part of my research, allowing me to evaluate the model I described above empirically. The experiment used five commercially available ICAs deployed by the Canadian Telecom Sector. A research firm I employed recruited participants who resided in Canada and were cognizant of customer service issues and the extent of customer help provided by these ICA services. My research determined whether service-oriented ICAs, acting as a stimulus, can engender a positive reaction from customers. This experiment was unique as the capabilities of the commercial ICA were compared and contrasted with that of a human customer service agent. My research studied six ICA capabilities: perceived conversational ability, friendliness, intelligence, responsiveness, task performance, and trust. These six capabilities directly impact customer satisfaction from using an ICA and suggest if the deployed ICA is effective enough to impact customer service positively. If the ICA capabilities influence customer service, it would also influence business value in cost savings by reducing human resource requirements and engaging customers beyond regular office hours for the organizations that deploy these systems.

My research study makes three significant contributions to the information systems (IS) and service management literature. First, it develops and verifies a theoretical framework that integrates ECT (Oliver, 1977; 1980) and TTF theories (Goodhue and Thompson, 1995) to explain end-user satisfaction with an ICA. It examines the practical utility of six ICA capabilities. Second, it contributes to a better understanding of customer satisfaction concerning this new AI technology as a customer service platform. Third, the findings of this research have practical implications for corporate strategies to improve customer satisfaction and encourage using ICAs in customer service.

My thesis is organized into the following chapters:

Chapter 1–Introduction: Chapter 1 focuses on the scope and rationale of this research. It briefly outlines the research from an AI perspective.

Chapter 2–Literature Review: Chapter 2 provides a literature review of ICAs and a foundation for this study through the contextualized HCI framework of Zhang and Li (2004).

Chapter 3–Research Model: Chapter 3 describes the theoretical foundation of the research by describing the ECT and TTF theories and developing the research model.

Chapter 4–Research Methodology: Chapter 4 explains the survey instruments and the data collection procedure. The chapter also elaborates on the experimental scenario.

Chapter 5–Data Collection: Chapter 5 focuses on the pilot study, preliminary data analysis, methods, and measurement criteria. The chapter presents the measurement model and structural model analysis. The chapter delivers comprehensive results of the hypothesis testing, post hoc analysis, importance-performance matrix analysis, and qualitative feedback for model validation and explanation.

Chapter 6–Conclusion: Chapter 6 discusses the experimental results and their theoretical and practical contributions to the field.

Chapter 2: Literature Review

Chapter 2 reviews existing research on ICA usage: Section 2.1 identifies five popular streams of ICA research according to Zhang and Li's (2004) HCI framework, enabling an investigation of user perceptions of AI in the ICA application domain; Section 2.2 identifies the research gap in user behaviour studies using the ICA service, and Section 2.3 summarizes this chapter.

2.1. An HCI Framework to Study User Interaction with ICAs

Zhang and Li (2004) provide a general framework for studying HCI. This HCI framework is suitable for reviewing critical aspects of user–ICA interaction. Zhang and Li’s (2004) framework, as shown in Figure 2.1, comprises five themed areas: system attributes, user traits, interactions, tasks, and context and outcomes.

2.1.1. Theme 1: System Characteristics (ICA Capabilities)

This research theme includes ICA capabilities, ICA transparency, human-like characteristics, and gestural and conversational behaviour (Rzepka and Berger, 2018; Diederich et al., 2021).

Theme 1 focuses on ICA capabilities regarding technical and social features (Cohen et al., 2016; Cowan et al., 2017; Luger and Sellen, 2016) and its role as an intelligent, personal, and high-performing service representative (Zamora, 2017). Theme 1 also concentrates on the design challenges that ICAs face. This theme suggests that ICAs should understand, process, and respond to user queries (Suhaili et al., 2021) and perform tasks or conversations intellectually and indistinguishably from humans (Rapp et al., 2021). These design challenges are critical and have the potential to influence ICA user behaviour.

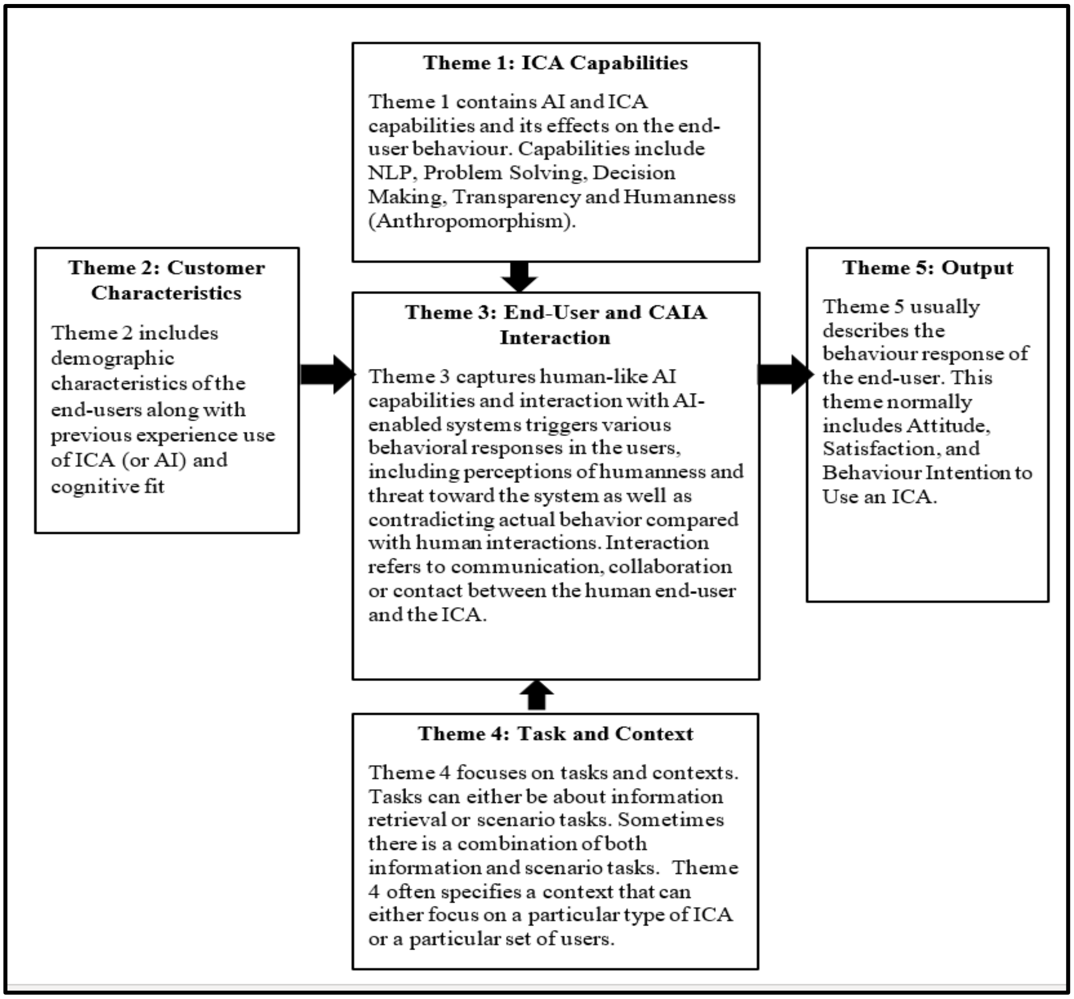

Figure 2.1: Research framework adapted from Zhang and Li's (2004) HCI Framework

Research under theme 1 for ICAs suggests that personification increases the social intelligence of the ICA and user satisfaction. Under theme 1, researchers have shown how ICAs should identify and respond to customer emotions, which can also influence future ICA design (Cohen et al., 2017; Purington et al., 2017). Anthropomorphic cues show ICAs' ability to chat and establish the perception of intelligence (Araujo, 2018). Researchers have studied the effects of ICA emotional capacities on customer satisfaction with the help of an emotional comfort framework in the e-commerce context; research also shows that the ICA's final answer selection uses topic classification and text matching (Song et al., 2021).

Theme 1 captures ICAs' ability to combine speech, touch, and visual input modes with the dynamic user experience (Kiseleva et al., 2016). Researchers have also pointed out that communicating with users using a name or an avatar can influence perceived humanity and social presence of ICAs (Wünderlich and Paluch, 2017). Text-based ICAs provide predefined design features, such as clickable buttons, allowing the end-users to respond to messages without requiring manual typing (Brandtzg and Følstad, 2018). Theme 1 also consists conceptual and descriptive studies that discuss ICA capabilities, features, and prospective applications (Kuo et al., 2017; Meyer von Wolff et al., 2019).

2.1.2. Theme 2: User Characteristics

User characteristics include demographics and reasons for usage. Brandtzaeg and Følstad (2018) claim that individuals use chatbots to boost productivity and to get information efficiently and accurately while receiving motivations like enjoyment, social reasons, and curiosity. The most frequently reported motivational factor is "productivity"; chatbots help users obtain timely and efficient assistance or information. Chatbot users also reported motivations about entertainment, social and relational factors, and curiosity about what they view as a novel phenomenon. Researchers have studied extensively and continue to explore user characteristics and experiences (Rzepka and Berger, 2018; Diederich et al., 2021).

Moreover, theme 2 consists of research on user or customer experiences with ICAs. The emphasis is on the future ability of ICAs to recognize, fulfill, collaborate with, and interact with humans and other conversational assistants (Cohen et al., 2017). A "gap between user expectation and experience" is another prevalent theme in the literature (Luger and Sellen, 2016), with increased research emphasis on "smart, smooth, personal, and high-performing" service agents (Zamora, 2017). Research on ICAs covers topics like complex searches (Kiseleva et al., 2016;

Vtyurina et al., 2017) and personas in design (Graf et al., 2015; Vandenberghe, 2017). The personification of the Amazon Alexa has been found to affect customer happiness (Purington et al., 2017).

Theme 2 has allowed researchers to study customer satisfaction with ICA usage (Luger and Sellen, 2016; Zamora, 2017; Nguyen and Sidorova, 2020), emphasizing expectations, experiences, and sociability (Lopatovska et al., 2020). Contact sequence and speech recognition quality predict customer satisfaction (Jiang et al., 2015). Customer satisfaction directly impacts and improves the quality of the perceived service of the ICA (Suh and Yoon, 2019). These studies focus on the effectiveness of an ICA and its effect on customer satisfaction. Researchers have studied customer relationships with ICA adoption and usage, including the intention to use and customer satisfaction (Ashfaq et al., 2020; Eren, 2021), which will influence future research.

2.1.3. Theme 3: Human-Chatbot Interactions

Human-ICA (chatbot) interactions influence end-user behaviours and improve ICA design and application (Rzepka and Berger, 2018; Diederich et al., 2021). ICAs (chatbots) provide a new type of conversational HCI besides the traditional menu-driven user interface (Nguyen et al., 2021b). “Chatbots are virtual customer assistants which advise customers with queries via texts or online web chat" (Lui and Lam, 2018, p. 271). ICA allows users to freely ask questions, influencing customer satisfaction, such as trust and autonomy. The ICA design influences customer interaction (Diederich et al., 2022). Although HCI communications are like human communications, the content and quality of such chats differ significantly (Rapp et al., 2021). Hill et al. (2015) discovered that human–chatbot interactions, compared to human-human interactions, were less language-rich and more profane. Corti and Gillespie (2016) found that users who saw chatbots as humanoid were more inclined to correct faults than users who perceived chatbots as automated. ICA's communication style incorporates emoticons and self-references (Seeger and Heinzl, 2018).

Human-like communication will influence ICA design and, thus, ICA research (Van Pinxteren et al., 2020). ICA research in HCI and computer science fields studies customer trust in HCI and improves natural language understanding (Gnewuch et al., 2017). ICA influences both businesses and individuals (Morana et al., 2017). Various factors include design principles (Gnewuch et al., 2017), user disclosure of information (Morana et al., 2017; Schroeder and Schroeder, 2018), and ICA effects on the user's cognitive capacities (Schuetzler et al., 2018; Schroeder and Schroeder, 2018). Often under this theme, studies capture an ICA's impact on business customer services, like cost reductions and employment losses (Følstad and Skjuve, 2019). Theme 3 also includes Human Chatbot Relationships (HCR). Skjuve et al. (2021), in their research on the HCR, used Social Penetration Theory to compare the evolution of the HCR with human-to-human relationships and found ICA qualities of being accepting, understanding, and non-judgmental to enhance HCR.

Theme 3 also studies the human end-users' social responses while interacting with an ICA. Social cues provided by the ICA can influence the ICA design process (Seeger and Heinzl, 2018). The perceived humanness of an ICA includes its representation. Furthermore, research has shown that ICA communicative behaviour positively perceives usefulness (Araujo, 2018; Seeger et al., 2021). The social response includes delayed response to display pauses for thinking and typing (Gnewuch et al., 2017). ICA research under theme 3 has emphasized appearance, mapping, image recognition, and voice activation. Customers interacting with AI-enabled ICA observe when an ICA provides inappropriate NLP responses to customer queries (Gnewuch et al., 2017; Pfeuffer et al., 2019). It leads to a mismatch between the customer's expectations and experience, resulting in poor system performance (Luger and Sellen, 2016; Orlowski, 2017) and raising customer doubts about the effectiveness of ICA services.

2.1.4. Theme 4: Task and Context

Theme 4 focuses on task and context, which research identifies as moderating variables in HCI research (Rzepka and Berger, 2018). Studies in this stream focus on ICA's usefulness for different tasks and contexts for individuals and businesses (Diederich et al., 2021). ICAs find usage in a variety of contexts, like e-commerce (Chen et al., 2021), travelling (Ukpai et al., 2019), entertainment (Brandtzaeg and Følstad, 2018), healthcare (Nadarzynski et al., 2019), education (Winkler and Söllner, 2018), and public service (Park, 2017).

ICAs have been used to elaborate on customer service accessed via chat instead of a phone, and live chat services increase trust, satisfaction, repurchase, and referrals (Mero, 2018). As a result, business performance increases by using ICAs to replace human operators with ICA agents based on frameworks that resemble human-like systems (Gnewuch et al., 2017; Maedche et al., 2019; Pfeuffer et al., 2019). Researchers have studied ICA-enabled AI service benefits with a focus on appropriate interactive design and development of ICA systems (Feine et al., 2020). This research stream includes instant service feedback, cost and time savings (Adam et al., 2020), extended hours of operation (Van Esch and Mente, 2018), and an effective problem-solving tool for use in a customer support setting (Ostrom et al., 2019), adjustable response (Kaplan and Haenlein, 2019), proactive intent recognition (Wu et al., 2021), and personalized customer context (Trivedi, 2019). Including appropriate data, AI algorithms, and robotics can reduce errors (Zhang et al., 2021). These systems can typically collect and store customer data to make targeted product and service recommendations (Shen, 2014; Brill et al., 2019; Mari et al., 2020). Factual communication and rule-based reasoning can encourage customer sales (Wang et al., 2016). ICA systems can also mimic human response time through response delays (Gnewuch et al., 2017), creating a perceived similarity between the end-user and the ICA (Gnewuch et al., 2020). ICAs can influence customer services by solving simple or complex tasks for customers (Luger and Sellen, 2016; Cheng et al., 2021) while offering "untact" client assistance (Lee and Lee, 2020). The word “untact” is a Korean English word similar to 'non-contact.' Untact technology enables services without contact with a human salesperson in a non-face-to-face format (Lee and Lee, 2020).

Theme 4 allows researchers to examine the influence of an agent's interactive representation and nonverbal communication behaviour on their persuasiveness in decision-making tasks. According to Goodhue and Thompson's (1995) task–technology fit theory, ICA technology should meet the customer's needs (requirements) for specific tasks (Blut et al., 2021). Task complexity negatively impacts a customer's perceptions of friendliness and trust in the ICA technology (Cheng et al., 2021). Human customer service is considered superior to ICA-enabled customer service. Therefore, task complexity negatively influences the intention to use ICA technology (Xu et al., 2020).

Theme 4 has captured research studies that often do not identify a context explicitly (Chaves and Gerosa, 2021; Jain et al., 2018). Studies under this theme occasionally identify professional contexts like customer service (Xu et al., 2017), education (Hobert and Wolff, 2019; Winkler and Roos, 2019), health applications (Sebastian and Richards, 2017) or marketing and sales (Kim et al., 2018; Vaccaro et al., 2018). Research on the theme talks about private individual task support (Porcheron et al., 2018; Purington et al., 2017), multiple contexts (Meyer von Wolff et al., 2019), and ICA as role models (Rosenberg-Kima et al., 2008). ICA finds utilization for general communication, specific tasks, business functions (Gnewuch et al., 2017), legal research (Sugumaran and Davis, 2001), lie detection (Nunamaker et al., 2011), financial advisory (Morana et al., 2020a), data analytics (Morana et al., 2020b), human resources (Diederich et al., 2020; Liao et al., 2018) or marketing and sales (Vaccaro et al., 2018). The socio-technical framework is a lens to investigate the HCI phenomenon (Diederich et al., 2021).

Theme 4 also has allowed researchers, while studying human-computer conversations, specifically text-based interactions in the ICA context, to point out that an ICA system's information representation and user requests must match (Rzepka et al., 2020). A friendlier conversational style suits decisive tasks (Chen et al., 2021).

2.1.5. Theme 5: Outcomes

This theme captures outcomes like satisfaction, attitude, behavioural intention and loyalty to the ICA. In a competitive climate, firms must measure the impact of customer satisfaction on intent to use (Bhattacherjee and Lin, 2015). Research shows that customers rank service experiences that influence customer satisfaction and intention to use the service again (Jiang et al., 2016). Research on ICA displays factors affecting end-user satisfaction and loyalty due to service customization (Brill et al., 2019; Chung et al., 2020).

Research has found that customers display a favourable attitude toward self-service and humanizing service chatbots (Schanke et al., 2021). Trust in ICAs is influenced by trust in online platforms (Sharma and Lijuan, 2015), the ICA itself (Ojha, 2019) and the impact of live chat on service quality (Rajaobelina et al., 2021). Customer trust in an ICA system is essential and is similar to trust in online recommendation agents providing convincing product and service suggestions (Dabholkar and Sheng, 2012; Ischen et al., 2020). ECT-based research has investigated trust regarding human-like trust constructs like benevolence, integrity, and ability, while other researchers use system-like trust constructs like helpfulness, reliability, and functionality (Lankton et al., 2014; Lankton et al., 2015). The effect of humanness on the design of interactive ICA systems and its influence on the decision to continue using the ICA (Li et al., 2021) influences customer perceptions across ICA service systems. Customers dissatisfied with an ICA's performance (Feine et al., 2019) or its negative emotional response (Crolic et al., 2021) tend to use ICAs less frequently.

Researchers have studied ICAs for user experience (Foldstad and Skjuve, 2019) and observed that customers might prefer a human agent over an ICA in challenging situations (Nguyen et al., 2021b), and customers especially prefer human customer assistance for high-complexity tasks (Kirkpatrick, 2017; Xu et al., 2020). ICAs use NLP to replicate human-to-human conversations. Because of this replication, ICA research often covers anthropomorphism (Roy and Naidoo, 2020; Seeger et al., 2021) for service robots, clients, and personnel (Lu et al., 2020) and impacts AI-enabled customer services.

Researchers have compared the impact of AI-enabled customer service with human customer service regarding usage intention. They found that customers perceive AI to solve problems better and are more suitable than human customer service representatives for low-complexity tasks (Xu et al., 2020). Learning, reasoning, problem-solving, perception and understanding of language can lead to many potential AI applications for human-level intelligence (Jackson, 2019). My study used task complexity as a boundary condition while simulating an AI-enabled service by incorporating more straightforward and complex tasks where the nature of tasks varied from information retrieval to performance of tasks.

Researchers have suggested that AI can either "think" or "act" rationally or can "think" or "act" like humans. AI refers to machines (computers) that replicate the cognitive and affective functions of the human mind (Russell and Norvig, 2020). Thus, ICAs should display human or rational capabilities. My study aligns with an AI-performed service encounter- type of category. This service type allows AI to take an employee's place, interacting directly with the customer to co-create and deliver the entire service experience. E.g., the chatbots used in retailing, banking, and virtual assistants like Apple's Siri (Ostrom et al., 2019).

Presently, AI services lag behind human services in high-complexity task situations, while human agents are also considered more effective at problem-solving than AI agents (Kirkpatrick, 2017; Xu et al., 2020). Businesses require a unique combination of organizational resources to successfully achieve a competitive AI capability (Davenport and Ronanki, 2018; Ransbotham et al., 2018). Researchers view AI in the context of customer service as a technology-enabled system that evaluates real-time service situations using data collected from digital and physical sources to provide personalized recommendations, alternatives, and solutions to customers' enquiries or more complex problems (Xu et al., 2020). By imitating human conversation, ICAs can create a favourable service and keep customers happy (Tatai et al., 2003). Studies observe that some customers are more motivated to use technology due to intrinsic factors of autonomy, competence and relatedness (Nikou and Economides, 2017).

2.2. Research Gaps in Human Behavior Study of Using ICA Service

While extant research has presented essential antecedents and valuable insights into conceptualizing ICA's customer behaviours, the literature review reveals certain limitations and gaps that warrant deeper investigation.

Firstly, the earlier research has overly-used traditional adoption models and theories such as Technology Adoption Model (TAM), Theory of Planned Behaviour (TPB), Theory of Reasoned Action (TRA) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain the use of ICA in E-Commerce (Nichifor et al., 2021) and enterprise use of chatbots (Brachten et al., 2021). These studies are essential as they explain the adoption intentions of ICAs. However, these studies do not capture the AI capabilities of an ICA and do not discuss the effect of the AI capabilities of an ICA on user satisfaction. My research has attempted to overcome this gap by first conducting an experiment by informing participants about the AI capabilities of the ICA and then allowing the participants to interact with the ICA. Further, my research used ECT and TTF theories to record the perceptions about ICA capabilities, attitude, satisfaction, and the fit between deployed ICA technology and the assigned tasks.

Secondly, researchers have discussed end-user satisfaction for ICAs deployed for corporate applications (Cheng and Jiang, 2020), online food ordering (Gârdan et al., 2021), and e-commerce (Moriuchi et al., 2021). These critical studies capture the end-users' satisfaction with ICA performance. Similarly, in another study, researchers show that an ICA requires performance improvement to meet user expectations regarding online retail shopping (Chan and Leung, 2021). Studies have also focused on customer experience values influenced by usability, responsiveness, and satisfaction while using an ICA (Chen et al., 2021). These studies focus on post-adoption ICA satisfaction from several unique aspects but do not discuss expectations and experiences concerning end-user satisfaction. My study includes an experiment (interaction between ICA and the participant) and attempts to capture the customer journey with expectations, perceived performance, satisfaction, and behavioural intention.

Thirdly, researchers have studied behavioural intention towards ICAs in various contexts and unique settings using survey method research. These include financial services (Sugumar and Chandra, 2021), business-to-business (Behera et al., 2021), public transport (Kuberkar and Singhal, 2020) and hospitality services (Um et al., 2020). While studying customer behaviour, these research studies use survey methods based on influential IS theories of TAM, TRA and TPB to explain the adoption intention towards ICAs. Since these studies do not provide an actual interaction (experience) with an ICA, a gap exists between expectations, experience and behavioural intention. My research study aims to explain behavioural intention to use an ICA by using an empirical experiment and considering the impact of ICA capabilities on satisfaction and behavioural intention before and after the experimental experience.

Fourthly, researchers have studied satisfaction through the lens of both ECT and ECM within the context of ICAs. Researchers using ECM have studied customer service encounters (Ashfaq et al., 2020) and online banking services (Nguyen et al., 2021a). These studies substantiate the importance of the ICA context by explaining the continuation intention for ICAs. In another study on ICA deployment in the banking industry (Eren, 2021), ECT theory explains satisfaction and shows expectations as a powerful predictor of satisfaction. In one particular study on the online travel industry (Nguyen et al., 2021b), the researchers considered the AI capability of NLP to investigate system satisfaction. However, none of these studies explore the fit between ICA technology and the assigned tasks. Also, further study is needed to understand why Satisfaction can influence behavioural intention to use an ICA. My study takes a holistic view and includes the Task Technology Fit theory (Goodhue and Thompson, 1995) to seek further elaboration.

Finally, researchers have explored the impact of the usefulness of ICAs on behavioural intention to use. However, they only study the use of ICAs in general without focusing on ICA's exceptional AI capabilities. My study has attempted to study user perception of ICA capabilities and the influence of user satisfaction on them with the direct effect of Perceived Task-technology

Fit on Behavior Intention to Use. Table 2.1 presents the user attitude and behavioural intention research conducted on ICAs in the past and the current study.

Table 2.1: Research on ICAs Focusing on Behavioural Intention

SR	Study	Research Context	Theory	Independent Variables	Dependent Variable
1	Lei et al., 2021	Tourism and Hospitality	TAM, UTAUT, Social Actor paradigm	Media Richness, Social Presence, Task, Social Attractiveness, Trust	Reuse Intention
2	McLean et al.,2020	Online Travel	Social Presence Theory	Perceived Usefulness, Human attentiveness, Attitude, and Trust	Intention to Use
3	Brachten et al., 2021	Employee Enterprise Context	Extended Decomposed TPB	Attitude, Perceived Usefulness, Perceived Ease of Use	Intention to use Enterprise Bots
4	Pookulangara et al., 2021	Retail fashion/ E-Commerce	TAM	Perceived Usefulness, Perceived Ease of Use, and Fit	Intention to Use
5	Balakrishnan et al., 2022	Service Industry	An Extended meta-UTAUT framework	Technology Anxiety, Confirmation, Satisfaction	Use Continuance
Current Study		AI-Enabled Customer Service	ECT and TTF	ICA Capabilities, Satisfaction, and Perceived Overall Fit	Behavioural Intention

The outcomes of this study will also inform customer service policymakers and chatbot developers. The results will include understanding customer reluctance or acceptance of ICAs, their readiness to continue using and adopting additional ICA functionalities, the value of ICAs to the customer and the extent to which perceived risks impact the continuance of ICA use.

2.3. Chapter Summary

Chapter 2 provides the theoretical foundations that attempt to scope the research landscape on ICAs. Section 2.1 presents the Zhang and Li (2005) framework to classify five ICA research streams. Further, section 2.1 describes the importance of ICA capabilities and their impact on user behaviour while considering the interaction between ICAs and the customer. Section 2.2 identifies the gaps in the current research on ICAs, forming my research's motivation.

Chapter 3: Research Model Development

Chapter 3 presents six sections. Section 3.1 introduces the objective of my research. Section 3.2 presents the rationale for the research model used and highlights its unique salient and significant features. Section 3.3 establishes the theoretical foundations used for the research model. Correspondingly, Section 3.4 describes the hypotheses development for the ECT part of the model in detail. Section 3.5 explains the constructs (variables) and the hypotheses developed for the TTF part of the model. Finally, Section 3.6 offers a summary of Chapter 3.

3.1. Objective of the Research Study

My research study investigated if the customers' initial expectation about ICA capabilities changes after customers interact with the ICA. Also, whether customer-ICA interactions lead to satisfaction and intention to use the ICA; furthermore, the study explored if there is a fit between ICA capabilities and the tasks assigned to the ICA. My research pursued four key objectives:

1. To identify what are the primary ICA Capabilities.
2. To explore customer perceptions about ICA Capabilities before using the ICA.
3. To examine if customers' perceptions and attitudes toward ICA technology change after interacting with an ICA, thereby affecting Customer Satisfaction towards ICA.
4. To investigate how Customer Satisfaction with ICA Capabilities and Perceived Task Technology Fit affects the Behavioural intention of using the ICA.

The above problem statements helped to formulate my research questions as follows:

RQ 1: What are the unique features of ICAs for Customer Service? RQ1 explores the AI-enabled Customer Service environment, Human-AI Collaboration, current and future research trends, and challenges in ICAs.

RQ 2: What are customers' perceptions of ICAs? RQ2 examines customer perceptions of ICA capabilities, the factors influencing satisfaction and attitude, and the usefulness of ICAs for managing customer support duties.

RQ3: How does the use of an actual chatbot change end-user perceptions of AI usability? It involves using an ECT model to compare customer perceptions about ICA capabilities before and after an experience. RQ3 is significant because it investigates whether a favourable or unfavourable experience of ICA capabilities will change user satisfaction with an ICA.

RQ4: What factors influence the future use of ICAs, and how do these factors influence such use? This research question explores and explains the importance of fit between the task on hand for the ICA and the ICA technology. The fit aspect is critical and will use a detailed explanation of cognitive fit in terms of complexity, availability, and timeliness. RQ4 can potentially guide businesses to improve the use of a deployed ICA. This research question investigates the factors that will influence the future use of an ICA, applicable at the individual level to customers, users, and employees. Thus, the importance of this research question is to map how businesses can exploit and use ICAs.

My study investigates how customers' perceptions, attitudes, intentions, and use of IT innovations vary over time. The current research landscape is barren and provides scarce evidence of adoption and attitudes regarding AI and why they are essential. My study explains possible changes in customer perceptions and attitudes toward ICA usage, focusing on customer beliefs and attitudes toward ICA capabilities. Based on the literature review in Chapter 2, the popular ICA capabilities include perceived conversation ability, friendliness, intelligence, responsiveness, task performance, and trust. From this point onwards, the study will refer to them as the six (6) identified ICA capabilities. Thus, an organization's immediate attention may be on the future potential use of ICA. This strategy can boost the utility of ICAs by altering client perceptions and attitudes regarding AI-enabled services. It may also assist in quantifying the business value of ICA utilization.

Previous studies of ICAs have used constructs of expected performance, habit, hedonic components, propensity for self-service technology, and social influences from the Uniform Theory of Acceptance and Use of Technology (UTAUT) theory (Venkatesh et al., 2003), in addition to ICA human-like behaviour (Melián-González et al., 2021). The Technology Adoption Model (TAM) (Davis, 1989), the related Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), and the Theory of Planned Behavior (TPB) (Ajzen, 1991) are theories often used to characterize AI-enabled IS usage. Research has identified these theories as strong determinants of long-term IS usage (acceptance), intention, and behaviour (Bhattacherjee, 2001b; Davis et al., 1989). Any change in users' attitudes or beliefs will almost certainly alter customers' intentions, and actions to use IS (Bhattacherjee and Premkumar, 2004).

My study thus explored whether IS theories can be applied to ICA research to explain customer behaviour beyond the initial adoption. Also, the capabilities of ICAs might boost customer productivity, efficiency, and effectiveness at the individual, group and organizational levels. My study is the first to evaluate the likely evolution of user perceptions and attitudes about ICAs in a single sitting. My study evaluates this by measuring the customer's attitude before and after interaction with an ICA. A dynamic method-enabled experiment helped to evaluate critical influences on customer satisfaction and attitudes toward ICA usage.

By combining the two theories, ECT and TTF, my study provides an opportunity to establish the importance of each in explaining user intentions to continue using an ICA. Because of its dynamic nature, ECT explains customer satisfaction (Oliver, 1980, 1981) with ICA capability, while TTF elaborates if technology is suitable to perform a task that will improve the productivity of an individual (Goodhue and Thompson, 1994). My study used IS-usage-centric variables, like customer satisfaction and attitude, allowing customer perceptions of task-technology fit and their use of ICA system functions, motivating customers to use an ICA system.

The integrated ECT and TTF theories allowed the study to explore the influence of ICA capabilities on customer satisfaction and attitude while linking ICA capabilities with task support. This information is critical for businesses examining how cognitive customer concerns about AI attributes and perceived trust can influence ECT relationships. In my study, the combined ECT and TTF model also investigates why some customers, even after experiencing an ICA, still do not want to use it (Dreyer, 2016). My research uses attributes like complexity, timeliness, and availability to help explain the overall fit aspect.

3.2. The Rationale for the Research Model

Although deployed in high numbers, ICAs have not found widespread acceptance, primarily because the customer usage intention is unclear. Some ICA deployments are successful, while others, even with superior ICA capabilities, are unsuccessful. My research model addresses customer intention and potential yet unresearched reasons for these different outcomes. The extant literature does not provide a model investigating the relationship between ICA capabilities with customer attitude, satisfaction, and intention to use an ICA. My model explores this relationship and customer behaviour towards using a commercially available ICA deployed for customer service within the constraints of task complexity and problem-solving abilities. My model also allows businesses to explore if customers can use the ICA effectively. Finally, my model suggests the more influential ICA capabilities that significantly influence usage intention under the direct effects of perceived overall task-technology fit. Some of the more pertinent rationales for developing this model include:

1. There is an absence of models that focus on the interactions between customers and ICAs. My model directly explores whether ICA capabilities influence customer attitude, satisfaction, and usage intention and detect which of the six AI capabilities of the ICA are more significant.
2. Previous research models did not include customer effort to learn about ICA technology. I attempted to bridge this gap by introducing the Experiment Effort (EE) component. Including EE emphasizes that if the EE is high, the customer will have a positive attitude when using the ICA and may also be more easily satisfied with the ICA's problem-solving capabilities.
3. AI Enabled Customer Service (AIECS) using ICAs is conceptually compared to Human Customer Service (HAECS), specifically when the task complexity directly impacts the problem-solving abilities of customer service.
4. My model anchors the premise that customers want an ICA to engage with the customer using Natural Language for assigned customer service tasks (Adam et al., 2020). My research proposes that such an ICA customer service agent should be friendly, intelligent, responsive, capable of performing the task, trustworthy, and able to engage the customer. My model, in a way, compares an ICA agent with a human agent providing similar or identical customer service. My model also investigates customer expectations and experience relationships with the six identified ICA capabilities. Customers compared these six ICA capabilities with a

human agent's ability to provide customer service to assess if the ICA was fit to use in CRM services.

5. This model makes use of the Expectations Confirmation (ECT) Theory (Oliver, 1977, 1980), in concurrence with the direct effects of the Task Technology Fit (TTF) Model (Goodhue and Thompson, 1995). The integrated theories allowed the research to explore customer attitude and satisfaction under the direct effect of the fit between the task and ICA technology, showing behavioural intention to use the ICA. Figure 3.1 represents the model development.

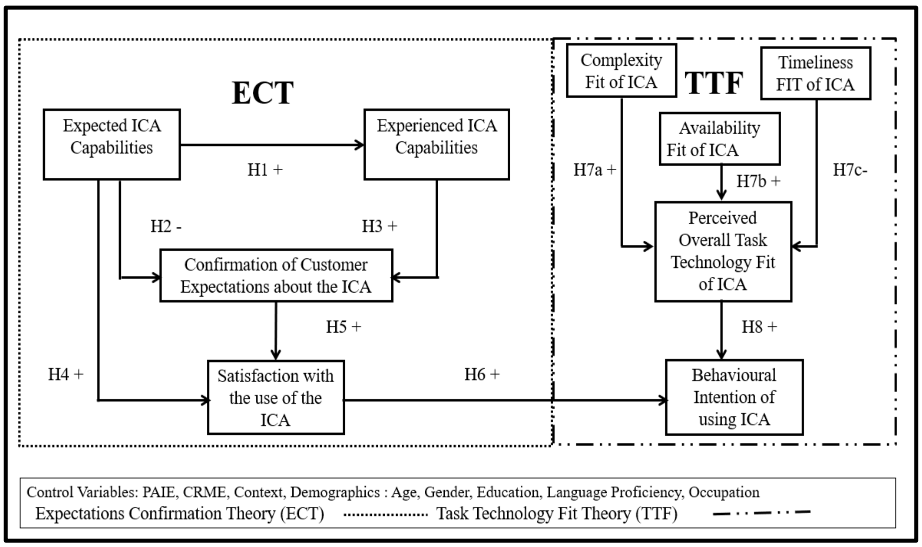

Figure 3.1: Model Development with Theoretical Foundations

My model has two parts and uniquely captures expectations and experiences (perceptions) with the six ICA capabilities. The first part explains customer behaviour concerning expectations, experience, and satisfaction using ICA through the lens of the Expectations Confirmation Theory. The second part uses Task Technology Fit Model TTF (Goodhue and Thompson, 1995) to explore if the ICA is fit to perform the tasks. The second part also seeks clarification if an ICA is fit to handle complex tasks, available to perform the tasks and capable of providing an answer promptly. The Cognitive Fit Theory informs these aspects (Vessey, 1991; Vessey and Galletta, 1991).

3.3. Theoretical Foundations

My research attempts to explain customer satisfaction and intention to use ICA (chatbot) service and applies two established theories: Expectation–Confirmation Theory (ECT) (Oliver, 1977; 1980) and the Task-Technology Fit (TTF) model (Goodhue and Thompson, 1995). ECT has been studied extensively and appears in different forms Expectations Disconfirmation Theory (Oliver,1997), the IS Continuation Model (Bhattacharjee, 2001), the Two-Stage Change in Beliefs and Attitude Model or the Two-Stage Change in Cognition Model (Bhattacharjee and Premkumar, 2004), a three-stage stage model (Venkatesh et al., 2011) and Expectations Violation Theory (Burgoon et al., 2016; Grimes et al., 2021).

For my research, I considered three periods (Pre-Experimental Stage, Experimental Stage, and Post-Experimental Stage) for applying ECT. This consideration is in line with earlier studies showing that increasing the number of time periods can help record increasing magnitudes of confirmation, satisfaction, belief change, and attitude change (Szajna and Scamell, 1993; Venkatesh et al., 2011). I used ECT to capture the users' perceived ICA capability through first-hand experience with real-world ICA service. Similarly, the perceived fit between ICA capability and the task assigned for the ICA to perform determines the user's intention to use or continue with the ICA service. Thus, my research used an extended form of ECT and the TTF lens to explain the fit between the ICA capability and service task, which remains true to its origin in cognitive fit theory (Vessey and Galletta, 1991).

The multi-stage research model developed for my study will contribute to the ECT and TTF literature. Expectations, performance, confirmation, and satisfaction are significant constructs predicting future product qualities (Spreng et al., 1996) and behaviour (Bhattacherjee, 2001b). ECT results assert that an accomplished customer's expectation about a product or service's performance leads to a positive confirmation that results in satisfaction. If the experience does not meet the customers' expectations, a negative confirmation (Oliver, 1980; Spreng et al., 1996) results in dissatisfaction.

3.3.1. Expectations Confirmation Theory (ECT)

ECT is a paradigm for defining and anticipating satisfaction based on customer experience (Oliver, 1980). Customer satisfaction drives behaviour by confirming customer expectations (Morgeson, 2012). ECT can assess consumer expectations and satisfaction before and after purchasing or consumption (Lin et al., 2005) through stages of expectations, performance, confirmation of expectations, and satisfaction (Oliver, 1977, 1980; Oliver and De Sarbo, 1988). Figure 3.2 displays a generic ECT model.

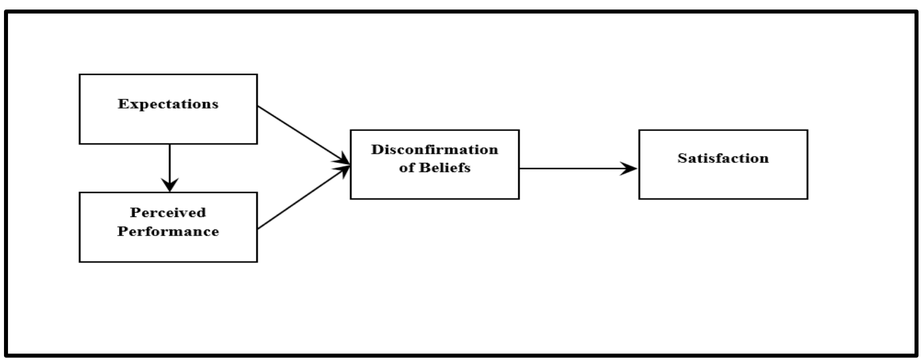

Figure 3.2: Basic Expectations Confirmation Theory (Oliver, 1977; 1980)

The first stage of ECT relates to customer expectations before buying or using a product or service. The second stage is perceived performance after using the product or service. The third stage determines if there is a gap between expectations and reality —perceived performance is measured as confirmation or disconfirmation based on whether the perceived performance is better than the expectation. In the fourth stage, when customer expectations are met, customer expectations influence and lead to a rise in satisfaction.

Satisfaction is a central concept in psychology, marketing, management, and IS research (Anderson, 1973; Oliver, 1980; Yi, 1990). Marketing literature asserts that customer satisfaction is critical for establishing and retaining customer relationships and generating profit (Fornell et al., 2006; Aksoy et al., 2008; Fornell et al., 2016; Hult et al., 2017). ECT is the fundamental theoretical lens through which researchers define customer satisfaction (Anderson and Sullivan, 1993; Caruana et al., 2016; Oliver and Swan, 1989; Park et al., 2012; Valvi and West, 2013). Expectation Disconfirmation Theory (EDT) established the technological usage intention concept (Oliver, 1980), elaborated further into the ECM or IS Continuation Model by Bhattacharjee (2001).

ECT, with its extension and variant forms, has been used in IS research to examine end-user purchase decisions (Bhattacherjee, 2001), changes in user beliefs and attitudes over time (Bhattacherjee and Premkumar, 2004), and post-usage satisfaction with the application service providers (Susarla et al., 2002). ECT has also been used to research mobile internet services (Thong et al., 2006), web-based learning systems (Liao et al., 2009), electronic procurement systems (Chang et al., 2008), and wireless technology (Yen et al., 2010). Similarly, ECT has explored the extended use of complex IS (Po-An Hsieh and Wang, 2007), extended two-stage IS Model (Venkatesh et al., 2011), Knowledge Management Systems (Lin and Huang, 2008), and technology adoption intentions (Deng et al., 2010; Stone and BakerEveleth, 2013).

Research using the Expectation Violation Theory showed that by setting low expectations about ICA capabilities, customers register a favourable experience (Grimes et al., 2021).

Similarly, mental models using the Expectations Violation Theory (also based on EDT theory by Oliver, 1980) were used to study violations in expectations about ICAs (Grimes et al., 2021).

A limitation observed in the research is that ECT and its derived models do not adequately explain the intention of a dissatisfied customer to use the product or service. Similarly, exceeding expectations does not always lead to satisfaction (Suh et al., 1994); also, ECT warrants that performance must exceed expectations (Au et al., 2002). ECT alone is incoherent and inadequate due to harsh expectations and performance (Khalifa and Liu, 2004). Premkumar and Bhattacherjee (2008) found that customers may be satisfied even with unmet expectations. Recently the ECT was used to describe an AI-enabled ICA (Ashfaq et al., 2020; Eren, 2021; Moriuchi et al., 2021), but these studies did not consider the fit between the task on hand and available ICA technology. In my model, I introduce the Task Technology Fit (TTF) theory to see if the concept of satisfaction can be understood more clearly. The TTF improves the performance of individuals, groups, and organizations when a technology's characteristics match a given task (Goodhue and Thompson, 1995; Zigurs and Buckland, 1998).

Using the research of Oliver (1980), Bhattacharjee and Premkumar (2004) suggested that pre-usage beliefs and attitudes may influence usage-stage beliefs and attitudes directly or indirectly via disconfirmation and satisfaction dimensions, which is in line with the observation of Helson (1964). Helson (1964) states that later-stage cognitions (perceptions) are an additive function of prior cognitions and real-world experience. Research suggests that cognitive shifts occur more frequently during the early stages of IS usage as customer cognitions settle and become more realistic (Szajna and Scamell, 1993). Thus, my research model uses previous research to capture the impact of pre-experimental and post-experimental attitudes on customer satisfaction and intention to use an ICA.

3.3.2. Task-Technology Fit (TTF) Theory

This Theory (Goodhue and Thompson, 1995) suggests that technology should suit specific customer needs (Blut et al., 2021). Customers are pleased with ICA-enabled service interactions if ICA technology meets their requirements. Businesses must exhibit ICA characteristics consistent with customer service. TTF indicates that task characteristics may serve as a moderator between ICA capabilities and customer behavioural intentions.

TTF provides the framework for my research study that focuses on task complexity and customer behaviour outcomes. Research has previously examined the effects of task complexity on task performance and team performance (Bjørn and Ngwenyama, 2009; Dayan and Di Benedetto, 2010). Marketing research literature suggests that tasks vary according to the customer's journey of pre-purchase, purchase, and post-purchase stages (Lemon and Verhoef, 2016). The experimental research setting of my research study allows task complexity to analyze consumer trust in chatbots effectively. When consumers cannot fix a problem themselves, they request customer service representatives (CSRs). Customers then focus on the expertise and skills of the CSR (Campbell et al., 2020) but tend to express dissatisfaction with increased task complexity while interacting with an ICA (Cheng et al., 2021).

The ability of technology to meet customer needs and obligations is a decisive factor in technology adoption (Dishaw and Strong, 1999; Furneaux, 2012; Gu and Black, 2020). The Task-Technology-Fit (TTF) Theory explains why a specific technology is adopted based on its characteristics and performance and how that technology supports individuals in accomplishing their tasks (Goodhue and Thompson, 1995). According to TTF, enhanced technology improves individual performance (Howard and Rose, 2019; Laumer and Eckhardt, 2012).

TTF is a popular theory in IS research (Aljukhadar et al., 2014) and has been used to explain technologies of cloud-based ERP (Cheng, 2020), hospitality (Pillai and Sivathanu, 2020a), mobile banking (Tam and Oliveira, 2016), gamification for training (Vanduhe et al., 2020), virtual learning systems (Lin, 2012), learning management systems (Qureshi et al., 2018; McGill and Klobas, 2009), AI-enabled Talent Acquisition services (Pillai and Sivathanu, 2020b), and wearable technology like smartwatches (Kim and Shin, 2015, Al-Emran et al., 2020). As seen in the model in Figure 3.3, TTF has explained the use of ICA technology in recent research (Wang et al., 2021; Rzepka et al., 2021). The adaptability of the TTF theory appears in various contexts, like Group Support Services (Zigurs and Buckland, 1998), information technology (Dishaw and Strong, 1999), the use of blogs (Shang et al., 2007), knowledge management systems (Lin and Huang, 2008), location-based services (Junglas et al., 2008), mobile commerce in the insurance industry (Lee et al., 2007), mobile IS (Gebauer et al., 2010), learning management systems (McGill and Klobas, 2009) and mobile work support (Yuan, Archer, Connelly, and Zheng, 2010).

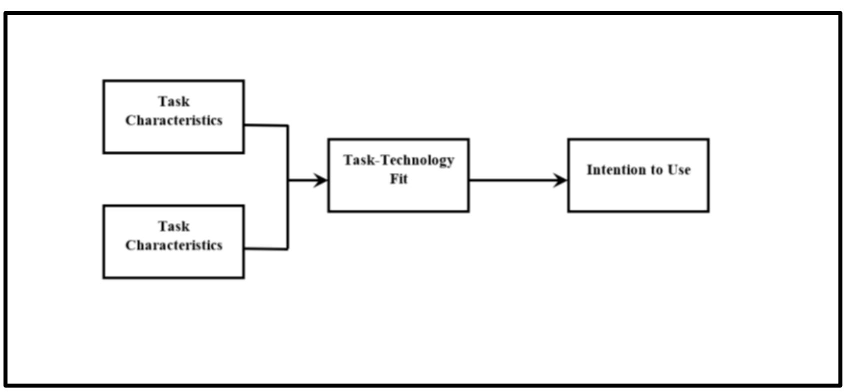

Figure 3.3: Task Technology Fit Model Goodhue and Thompson, 1995
(Adapted from Alkhalifah and D’Ambra, 2011)

The TTF model features in research studies with other theories. E.g., with the technology acceptance model (TAM) and m-banking adoption (Zhou et al., 2010) to explain user intention to use wireless technology in organizations where the initial trust model (ITM) explains m-banking adoption (Oliveira et al., 2014). The TTF model holds considerable promise, based on all the research results explaining the end-user motivation to use ICAs.

3.3.3. The Integration of ECT and TTF

Traditional IS research principles examine and explain chatbot and AI research (Rzepka and Berger, 2018). My study introduces a model integrating ECT and TTF. My research tests this model in an experimental scenario where participants interacted with ICAs of Canadian telecom companies. This model includes ICA capabilities of perceived conversation ability, friendliness, intelligence, responsiveness, task performance, and trust that make up the customer expectations and experience about ICA capabilities. The model also explores the constructs of Fit For Complexity (FFC), Fit For Availability (FFA), Fit For Timeliness (FFT) and Perceived Overall Fit (POF). The model for my study posits that as customers gain experience with ICA technology, their perspectives of ICA capabilities and attitudes toward ICAs will change. The study validates the suggested model in several scenarios (ICAs of various organizations) using task-specific differences.

The six ICA capabilities used in my research model affect emergent factors such as disconfirmation and satisfaction, which are critical to understanding changes in customer attitudes. My research model connects pre-experimental beliefs and attitudes to experimental beliefs and attitudes, which have yet to be studied. My model also hypothesizes that confirmation and satisfaction influence post-experiment beliefs and attitudes that influence behavioural intention to use. Negative confirmation occurs when events are worse than anticipated (Oliver, 1980; Spreng et al., 1996).

My model explores whether or not consumer perception changes after an experiment. Similarly, this approach draws on the Task Technology Fit (TTF) model's fundamental assumptions. My research calculates the confirmation construct by taking the differences between the experienced (perceived) ICA capabilities and the expected ICA capabilities. The study tests if the perceived ICA capability and confirmation affect satisfaction. My study explores if the Task-Technology Fit (TTF) model can explain the task-technology fit. Figure 3.4 illustrates the research model.

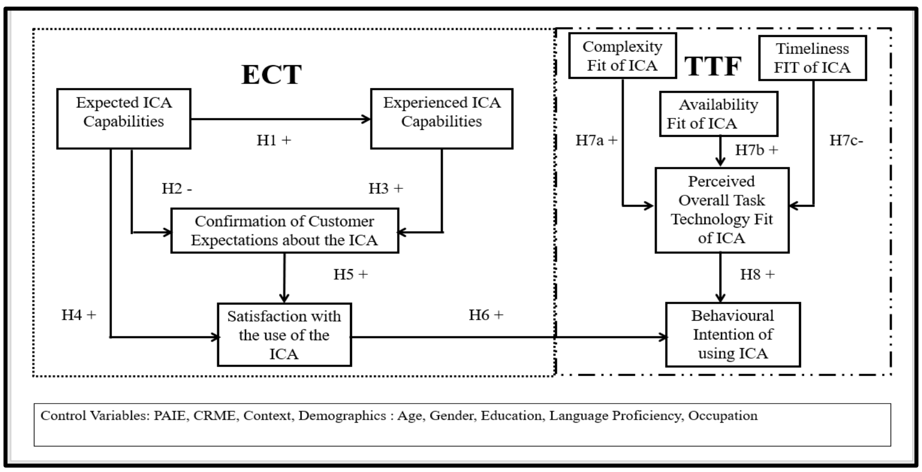

Figure 3.4: Proposed Research Model

My model focuses on prior AI and CRM experience as control variables that influence expectations about ICA capabilities and would allow for evaluating the model's generalizability across tasks and demographics within (ECT) (Oliver 1977, 1980). Based on the expected quality of a product/service against perceived performance after use, satisfaction is a consumer's cognitive and affective fulfilment following a purchase or use (McKinney et al., 2002; Oliver, 2010). Because ICAs are still new to the market, it is necessary to look at end-user satisfaction at all stages (including pre-usage and post-usage) rather than just the post-usage stage. As a result, my model considers both the direct and indirect effects of expectation and experience on satisfaction. Subsequently, satisfaction affects behavioural intention to use under the direct effect of perceived overall fit.

Customers face difficult personal and professional situations where AI-enabled customer technologies can help. In socio-technical infrastructures like healthcare and emergency response management systems, implicit automation may become explicit (Blandford, 2019). This automation involves Human ICA Interaction. When used appropriately, customers can seek service from business organizations as ICAs offer increased real-time information and support. The customer's satisfaction with utilizing an ICA depends on time and effort in terms of convenience. Research has also compared the experience received from ICAs to the experience received from human agents (Cheng and Jiang, 2020).

3.4. The Constructs and Hypotheses for ECT

I now introduce the six ICA capabilities and satisfaction and confirmation as constructs. This section also elaborates on the hypotheses based on ECT.

3.4.1. User-Expected and Experienced ICA Capabilities

My study identifies ICA capabilities as Expectations before the participant actually interacts with the ICA. Once the participant interacts with the ICA, these ICA capabilities are identified as perceived performance or experienced ICA capabilities. Perception is anything an end-user perceives or learns about, a mental image of something presented to the senses (Graham, 1981). User perception of an ICA is affected by ICA identity (Araujo, 2018; Go and Sundar, 2019), verbal communication, especially in the case of tone-aware chatbots (Schuetzler et al., 2018; Hu et al., 2018) and dynamic delayed response in HCI (Gnewuch et al., 2017). Perceptions about improved ICA technology-based self-service settings suggest that ICAs may eventually replace human service agents (Adam et al., 2021).

For my research, I used the concept that IT-enabled automation can engender positive and negative perceptions. Since machines can generate a perception of social actors (Nass and Moon, 2000), researchers have envisioned ICAs as social actors (Diederich et al., 2022; Gnewuch et al., 2017). At the same time, researchers have emphasized using conversation information retrieval theories (Thomas et al., 2021). To validate my model, I use an experiment (discussed in chapter 4) where the participant asks the ICA to retrieve information and perform specific tasks.

Conversational ability: Conversational ability is one of the more instantly recognizable characteristics of an ICA. An ICA (chatbot) refers to a disembodied conversational agent that holds a natural language conversation via a text or voice to engage the user in a general-purpose or task-oriented conversation (Chaves and Geora, 2020). Conversational ability is a critical factor for comparing human agents to ICAs (Lei et al., 2021) and has been studied to explain customer purchase behaviour within conversational commerce (Balakrishnan and Dwivedi, 2021). Conversational ability also elaborates on the acceptance of ICAs in the enterprise context (Brachten et al., 2021) and predicting ICA intention usage concerning travel and tourism (Melián-González et al., 2021). Researchers have used the Anthropomorphism theory to explain how improved conversational skills of ICA can increase user engagement with ICAs (Schuetzler et al., 2020). Studies have focused on customer dialogues for ICA (Følstad and Taylor,2021). Better insight into Human-ICA interaction increases customer satisfaction (Blut et al., 2021).

Friendliness: Friendliness refers to a level where customers believe a system is user-friendly and comfortable to use. Customers want service providers to be cordial, pleasant, and friendly (Tsai and Huang, 2002; Jayawardhena et al., 2007). Customers appreciate friendly service providers, which increases their positive perception of the service's quality (Chen et al., 2012). A pleasant disposition will positively affect consumer mood and perception of the store and its brands (Tsai and Huang, 2002). When employees show more positive emotions, customers are more satisfied with the service, which results in a positive response to the store, such as repurchasing and positive word of mouth (Pugh, 2001). Empathy and warmth are other anthropomorphic features in text-based chatbots if the ICA uses empathy (Yang et al., 2019). Customer acceptance of robots has revealed that users place a premium on the effects of Friendliness and Trust (Fridin and Belokopytov, 2014). Researchers have studied the Friendliness of ICAs in terms of personalization and anthropomorphism. Also, researchers have hypothesized that a conversational agent's friendly role is an effective strategy in voice-shopping scenarios and showed that agents with a friendliness role had a more significant impact on positive sentiments in a low-engagement condition (Rhee and Choi, 2020). Similarly, ICAs using customer-friendly text positively impact trust, leading to reliance on the ICA (Cheng et al., 2021).

Intelligence: The Turing test establishes an operational definition of computer intelligence where a computer is intelligent if it can convince the human interrogator that it is not a computer but a human (Russell and Norvig, 2020). The psychological literature on intelligence focuses on knowledge, mental abilities, acquiring knowledge, comprehension, and reasoning (Legg and Hutter, 2007). Perceived intelligence is the robot's ability to adapt its behaviours to varying situations (Bartneck, Kanda et al., 2009). Researchers have studied perceived intelligence and perceived anthropomorphism for intelligent personal agents (Moussawi and Koufaris, 2019) and have applied this concept and definition to ICAs. Based on Moussawi and Koufaris (2019), the perceived intelligence of an ICA is the degree to which an ICA’s behaviour is efficient, along with an effectual output that displays NLP capability.

Similarly, Chaves and Gerosa (2021) define ICA intelligence as having conversational, social, and personification aspects. Conversational intelligence includes characteristics that help the chatbot manage interactions, like proactivity and communication ability. Social intelligence focuses on habitual social protocols like damage control, manners, and emotional intelligence, while personification refers to the chatbot's perceived identity and personality representations.

Responsiveness: This capability refers to the ability of an information system to react quickly to online needs, its responsiveness to the online group, and the level of success of IS in meeting its strategic goals (Nelson et al., 1996). Tiwana (1998) refers to responsiveness as a systems response time, while researchers like Molla and Licker (2001) and DeLone and McLean (2004) have defined responsiveness as the timeliness of service. Thus, timeliness forms an essential part of responsiveness. Since ICAs can reply quickly, are easy to contact and are available when needed, responsiveness has become recognized as one of the superior ICA capabilities (Roy et al., 2018). Also, responsiveness is recognized as readiness to help a customer by offering accessible services instantly to bring about convenience (Van den Broeck et al., 2019). Responsiveness makes customers feel comfortable and valued and provides them with the satisfaction of chatting with a chatbot (Chung et al., 2020). Customers think a company is more innovative if its chatbot is more responsive (Chen et al., 2021). Extant literature defines perceived responsiveness as the level of instantaneous response to the IS interface (Hsiao et al., 2019). Responsiveness is an essential quality for ICAs; many businesses use ICAs to handle customer service requests, such as complaints or product information (Gnewuch et al., 2017; Pfeuffer et al., 2019). My model uses Responsiveness as an ICA capability, as ICA research shows that responsiveness of an ICA is a vital performance measure (Przegalinska et al., 2019). An ICA's responsiveness directly impacts human ICA interaction (Mogaji et al., 2021) and influences customer experience (Chen et al., 2021).

Task Performance: Task performance refers to the end-user's experience with the ability of a chatbot to perform or complete the task requested by the end user. Researchers have studied ICAs doing a job similar to a human agent and define task performance based on human resource literature, in which task performance reflects the degree to which an employee meets the requirements of his or her role or job (Carpenter et al., 2021). Task performance is often mentioned indirectly through an ICA's inaccurate responses or failure to perform a task (Chaves and Gerosa, 2021). Numerous researchers have studied task performance while discussing ICAs deployed for health management, medical analysis, and medical assistance in health. For instance, an ICA may be essential in finishing specific tasks such as appointment arrangements and providing medical information. However, at the same time, it may be weak in diagnosis and emotional communication (Palanica et al., 2019). Research has shown that task performance strongly impacts customer satisfaction while interacting with ICAs (Nguyen et al., 2021b).

Trustworthiness: Trust is an individual's belief that others behave and perform actions within an expected range (Luhmann, 1979). Trust also represents the willingness to make oneself vulnerable to others (Hoy and Tschannen-Moran, 1999; Mayer et al., 1995). Competence, integrity, and goodness are the three most widely accepted antecedents of trust (Jarvenpaa et al., 1998). Satisfaction and trust help better understand customer repurchase intentions (Hart and Johnson, 1999). Trust has been used to predict E-commerce adoption and retention intentions (Venkatesh et al., 2011). Trust focuses on emotions, which helps to explain the human-robot connection (Hoff and Bashir, 2015). Studies on user response to ICAs have focused on trust (Elson et al., 2018; Seeger et al., 2021) and trust, risk, loyalty, security, and privacy (Saffarizadeh et al., 2017; Sohn, 2019; Hasal et al., 2021; Hasan et al., 2021). Researchers have explored cognitive and emotional trust (Saffarizadeh et al., 2017), trust perceptions (Elson et al., 2018), and privacy concerns (Brill et al., 2019; Sohn, 2019), as well as trust models, developed to utilize in studies of service chatbots (Nordheim et al., 2019).

Trust studies have found that young males are more inclined to trust an ICA (Schroeder and Schroeder, 2018), and older users prefer dominating ICA behaviour over submissive ICA behaviour. According to social robot studies, strengthening human facial traits also boosts trustworthiness and trust judgments (Song and Luximon, 2020). Trustworthy building norms require trust in products and robots (Floridi, 2019). Trust for virtual teams using ICAs for sharing economies in businesses like Airbnb (Breuer et al., 2016; Ert et al., 2016) has explored customer confidence in text-based communication. Researchers suggest that, overall, users of ICAs trust that ICAs will help users attain their goals (Siddike and Kohda, 2018). However, due to its complexity, trust remains elusive despite substantial research in marketing, psychology, and IS fields (Ghanem et al., 2020).

Trust reduces perceived risk and uncertainty and thus influences customer participation in e-commerce (Seo and Lee, 2021). Therefore, trust is essential in enhancing user attitudes toward chatbots. Trust refers to a user's faith in the ICA system's dependability and quality (Nguyen et al., 2021a). While trust is well-established in electronic commerce, ICA services have only recently adopted it (Seo and Lee, 2021).

3.4.2. Expectation Confirmation

Confirmation, based on ECT, is the extent to which a customer perceives accomplishment of his or her initial expectations during actual use. In my study, confirmation is the degree to which the experienced ICA capabilities meet or exceed the expected ICA capabilities. For example, customer satisfaction with internet banking services has met their expectations for internet banking (Hoehle et al., 2012). ECT helps to elaborate on interactions with ICAs (Sheehan et al., 2020). Violation of Expectations for ICA capabilities relates to low performance, compared to original high expectations (Grimes et al., 2021), resulting in disconfirming expectations.

3.4.3. Satisfaction

Extant research shows a strong correlation between customer expectations and satisfaction (Oliver et al., 1994). Customer satisfaction is contingent upon meeting expectations (Oliver, 1980). Thus, customer satisfaction is a function of emotional service expectations. Satisfaction is a metric that measures how effectively a product or service meets expectations (Anderson and Sullivan, 1993; de Haan et al., 2018; Brill et al., 2019). ICA Service quality expectations affect service and product quality perceptions of customer satisfaction (Brill et al., 2019; Ashfaq et al., 2020; Balakrishnan and Dwivedi, 2021). ICA customer satisfaction is related to perceived performance (Mou and Xu., 2017). Confirmation, information quality, perceived performance, and loyalty rewards measure customer satisfaction (Eren, 2021). Similarly, ECT informs that customer satisfaction affects behavioural intention (Gupta and Stewart, 1996). My research explores the impact of ICA capabilities on consumer attitude, satisfaction and behavioural intention.

3.4.4. Behavioural Intention

BI is the degree to which an individual has expressed conscious plans to perform or not perform some specified future behaviour (Warshaw, 1985). BI is the degree to which a person has formulated prearranged plans to perform or not perform some specified future behaviour (Venkatesh et al., 2003). Research also suggests that attitude toward ICAs (Enterprise Bots) is one of the most important influencing factors for employees' actual usage intention of ICAs

(Brachten et al., 2021). Kasilingam (2020) has shown that consumer intention toward using ICAs depends on factors determined by the TAM model and personal innovation. Kasilingam (2020) also suggests that intention towards using an ICA indicates that customers may replace mobile applications with ICA usage in the future. Recent research on ICAs using the UTAUT framework has studied BI for using ICAs in the banking environment (Gümüş and Çark, 2021), healthcare (Sitthipon et al., 2022) and tourism (Melián-González et al., 2021). These studies show that BI is a significant variable for understanding customer behaviour.

The literature review in Chapter 2 explains the research that guides the hypotheses for my study. Since my model combines ICA capabilities with trust, it allows for capturing a broad range of customer beliefs and acts as an additional opportunity to improve the comprehension of ICA usage. Unlike Bhattacherjee and Premkumar (2004), my model compares customers' pre-usage expectations with their post-usage experiences after using an ICA. My research focuses on encouraging AI usage-related attitudes and behaviours toward the intention to use ICAs. Quest for customer satisfaction is a strategy for optimizing expectation and disconfirmation (Oliver, 1980). Denying these usage-related sentiments would decrease satisfaction (Oliver, 1981), and constantly raising unmet technology adoption aspirations causes cognitive dissonance (Marikyan et al., 2020). Trust forms the basis for customer perception of AI capabilities (Glikson and Woolley, 2020), and it forms the basis of inclusion in my model. Introducing trust when customers exchange personal and sensitive information online while interacting with ICA systems can alleviate concerns regarding the capabilities and performance of the ICA.

3.4.5. The Relationship between Expected and Experienced ICA Capabilities

Businesses shifting from product to service-centred logic (Vargo and Lusch, 2004) focus on exchange process and value. Researchers perceive the value concept as either excluding

(Schembri, 2006) or encompassing (Lemon and Verhoef, 2016) the customer's experiences with the product. My model considers customer experience as part of ICA value and explores user expectations and experiences with ICA capabilities. Prior research has shown that an ICA's attempt to produce human-like behaviour impresses most users, lowering user expectations and leading to more satisfying experiences with ICAs (Go and Sundar, 2019). With the help of an interaction (engagement) between the participant and an ICA, my proposed model investigates the relationship between expectations regarding ICA capabilities and actual experienced ICA capabilities. This interaction is ineffective if the ICA customer believes the task (experiment) is complex. Based on these findings, the recommended experimental interaction between an ICA and a participant may improve the customer experience. This experience will also help the end-user to have more evident knowledge about the confirmation or disconfirmation related to the ICA's capabilities. My research examines the relationship between experienced ICA capabilities and satisfaction. Numerous factors may influence a customer's satisfaction with an online service.

Accuracy of information and efficiency of the service method tend to determine satisfaction with a service encounter (Wolfinbarger and Gilly, 2003). Information transfer is crucial for service encounters, and businesses can improve their performance by understanding their customers' expectations and desires (Koufteros et al., 2014). The following hypothesis summarizes the above discussion.

H1: Expected ICA Capability positively impacts the Experienced ICA Capability.

Verhagen et al. (2014) claim that service provider friendliness (politeness or responsiveness) and professionalization (ability to respond competently) impact service satisfaction. Thus, competent, knowledgeable, conscientious responses generally meet customer expectations. There is a causal association between service encounter enjoyment and customer satisfaction with transactions. Like the internet, satisfaction with traditional service encounters impacts overall satisfaction with service encounters (Verhagen et al., 2014; Caruana, 2002), and online connections boost customer satisfaction with firms (Chan et al., 2016). This study recommends that the assigned job simulate a service interaction between an end-user for the experimental participant. Participants evaluated the ICA capabilities of conversation ability, friendliness, intelligence, and trustworthiness under four different task scenarios. Consequently, Post-Experiment (or Interaction) Satisfaction is essential to my study's findings and experienced ICA competencies impact satisfaction significantly.

3.4.5. The Impact of Experienced ICA Capabilities and Confirmation on Satisfaction

A product or service's perceived performance is confirmed when it matches customers' pre-purchase expectations or positive reviews of its performance (Kim, 2012). The pre-and post-service expectations and service evaluations allow customers to compare and confirm their expectations. Researchers have used Confirmation to describe how well a product or service meets the expectations of its users during actual use (Huang et al., 2021). For my research, "Confirmation" refers to the ICA service's capability to deliver the benefits, advantages, and practicality that customers expect. Customer expectations rely on the features and qualifications of the product or service. A product or service is successful if it matches the customer's pre-purchase expectations with its actual performance (Kim, 2012).

Based on the ECT model, my research assumes that customer expectations and perceived performance are the foundations of confirmation of customer expectations, which would influence the confirmation or disconfirmation of the ICAs' capabilities. How customers view the product or service's quality and value after acquiring it is known as perceived performance (Churchill and Surprenant, 1982). In IS research, extant literature shows that the customers' pre-experience expectations for the service and their judgement on the product's post-performance comparison constitute expectation confirmation (Bhattacherjee, 2001a). Also, a good evaluation of perceived performance can confirm customer expectations (Kim, 2012).

However, if the prior expectation is too high, the customer may feel disappointed when the actual performance is lower than expected. The higher the expectation, the lower the confirmation. Recent studies involving ICAs suggest that a high perceived performance is more likely to meet customers' expectations (Ashfaq et al., 2021). ICA research on personal assistants suggests that a product's perceived performance directly impacts consumer expectations, especially in the case of technology-based services (Brill et al., 2019). The perceived performance of ICA confirms customer expectations, which has a significant and positive effect. Thus, hypotheses H2, H3 and H4 posit:

H2: Expected ICA Capability negatively impacts the Confirmation of Customer Expectations about the ICA.

H3: Experienced (Perceived) ICA Capability positively impacts the Confirmation of Customer Expectations about the ICA.

H4: Confirmation of Customer Expectations about the ICA positively impacts Satisfaction with the use of ICA.

Customer interactions with an ICA influence their attitudes toward the ICA. Interactions may require an increased effort due to poor ICA capabilities or poor design of the ICA. This increased effort will negatively impact the relationship between expectation and experience about the ICA capabilities, thus affecting the experience of using the ICA. Accomplished ICA's expectations influence customer attitudes, whereas ICA's competencies influence customer attitudes and behaviours. Conversation ability, Friendliness, Intelligence, Responsiveness, Task

Performance, and Trustworthiness are ICA traits related to customer perceptions of human agents and ICA capabilities.

Customer expectations of ICA capabilities will be determined and validated if the ICA provides irrelevant, inaccurate, obsolete, or incorrect information. In this case, the customer would have unmet expectations and a Post-Experiment Attitude that was negative or lower than before the experiment. Poor service and information from online sources may waste customer time and effort (Gao et al., 2015). As a result, customers may have a negative service experience, decreasing their satisfaction.

Alternatively, the customer will be satisfied if the ICA provides accurate, accessible, personalized, and articulate information during task execution, resulting in a positive post-experiment attitude. IS research has a robust HCI component (Cardona et al., 2021), but human-chatbot interaction is still poorly understood (Nguyen and Sidorova, 2021b). Consumer acceptance of ICA services is often rated “slow” (Jung et al., 2019; Ransbotham et al., 2018).

Research has examined factors influencing customer attitudes and behaviours toward using chatbots (and Smartphone chatbots) to examine an individual's attitude toward and intent to utilize the technology (Kasilingam, 2020). Studies reveal that customers value IS capabilities, AI-enabled technologies, and ICA to match their expectations. ICAs tend to promise time savings, precise information, and quick support. Figure 3.5 represents the relationship between Expectations and ICA Experience Capabilities.

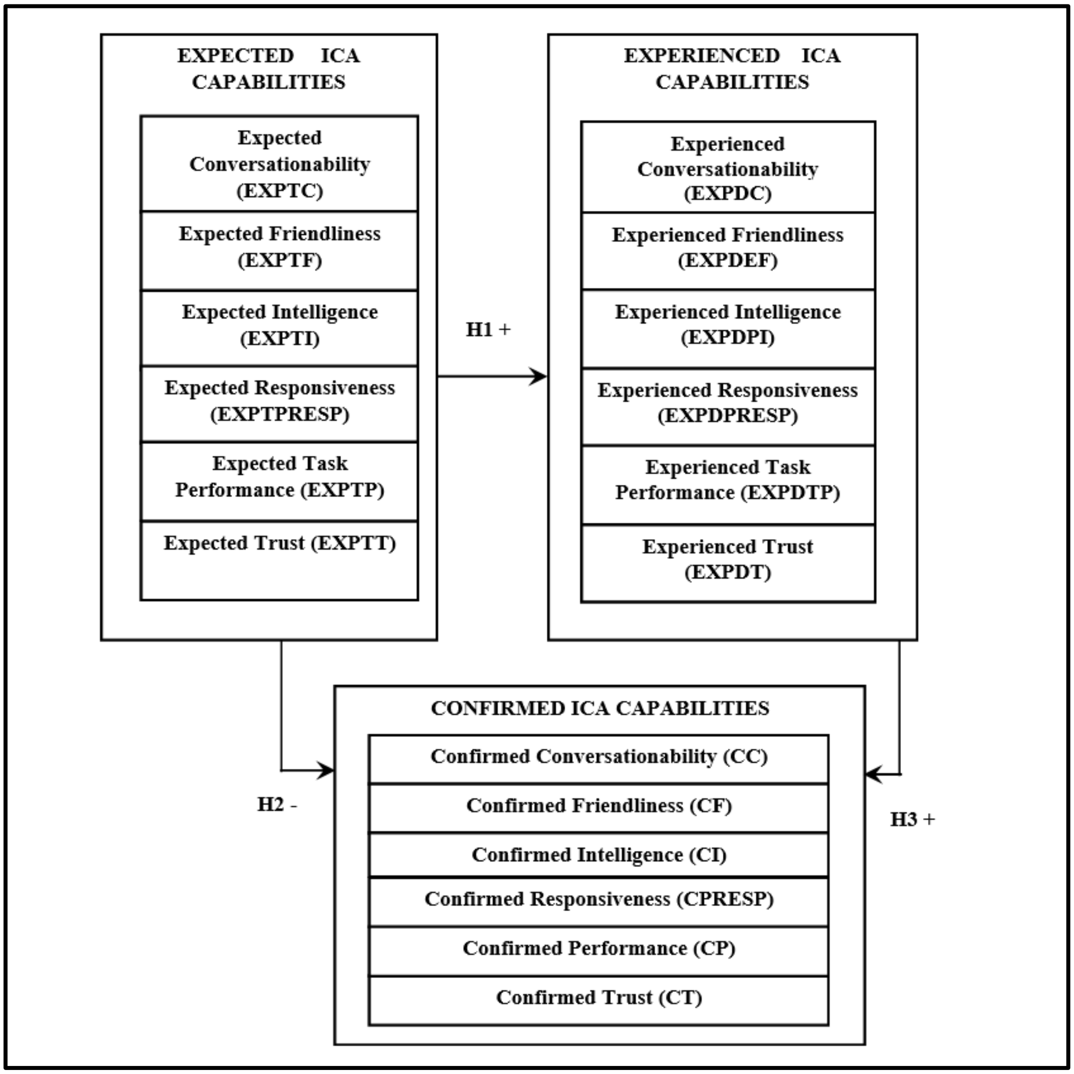

Figure 3.5: Relationship Between Expectations and ICA Experienced Capabilities

Customers will be satisfied if ICA services function properly and meet customer needs. This ICA performance will encourage their continued use in the future. Figure 3.6 below captures the hypothesized relationships.

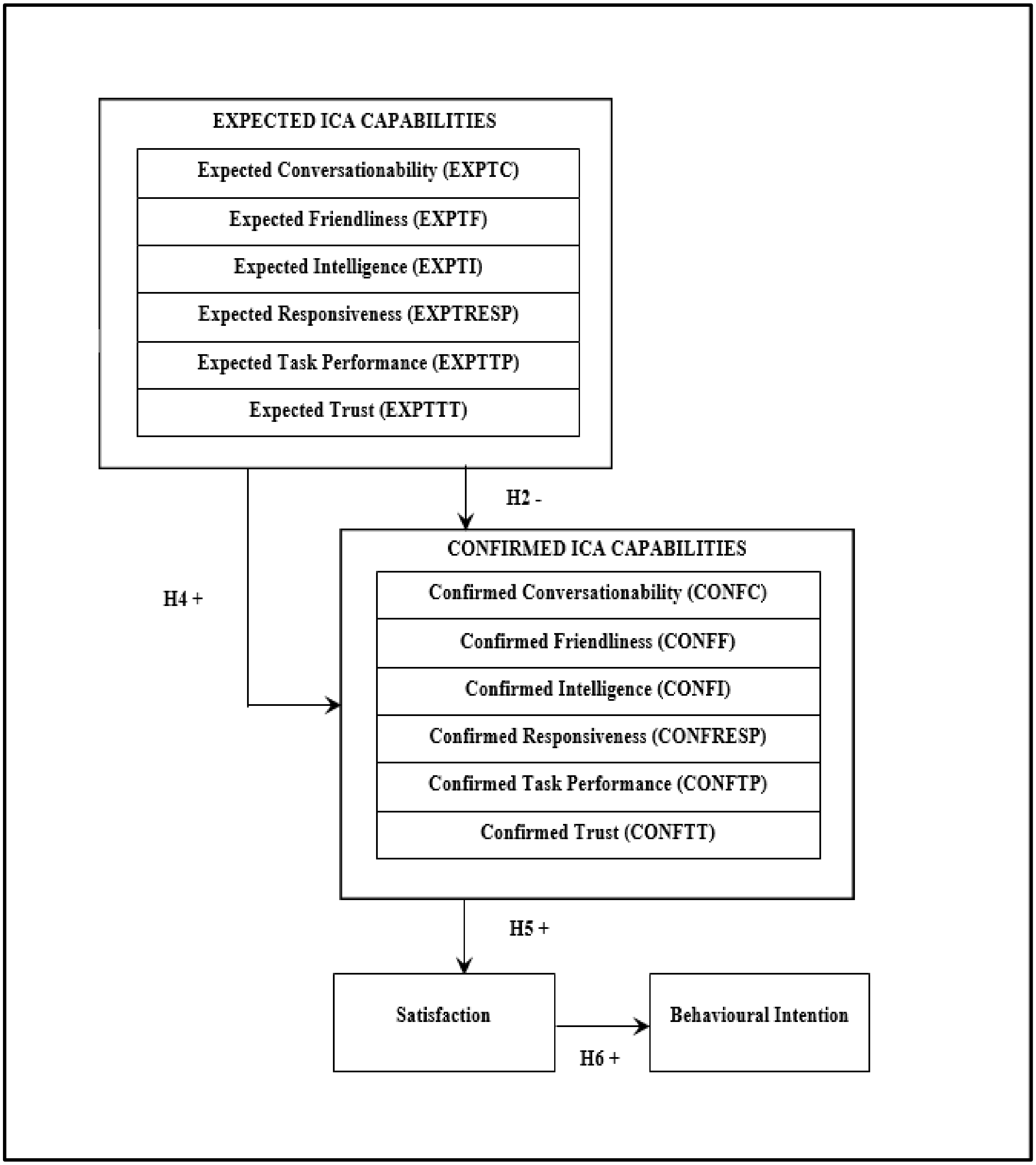

Figure 3.6: Relationship between EXPT, CONF, SATF and BI to Use ICA

Thus, hypotheses H5 and H6 suggest:

H5: Expected ICA Capabilities positively impact Satisfaction with ICA Capabilities.

H6: Satisfaction with ICA use positively impacts Behavioural Intention to use the ICA.

Increased communication and information processing capabilities will help individuals and teams be more productive and efficient (Dennis et al., 2001; McGrath and Hollingshead, 1994).

3.5. The Constructs and Hypotheses for TTF

3.5.1. Perceived Overall Fit of Use ICA

An ICA demonstrates overall fit, if available, to expeditiously (promptly) complete its assigned simple and complex tasks. A good fit benefits users' technology utilization, resulting in "improved efficiency, effectiveness, and quality" (Goodhue and Thompson, 1995). ICAs act as the technology of communication and task performance. Cognitive Fit Theory (Vessey and Galletta, 1991) elucidates the fit or misfit of communication modes and task types. The term 'cognitive load' refers to an individual's working memory capacity to complete a task, which varies according to the task's characteristics and the user's cognitive resources (Paas et al., 2004). User performance with a system may reduce cognitive load, depending on the match between the task and its information representation form. If the user's cognitive ability for information processing surpasses their attention, they become overwhelmed and lose information. My study investigates whether increased complexity, absence of availability and delayed timeliness are reasons for potential overload. When applied to ICAs, the TTF model makes us believe that text or speech is more suited to specific tasks, affecting user performance.

Researchers have proposed using ICA-enabled user-expert systems for decision support services (Galitsky and Goldberg, 2019) and studied the impact of the user-expert system fit on system utilization. If an expert system is considered a source of knowledge for the end-user, an ICA can help us assess how stable the problem-solving activity is. An expert system's interaction with user cognitive processes affects users' confidence and performance and helps to encourage its use by the end-user (Dalal and Kasper, 1994; Jiang et al., 2000b; Verhagen et al., 2014; Gnewuch et al., 2017; Diederich et al., 2019). As a result, the system's decision processes and outputs influence the user's decision-making actions and outcomes (Rhee and Choi, 2020). A newer approach has focused on cognitive user style (Schuetzler et al., 2019) and the fit between end-user cognitive processes and system presentation (Shmueli et al., 2016). Customer satisfaction and perceptions of the system tend to improve when system characteristics, such as avatar appearances, influence e-consumer productivity (Mimoun et al., 2017) and increase the use of ICAs in conversational commerce (Gnewuch et al., 2020).

My study draws inspiration from a previous study by Sturm and Peters (2020), which concluded that data availability and quality significantly impact the usability of AI technology for specific applications. My research determines unique TTF construct dimensions by applying the TTF model to the ICA context. Perceived Overall Fit is the generic response studied with unique dimensions of Fit For Complexity, Availability, and Time. My study explores if customers will use the deployed ICA more if the firm has demonstrated machine learning capabilities and that data collection can improve the perceived overall fit. The ICA end-user interaction can result in either an over-or under-fit state. Overfit occurs when the ICA's capability surpasses the task's requirements (e.g., using an ICA to offer generic or basic information to the end-user).

Fit For Complexity: This specific type of fit refers to an ICAs' capability to handle task complexity. Suppose an ICA capability is limited to handling simple tasks and cannot handle complex ones. In that case, the ICA is considered unfit for complexity or incapable of handling complex tasks. Researchers have conceptualized task complexity in a variety of ways. According to Campbell (1988), task complexity is conceptualized as objective (characteristic of a task) or subjective (a psychological experience), or person-task interaction. The complexity of the task, if not overcome by the ICA capability, can negatively impact the ICA performance. Perceived task performance is how individuals think a system will perform the task (Churchill and Surprenant, 1982; Kim et al., 2008). The effects of task complexity from various perspectives impact task performance and team performance (Bjørn and Ngwenyama, 2009; Dayan and Di Benedetto, 2010). Figure 3.7 presents the relationships between BI and POAF (Perceived Over All Fit).

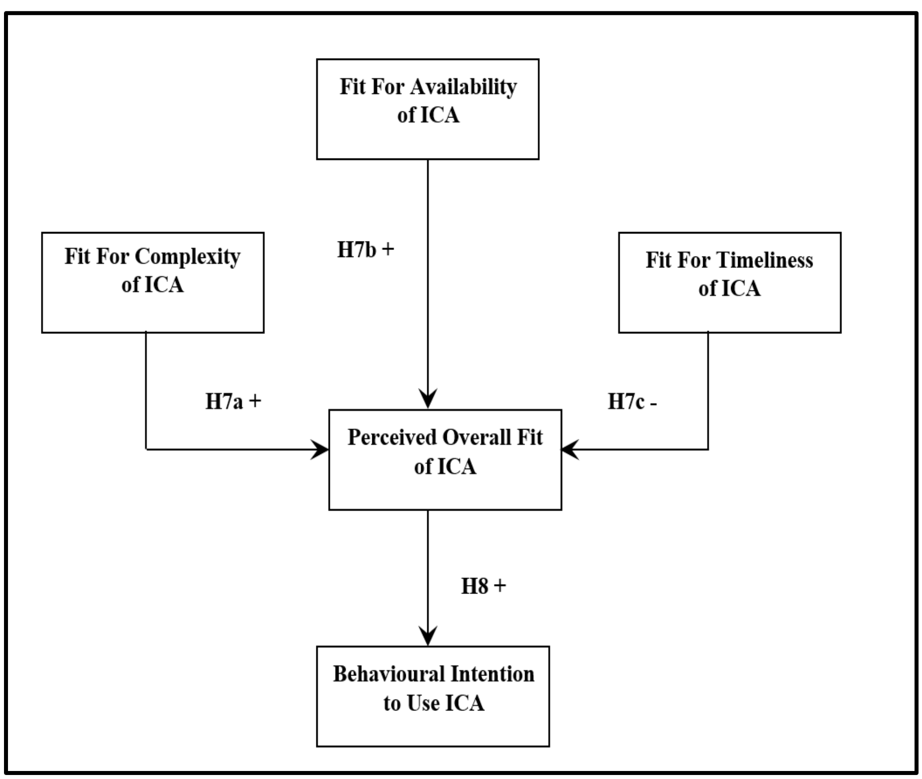

Figure 3.7: Relationships among FFC, FFA, FFT, POF and BI

Parkes (2013) defines Task–Technology Fit (TTF) as the extent to which the complexity of the undertaken task matches the decisional guidance the technology provides. Also, the fit for complexity is the extent to which the capability of the ICA matches (or fits) the complexity of the task. An ICA can only handle specific tasks. If the task is too complex, the ICA should pass it to a human, thus avoiding mistakes. Research has found that people are satisfied with simple tasks, such as searching for products performed by ICAs but not the complex tasks, such as resolving or explaining service problems (Cheng et al., 2021). The task complexity will affect the customer's perception of the ICA system—the sense of technology fit—and will change the user's usage behaviour and overall perception of the Task Technology Fit of the ICA. Thus, my study posits that:

H7a: Fit For Complexity positively affects the Perceived Overall Task-Technology Fit.

Fit For Availability: Availability refers to customer perceptions of their device's ability to provide on-demand access to services and information (Kim and Shin, 2015). Fit For Availability (FFA) is a critical feature of ICA's success. FFA refers to an ICA being available 24/7 to any customer with an internet connection. ICA deployments are often found on websites but lost in the navigation bars or search results due to material saturation. Researchers have studied FFA in detail in numerous contexts. These studies do not specifically identify or use the term FFA but show the importance of the availability of an ICA. These studies include health care for female cancer patients (Chetlen et al., 2019) and government services for communicating essential and critical information to citizens (Petriv et al., 2019).

FFA of an ICA is critical in e-commerce because customers expect customer service support from businesses 24 hours a day, seven days a week. Providing no customer service at night or hiring additional employees in different locations would lead to businesses' increased costs or lost customers. Customers value an ICA's clear communication, prompt response, and query assistance while being provided with tailored and individualized service capable of meeting customer demand 24 hours a day, seven days a week (Chung et al., 2020). FFA for an ICA deployed in customer service can also improve customer satisfaction by providing timely information to help make decisions and reduce customer problems (Chong et al., 2021). ICAs can also be made accessible via a mobile device where customers can chat with service agents using mobile chatbots (Wang and Petrina, 2013). Customers are satisfied when an ICA communicates with them because they are quick to respond, comprehensive, and detailed in their information and intelligence (Chung et al., 2018). Customers can access typical ICAs 24 hours a day, seven days a week, independent of traditional business hours (Zumstein and Hundertmark, 2017). When human resources or other customer service options are unavailable, a chatbot can give automated responses (De Cicco et al., 2020). The ICA can help display short conversational messages that can be retrieved quickly and influence the ICA's overall fit. Thus, this study hypothesizes that FFA directly impacts the POF:

> *H7b: Fit For Availability (FFA) positively affects the ICA's Perceived Overall Task-Technology Fit (POTTF).*

Fit For Timeliness (Responsiveness): An information system is said to respond if it adheres to predetermined production turnaround schedules and is deemed capable of responding promptly (Goodhue, 1995). For example, an ICA is Fit For Timeliness (FFT) if it provides a quick response without requiring the end-user to wait, repeat their request, or reword their query. Businesses often use generative or retrieval chatbots. The retrieval model finds the best interaction or dialogue for the situation, but a retrieval-based strategy can only select lectures in preexisting forms. These models work independently of the user but produce new conversations (Adamopoulou and Moussiades, 2020). Generative models translate the input to output via machine translation techniques. Deep learning, a type of machine learning, is being used to train chatbots so that the bots learn continuously from previous conversations (Przegalinska et al., 2019, Adamopoulou and Moussiades, 2020).

One of the primary reasons customers use an ICA is its instant response (Brandtzaeg and Følstad, 2017). An ICA can access the database and quickly conduct searches for customers. Organizations employ chatbots for dyadic interactions in several domains, including customer service (Xu et al., 2017; Hu et al., 2018). If the timely response generates inaccurate, ineffective, or no response, it will force the end-user to interact with the ICA again. Sometimes this interaction can be repeated several times to ensure that the ICA provides the relevant information, or the end-user gives up interacting with the ICA and requests a human service agent. In such cases, the timeliness of the ICA becomes an issue. Therefore, my study proposes the following relationship:

H7c: Timeliness for Fit negatively affects Perceived Overall Task-Technology Fit

3.5.2. Perceived Overall Task Technology Fit and Behavioural Intention

Research distinguishes between two types of fit influencing human-machine interaction: the fit between user and system and the fit between technology and task (Sturm and Peters, 2020). Cognitive Fit Theory elaborates that when the problem representation emphasizes the same types of problem-solving information and processes as a task, it creates a cognitive fit (Chan et al., 2017). My model has merit, as it suggests that the ICA should fulfill conditions considered fit for complexity, availability, and timeliness, which could significantly impact practice. Task-ICA compatibility will be the model's main predictor of utilization and performance improvement. While my research focuses on individual performance, the model can also assess TTF's impact on a group or organizational performance (Zigurs and Buckland, 1998). This condition ensures the ICA attains an overall fit. Table 3.1 represents the relevant fit conditions.

Table 3.1: Defining FFC, FFA, FFT and POF

<table>
<tr><th>SR #</th><th>Conditional definitions developed for my research study</th><th>Research Studies</th></tr>
<tr><td>1</td><td>FIT FOR COMPLEXITY: A deployed ICA is rated Fit For Complexity if it can resolve task-related ambiguity (complexity) and provide necessary information or complete the tasks.</td><td rowspan="4">Developed for this study, based on Goodhue and Thompson (1995)</td></tr>
<tr><td>2</td><td>FIT FOR AVAILABILITY: A deployed ICA is rated Fit For Availability if it can complete the required task and provide necessary information or complete the tasks.</td></tr>
<tr><td>3</td><td>FIT FOR TIMELINESS: A deployed ICA is rated Fit For Timeliness if it can complete the required task and provide the necessary information within the acceptable time requirements of the end-user or the customer service rules set by the business.</td></tr>
<tr><td>4</td><td>PERCEIVED OVERALL FIT: A deployed ICA is rated Overall Fit if it can resolve task-related ambiguity (complexity), complete the required task with an acceptable response, and provide the necessary information in the acceptable time requirements of the end-user or the customer service rules set by the business.</td></tr>
</table>

My research model's reasoning capacity will validate potential machine learning-based ICA deployments for specific use cases. My research tests the model by evaluating it in the telecom sector, where machine learning-based ICA can assist human consumers (and employees) 24 hours a day, seven (7) days a week. A link between FFC and POF, FFA and POF, and FFT and POF allows for predicting the relationship between POF and BI. Suppose the task is complex (or unknown). In that case, the ICA technology is unavailable or constrained, or the ICA technology produces a delayed solution; in that case, an ICA user will have a weak BI. POF is the critical predictor of BI and substantially impacts utilization and individual customer performance. Thus, this model can increase knowledge about the fit between ICA task performance and contribute to a sophisticated theorization of the relationships between the customer and the ICA task.

H8: Perceived Overall Task Technology Fit positively impacts the Behavioural Intention To Use the ICA.

Customers perceive deployed ICAs to obtain information or services as either negative or positive in terms of customer service. Attitude explains when customers consider the consequences of their actions (Athiyaman, 2002). The theory of Planned Behaviour (TPB) is an extended version of Ajzen's (1991) Theory of Reasoned Action (TRA). TRA proposes that an individual's attitude influences their conduct, influencing behavioural intention. This relationship is relevant in a variety of technologies, including travel to travel (Nguyen, 2018), e-banking (Ahmad et al., 2019), smart homes (Shuhaiber and Mashal, 2019), mobile payment services (Park et al., 2019), Robo-advisers (Belanche, 2019), virtual worlds (Ahmad and Abdulkarim, 2019), and academic, social networking sites (Rad et al., 2019; Cardona, 2019). Figures 3.5 and 3.6 present the relationships proposed by ECT theory, while Figure 3.7 captures the hypothesized relationships between FFC, FFA, FFT, POAF and BI in my model.

3.6 Chapter Summary

This chapter presented the research model and hypotheses, signifying essential relationships. The model consists of two parts. The first part pivots on the Expectations Confirmation Theory (Oliver, 1977; 1980), and the second part centres on Task Technology Fit (Goodhue and Thompson, 1995). Combining these two theories gives more explanatory power to the model and improves the model's predictive power. This chapter also provided a very elaborative treatise on Perceived Overall Fit in terms of Fit For Complexity, Fit For Availability and Fit For Timeliness.

Chapter 4: Research Methodology

Chapter 4 has five sections; each section describes the methodological preferences chosen for my research study. Section 4.1 presents the research design. Section 4.2 discusses the operationalization of the construct and provides adapted questionnaire items. Section 4.3 considers the sampling strategy and the data collection process. Section 4.4 elaborates upon the experimental design. Finally, Section 4.5 presents the summary of the chapter.

4.1. Research Design

Research Design involves choosing a research method, operationalizing research constructs, and designing a sampling strategy (Bhattacharjee, 2012). The researcher's worldview influences the research plan, philosophical assumptions, research methods, data collection, analysis, and interpretation. The research design also depends on the study's purpose and target audience. Positivist researchers use quantitative methods, while interpretive researchers use qualitative research methods to conduct their research (Creswell and Creswell, 2017).

Researchers have suggested that most research uses quantitative research (Myers and Avison, 2002; Myers, 2019). The quantitative method gathers data from a large population and analyzes it but ignores an individual's emotions, feelings, and environmental context. Thus, researchers describe rather than interpret data using the quantitative strategy (Rahi, 2017). Quantitative research examines relationships between variables to test hypotheses. These variables can be quantified using survey questionnaires, allowing statistical analysis of the data (Creswell and Creswell, 2017). My research includes Canadian users of the telecom sector in an experimental study. Here, ICA-enabled customer service supports customers twenty-four hours a day, seven days a week.

In contrast, other sectors, such as the retail sector, have limited ICA coverage and are only available when there are limited human resources during daytime hours. My research required participants to interact with an ICA and respond to survey questions. This allowed us to examine the relationship among ICA capabilities at the expectation and experience stages through the lens of ECT and TTF in the ICA context.

My research tested the model explained in Chapter 3 by using a pilot study which informed the actual study. The pilot study used an experiment (interaction) between the participants and the ICA. The pilot study also presented brief pre-experiment and post-preliminary experiment surveys using a small, convenient sample, per pilot study guidelines (Alreck and Settle, 2004). The pilot study also ensured that the final research project utilized a meticulous structure and developed validated reliability scales (Straub, 1989). My pilot study validated the proposed instrumentation before finalizing the project's details by administering the comprehensive final survey (Boudreau et al.,2001).

This research also examines the mediating effects of ICA capabilities (at the Pre-Experiment and Post Experiment stages) and Satisfaction due to the direct effects of the Perceived Fit with the behavioural intention to use an ICA. This examination complies with the subjective nature of the constructs and the fact that empirical research frequently employs surveys to examine customer satisfaction (Oliver, 2006). The pilot and final studies were approved by the Research Ethics Board of McMaster University and Wilfred Laurier University, as shown in Appendix A.

4.2. Construct Measurement

Due to a dearth of empirical research on ICA usage from a behavioural perspective, very few definitions and scales for ICA exist. To overcome this deficiency, my study introduces new multi-item measures. A seven-point Likert scale was used in the participant survey, ranging from 1 specifying strong disagreement to 7 indicating strong agreement, and 8 (eighth choice) signifying "Prefer Not To Answer."

My study operationalized the constructs using ECT and TTF theories while capturing the customer service's level of success in meeting organizational objectives, requirements, and business value (Kim, 2009). My research focused on ICA capabilities that influence the expectations and experiences of customers. Table 4.1 presents the definition, item scale questions and respective references for each of the 14 constructs, including control variables. I have included the generic definition of all the constructs, which can be contextualized at the expectation and perceived performance stage.

Table 4.1: Operationalization Table

<table>
<tr><th colspan="2">CONSTRUCTS (EXOGENOUS, ENDOGENOUS AND CONTROL VARIABLES)</th><th>Reference</th></tr>
<tr><td colspan="3">1. ICA CONVERSATION ABILITY refers to the ability of a chatbot to carry out a meaningful conversation with the end-user. It is measured at the Expectations and Perceived Performance stage as EXPTC and PPC, respectively.</td></tr>
<tr><td rowspan="4">EXPTC</td><td>Questions (Pre-Experiment Stage or Expectations Stage)

My pre-experimental expectations regarding Conversation ability with the chatbot (Artificially Intelligent Conversational Agent, ICA),</td><td rowspan="4">Developed for this study, based on ECT (Oliver, 1977)</td></tr>
<tr><td>EXPTC1. I expect the chatbot (ICA) will understand my message.</td></tr>
<tr><td>EXPTC2. I expect that the chatbot (ICA) can talk or send a meaningful message to me.</td></tr>
<tr><td>EXPTC3. I expect that the chatbot (ICA) will be able to communicate with me like a human.</td></tr>
<tr><td rowspan="2">PPC</td><td>Questions (Perceived Performance Stage)

My perceived chatbot (ICA) Conversation ability after my experimentation with the chatbot (ICA),</td><td rowspan="2"></td></tr>
<tr><td>PPTC1. I feel that the chatbot (ICA) can understand my message.</td></tr>
</table>

	PPTC2. I feel that the chatbot (ICA) can talk or send a meaningful message to me.	
	PPTC3. I feel that the chatbot (ICA) can communicate with me like a human.	
	PPTC4. I feel that the chatbot (ICA) was able to keep track of the conversation.	
	PPTC5. I feel that the conversation with the chatbot (ICA) was smooth.	
	PPTC6. I feel that I had to rephrase my words in order for the chatbot (ICA) to understand me.	
	PPTC7. I feel that, at times, the chatbot (ICA) misunderstands my message.	
2. ICA FRIENDLINESS refers to the ability of a chatbot to display Friendliness towards or with the end-user. It is measured at the Expectations and Perceived Performance stage as EXPTF and PPF, respectively.		
EXPTF	Questions (Pre-Experiment Stage or Expectations Stage) **My pre-experimental expectations regarding Friendliness with the chatbot (Artificially Intelligent Conversational Agent, ICA),**	
	EXPTF1. I expect that the chatbot (ICA) will be collaborative.	Developed for this study, based on ECT (Oliver, 1977)
	EXPTF2. I expect the chatbot (ICA) will be friendly, like a human agent.	
	EXPTF3. I expect that I will enjoy talking with the chatbot (ICA).	
PPF	Questions (Perceived Performance Stage) **My perceived Chatbot (ICA) Friendliness after my experimentation with the chatbot (ICA),**	
	PPF1. the chatbot (ICA) introduced itself like a human (friend).	Developed for this study, based on ECT (Oliver, 1977)
	PPF2. the chatbot (ICA) was polite and respectful towards me, like a friend.	
	PPF3. the chatbot (ICA) was cooperative and friendly.	
	PPF4. I enjoyed my relationship with the chatbot (ICA).	
	PPF5. The chatbot (ICA) was never impatient or became irritated with my questions.	
3. ICA INTELLIGENCE refers to the ability of a chatbot to display Intelligence towards or with the end-user for the assigned tasks. It is measured at the Expectations and Perceived Performance stage as EXPTI and PPI, respectively.		
EXPTI	Questions (Pre-Experiment Stage or Expectations Stage) **My pre-experimental expectations regarding Intelligence with the chatbot (Artificially Intelligent Conversational Agent, ICA),**	
	EXPTI1. I expect that the chatbot (ICA) can explain the reasons while answering my queries.	Developed for this study, based on ECT (Oliver, 1977)
	EXPTI2. I expect that the chatbot (ICA) can understand my needs or requests.	
	EXPTI3. I expect that the chatbot (ICA) is capable of answering my questions intelligently.	
	EXPTI4. I expect that the chatbot (ICA) is as smart as a human agent.	
PPI	Questions (Perceived Performance Stage) **My perceived chatbot (ICA) Intelligence after my experimentation with the Chatbot (ICA),**	
	PPI1(P). I feel that the chatbot (ICA) can explain the reasons while answering my queries.	Developed for this study, based on ECT (Oliver, 1977)
	PPI2(P). I feel that the chatbot (ICA) can understand my needs or requests.	
	PPI3(P). I feel that the chatbot (ICA) can answer my questions intelligently.	
	PPI4(P). I feel that the chatbot (ICA) is as smart as a human agent.	
	PPI5(P). I feel that the chatbot (ICA) can anticipate my intentions behind the questions I ask.	
	PPI6(P). I feel that the chatbot (ICA) can follow my switching or changing the topic or question.	
	PPI7(P). I feel that the chatbot (ICA) can influence me to reach a decision by recommending alternative solutions.	

4. ICA RESPONSIVENESS EXPECTATIONS (PRESPE) refer to a chatbot's ability to respond promptly to the end-user request. It is measured at the Expectations and Perceived Performance stage as EXPTRESP and PPRESP, respectively.		
EXPTRESP	Questions (Pre-Experiment Stage or Expectations Stage) **My pre-experimental expectations regarding Responsiveness with the chatbot (Artificially Intelligent Conversational Agent, ICA),**	Developed for this study, based on ECT (Oliver, 1977)
	EXPTRESP1. I expect that the chatbot (ICA) can provide a timely response to my questions.	
	EXPTRESP2. I expect that the chatbot (ICA) can respond to me quickly.	
	EXPTRESP3. I expect that the chatbot (ICA) can communicate with me without significant delay.	
PPRESP	Questions (Perceived Performance Stage) **My perceived chatbot (ICA) Responsiveness after my experimentation with the Chatbot (ICA),**	
	PPRESP1(P). I feel that the chatbot (ICA) can provide a timely response to my questions.	Developed for this study, based on ECT (Oliver, 1977)
	PPRESP2(P). I feel that the chatbot (ICA) can respond to me quickly.	
	PPRESP3(P). I feel that the chatbot (ICA) can communicate with me without significant delay.	
	PPRESP4(P). I found that the chatbot (ICA) exhibited a delay in response to vague or complex questions (Reverse).	
	PPRESP5(P). I found that the chatbot (ICA) responded slower than a human agent (Reverse).	
	PPRESP6(P). I found that the chatbot (ICA) often stopped or offered no response to me (Reverse).	
5. ICA TASK PERFORMANCE refers to the ability of a chatbot to perform or complete the task requested by the end-user. It is measured at the Expectations and Perceived Performance stage as EXPTTP and PPTP, respectively.		
EXPTP	Questions (Pre-Experiment Stage or Expectations Stage) **My pre-experimental expectations regarding Task Performance with the chatbot (Artificially Intelligent Conversational Agent, ICA),**	
	EXPTTP1. I expect that the chatbot (ICA) can search and provide the necessary information for me.	Developed for this study, based on ECT (Oliver, 1977)
	EXPTTP2. I expect that the chatbot (ICA) can perform the task in the same way as a human agent.	
	EXPTTP3. I expect that the chatbot (ICA) can solve the problem I faced or encountered.	
	EXPTTP4. I expect that the chatbot (ICA) can provide me with a recommendation.	
PPTP	Questions (Perceived Performance Stage) **My perceived chatbot (ICA) Task Performance after my experimentation with the chatbot (ICA),**	
	PPTP1. I feel that the chatbot (ICA) can search and provide the necessary information for me.	Developed for this study, based on ECT (Oliver, 1977)
	PPTP2. I feel that the chatbot (ICA) can perform the task in the same way as a human agent	
	PPTP3. I feel that the chatbot (ICA) can solve the problem I faced or encountered.	
	PPTP4. I feel that the chatbot (ICA) can provide me with a recommendation	
	PPTP5. I feel that the chatbot (ICA) was not qualified to perform the assigned tasks (Reverse).	
	PPTP6. I feel that the chatbot (ICA) was not performing well for the assigned tasks (Reverse).	

<table>
<tr><td colspan="3">6. ICA TRUST refers to the perceived trustworthiness of the chatbot. It is measured at the Expectations and Perceived Performance stage as EXPTT and PPTT, respectively.</td></tr>
<tr><td rowspan="5">EXPTTT</td><td>Questions (Pre-Experiment Stage or Expectations Stage)
My pre-experimental expectations regarding Trust with the chatbot (ICA)</td><td rowspan="5">Developed for this study, based on ECT (Oliver, 1977)</td></tr>
<tr><td>EXPTTT1. I expect that the chatbot (ICA) will act for the benefit of the end-user.</td></tr>
<tr><td>EXPTTT2. I expect that the chatbot (ICA) can perform based on customer service policies and regulations.</td></tr>
<tr><td>EXPTTT3. I expect that the chatbot (ICA) will be fair in its conduct of my service request.</td></tr>
<tr><td>EXPTTT4. I expect that the chatbot (ICA) will be trustful.</td></tr>
<tr><td rowspan="7">PPTT</td><td colspan="2">Questions (Perceived Performance Stage)
My perceived chatbot (ICA) Trust, after my experimentation with the ICA,</td></tr>
<tr><td>PPTT1. I feel that the chatbot (ICA) acted for the benefit of the end-user.</td><td rowspan="6">Developed for this study, based on ECT (Oliver, 1977)</td></tr>
<tr><td>PPTT2. I feel that the chatbot (ICA) performed based on customer service policies and regulations.</td></tr>
<tr><td>PPTT3. I feel that the chatbot (ICA) was fair in its conduct of my service request.</td></tr>
<tr><td>PPTT4. I feel that the chatbot (ICA) was trustful.</td></tr>
<tr><td>PPTT5. I feel that I can trust a chatbot (ICA) the same as a human agent.</td></tr>
<tr><td>PPTT6. I feel that the chatbot (ICA) was competent to deliver the service.</td></tr>
<tr><td colspan="3">7. CONFIRMATION (CNF) confirmation is the degree to which the experienced ICA capabilities meet or exceed the expected ICA capabilities—measured at Experiment stage time t2. 1: Significantly lower than expected, 2: Lower than Expected, 3: Slightly lower than expected, 4: the same, 5: slightly higher than expected, 6: higher than expected, and 7: Significantly higher than expected. 8: Prefer not to answer</td></tr>
<tr><td colspan="2">CONFIRMATION/DISCONFIRMATION: My post-experimental confirmation regarding Interaction with the Chatbot (ICA) suggests that:</td><td rowspan="8">Developed for this study, based on ECT (Oliver, 1977)</td></tr>
<tr><td></td><td>Questions</td></tr>
<tr><td rowspan="6">CONF</td><td>CONFC1: Compared with my initial expectation, my experienced chatbot (ICA) conversation ability is</td></tr>
<tr><td>CONFF: Compared with my initial expectation, my experienced chatbot (ICA) Friendliness is</td></tr>
<tr><td>CONFI: Compared with my initial expectation, my experienced chatbot (ICA) Intelligence is</td></tr>
<tr><td>CONFRESP: Compared with my initial expectation, my experienced chatbot (ICA) Responsiveness is</td></tr>
<tr><td>CONFTP: Compared with my initial expectation, my experienced chatbot (ICA) Task Performance is</td></tr>
<tr><td>CONFTT: Compared with my initial expectation, my experienced chatbot (ICA) Trust is</td></tr>
<tr><td colspan="3">Note: For my pilot study, I measured the construct of Confirmation (CONF) with the help of the above item questions. For the final study, my study measured the construct of CONF with the help of the difference between measured values of Perceived Performance and measured values of Expected values for all six ICA Capabilities.</td></tr>
<tr><td colspan="3">8. SATISFACTION (SATF): An individual's emotional feelings comparing a chatbot with a human agent.</td></tr>
<tr><td></td><td>Question:

My overall Satisfaction with the chatbot (Conversational Artificial Intelligence Agent, ICA) in the service, compared to a human agent.</td><td rowspan="4">Developed for this study, based on Lechner et al. (2010)</td></tr>
<tr><td rowspan="3">SATF</td><td>SATF1. I am satisfied with the chatbot (ICA) service.</td></tr>
<tr><td>SATF2. The chatbot (ICA) Conversation ability is at the same level as the human agent.</td></tr>
<tr><td>SATF3. The chatbot (ICA) Friendliness is at the same level as the human agent.</td></tr>
</table>

	SATF4. The chatbot (ICA) Intelligence is at the same level as the human agent.	
	SATF5. The chatbot's (ICA) Responsiveness is at the same level as the human agent.	
	SATF6. The chatbot (ICA) Task Performance is at the same level as the human agent.	
	SATF7. The chatbot (ICA) Trust is at the same level as the human agent.	
9. Fit For Complexity (FFC): Extent of fit between the target task complexity and capability of ICA technology to perform the task.		
	Questions	**References**
FFC	FFC1. The task is reasonable for the chatbot (ICA) to deal with.	Developed for this study, based on TTF (Goodhue and Thompson, 1995)
	FFC2. The chatbot (ICA) is capable to perform the task assigned for customer service.	
	FFC3. I found that the task is within the capability of the chatbot (ICA)	
10. Fit For Availability (FFA): Extent of fit between the target task that needs to be performed and available ICA technology to accomplish the task.		
	Questions	**References**
FFA	FFA1. The chatbot (ICA) enabled Customer Service beyond regular office hours.	Developed for this study, based on TTF (Goodhue and Thompson, 1995)
	FFA2. The chatbot (ICA) can do the job when a human agent is not available.	
	FFA3. The chatbot (ICA) can do the job when the human agent is busy.	
11. Fit For Timeliness (FFT): Extent of fit between the timely task completion and responsiveness of ICA technology.		
	Questions	**References**
FFT	FFT1. This chatbot (ICA) can respond to Customers request quickly.	Developed for this study, based on TTF (Goodhue and Thompson, 1995)
	FFT2. The chatbot (ICA) can respond without a long waiting time.	
	FFT3. The chatbot (ICA) can search for information very quickly.	
12. Perceived Overall Fit (POAF): Extent of overall fit between the target task and capability of ICA technology.		
	Questions	**References**
POAF	POAF1. The chatbot (ICA) can fit Customer service well.	Developed for this study, based on TTF (Goodhue and Thompson, 1995)
	POAF2. The chatbot (ICA) can meet Customer service requirements.	
	POAF3. The chatbot (ICA) can do a reasonable job for the Customer Service	
INDEPENDENT VARIABLE		
13. Behavioural intention (BI): User's intention to use the chatbot (ICA) Service		
	Questions	**References**
BI	BI1. I intend to use the chatbot (ICA) for Customer Service.	Adapted from Venkatesh et al. (2003)
	BI2. I predict I would use the chatbot (ICA) for Customer Service.	
	BI3. I plan to use a chatbot (ICA) for Customer Service.	
14. CONTROL VARIABLES		
14a.	**CONTEXT**: Context refers to the telecom companies. A participant will select one of the five telecom companies.	
CONTEXT (CONT): We measure context in terms of the chatbot (ICA) deployed for different services like Telecom companies, Retail outlets, and Airlines. Here we include only the chatbots (ICAs) from the Telecom companies.		

<table>
<tr><td rowspan="6">CONT</td><td colspan="3"></td></tr>
<tr><td rowspan="5">I selected the ICA that represented one of the Telecom companies (please select and check one ICA)</td><td>ROGERS</td><td>☐</td></tr>
<tr><td>SHAW</td><td>☐</td></tr>
<tr><td>TELUS</td><td>☐</td></tr>
<tr><td>FIDO</td><td>☐</td></tr>
<tr><td>KOODO</td><td>☐</td></tr>
<tr><td>14b.</td><td colspan="3">DQ1. What is your age?
a. Less than 20 years
b. 21-40 years
c. 41-60
d. 61-above
e. Prefer not to answer</td></tr>
<tr><td>14c.</td><td colspan="3">DQ2. Please identify your gender.
a. Female
b. Male
c. Prefer not to answer</td></tr>
<tr><td>14d.</td><td colspan="3">DQ3.What is your highest completed level of education?
a. High school
b. College/University
c. Postgraduate
d. Prefer not to answer</td></tr>
<tr><td>14e.</td><td colspan="3">DQ4. With regards to English Language Proficiency, are you?
a. Native Speaker
b. Non-Native Speaker
c. Prefer not to answer</td></tr>
<tr><td>14f.</td><td colspan="3">DQ5. What type of Job are you associated with?</td></tr>
<tr><td>14g.</td><td colspan="3">PREVIOUS ARTIFICIAL INTELLIGENCE EXPERIENCE: Refers to the participant's experience or knowledge about Artificial Intelligence (AI).</td></tr>
</table>

<table>
<tr><td colspan="3">Previous AI Experience (PAIE): Experiment participants' prior AI knowledge and users included a variety of past encounters with technology. Previous AI Experience (PAIE): Experiment participants' prior AI knowledge and users a variety of past encounters with technology. 1= Strongly Disagree, 2=Disagree, 3=Somehow Disagree, 4=Neutral, 5= Somehow Agree, 6= Agree, 7 = Strongly Agree, and 8=Prefer not to answer</td></tr>
<tr><td></td><td>Questions</td><td></td></tr>
<tr><td rowspan="5">PAIE</td><td>PAIE1: I have watched movies or videos about robots (General).</td><td rowspan="5">Self-Developed based</td></tr>
<tr><td>PAIE2: I have interacted with talking robots in exhibition shows or public tourism places.</td></tr>
<tr><td>PAIE3: I have played with smart speakers such as Amazon Echo, Siri, Alexa, Google nest, and Apple home pot.</td></tr>
<tr><td>PAIE4: I have used the voice interface for google search or smartphone car navigator.</td></tr>
<tr><td>PAIE5: I have used or seen the use of social robots for the care of patients.</td></tr>
<tr><td>14h.</td><td colspan="2">CUSTOMER RELATIONSHIP MANAGEMENT EXPECTATIONS: Refers to customer expectations that encompass any collection of behaviours or actions that end-users anticipate from a business when dealing with it. Customer Relationship Management Experience (CRME): Extent of fit between the target Customer Relationship technology and users a variety of past encounters with technology. 1= Strongly Disagree, 2=Disagree, 3=Somehow Disagree, 4=Neutral, 5= Somehow Agree, 6= Agree, 7 = Strongly Agree, and 8=Prefer not to answer</td></tr>
<tr><td></td><td>Questions</td><td></td></tr>
</table>

CRME	CRME1: I have used phone calls for online customer service with a human agent.	Self-Developed
	CRME2: I have interacted with talking robots in exhibition shows or Public tourism places.	
	CRME3: I have used an automated question-and-answer service on a company's website.	
	CRME4: I have used an automated conversational agent (chatbot) in customer service on the web.	
14i.	**Experiment Effort (EE):** Experiment Effort refers to the time and effort the end-user spends interacting with an ICA to receive relevant information (Jiao et al.,2019). 1= Strongly Disagree, 2=Disagree, 3=Somehow Disagree, 4=Neutral, 5= Somehow Agree, 6= Agree, 7 = Strongly Agree, and 8=Prefer not to answer	
Experiment Effort (EE): While interacting with the chatbot (ICA), the experimental effort showed that		
EE	Questions	**Reference**
	EE1. I spend considerable time interacting with the chatbot (ICA).	Self-Developed based on Jiao, Chen and Yuan (2019).
	EE2. I spend time and energy trying different tasks with the chatbot (ICA).	
	EE3. I spend time and energy exploring the functions of the chatbot (ICA).	

As shown in Table 4.1 above, my research model includes fourteen constructs and adopted measurement items from existing literature or self-developed. Second, with the assistance of IS Ph.D. students, these items were evaluated and revised per the evaluators' suggestions. Third, data were collected and used to refine the items using SmartPLS to validate the reliability of the constructs. The scale items were adjusted slightly to fit the proposed study's context. Also, Table 4.2 illustrates the open-ended questions used to generate and collect qualitative data from the participants.

Table 4.2: Open-ended questions for qualitative data collection

OPEN-ENDED QUESTIONS
OE1: Which part of the chatbot (ICA) experience made you feel surprised or excited? Please provide a sample of your dialogue (or conversation) with the chatbot (ICA).
OE2: Which part of the chatbot (ICA) experience made you feel disappointed? Please provide a sample of your dialogue (or conversation) with the chatbot (ICA).
OE3: Under what scenarios, situations, or aspects do you think the chatbot (ICA) is useful?

4.3. Sample Strategy

Sampling is the process of selecting cases representative of a population (Sharma, 2017). My research studies used the ICAs deployed by the Canadian Telecom sector for the use of

Canadian customers. The research firm (Maru Blue)[1] recruited study participants from Canada who knew the service quality provided by the telecom companies and the problems faced by Canadian users of telecom services. A pilot study using purposive sampling (Sarstedt et al., 2018) was conducted with 100 respondents to remove ambiguity, identify errors, and optimize the survey design and results, allowing for modifying the item descriptions and expressions before administering the formal questionnaire for the final study (Hulland et al., 2018).

4.3.1. Sample Size for the Pilot and Actual Studies

Recommendations for pilot study sample size vary based on previous research studies (Hill, 1998; Julious, 2005; Whitehead et al., 2016). Research suggests that the sample size for the pilot study should be 10 percent of the sample size of the actual study (Connelly, 2008), or they should capture 30 to 100 data points (Hertzog, 2008). Based on these guidelines, I used a sample size of 100 participants for the pilot study and 500 for the final study.

4.3.2. Data Collection Procedure

The participant list for my study (for both the pilot and final study), which contained the research firm's respondent survey ids, was accessed via Lime Survey. A clause stated that participants must complete the survey to be eligible for reimbursement. Lime Survey (https://surveys.mcmaster.ca/limesurvey.com) assigned each respondent an auto-generated unique link in the customized email. The link then asked respondents to respond and answer survey questions. Accordingly, a relevant survey link opened and noted the id of the survey respondent.

[1] https://www.marugroup.net/maru-blue

My study ensured that the unique customized link sent to respondents identified them correctly for compensation. After two weeks, survey respondents were sent reminders if they did not complete or respond to the initial invitation. The research firm informed the participants that if they were interested in knowing about the findings of my study, they could access the Ph.D. thesis at the following link (https://macsphere.mcmaster.ca/handle/11375/271) or contact the researcher directly with any specific questions. The Appendix provides the survey invitation email script and the pilot and final studies consent form.

4.4. Experimental Design

I initially developed an e-commerce website for my research and deployed an ICA with AI capabilities. However, the interaction with the chatbot could not capture the actual real-life business organization, and I scratched it in favour of a real business ICA. I searched available real business ICAs on the web and interacted with these ICAs myself. There were 11 (eleven) candidate business ICAs for online customer service. I finally selected 5 (five) telecom companies' ICAs as they were available 24 hours a day and 7 days a week. Also, customers facing issues with Telecom service usually need a prompt and actual remedial solution, even after office hours.

4.4.1. Experimental Task

The experiment ensured that each subject interacted with an ICA by performing four typical customer service tasks with different levels of complexity. The four tasks were 1) asking the ICA about new deals and promotions, 2) reporting and dealing with a lost (stolen) phone, 3) travelling abroad, asking for service coverage, and 4) reporting a service problem. The subjects were at liberty to construct conversational phrases to communicate with the ICA and obtain a response from the ICA to complete the four assigned tasks.

The experiment exposed all the participants to tasks of varying complexity. For instance, participants carried out different tasks with the freedom to choose words. These queries generated responses from the ICA, like a dialogue or conversation trail for each participant. Thus, by changing the levels of context and varying the task complexity, the participant's responses were manipulated, influencing their responses to online survey questions.

Before the experiment, subjects answered survey questions regarding their expected ICA capabilities. The subjects were then assigned to complete the interaction for the four tasks. After the experiment, the subjects answered survey questions regarding their experienced ICA capabilities, satisfaction, perceived task technology fit, and intention to use ICA service in the future. Participants performed two search-related tasks and two interaction-related activities. Figure 4.1 shows the three stages of the experiment Pre-Experiment, Experiment and Post Experiment Stages.

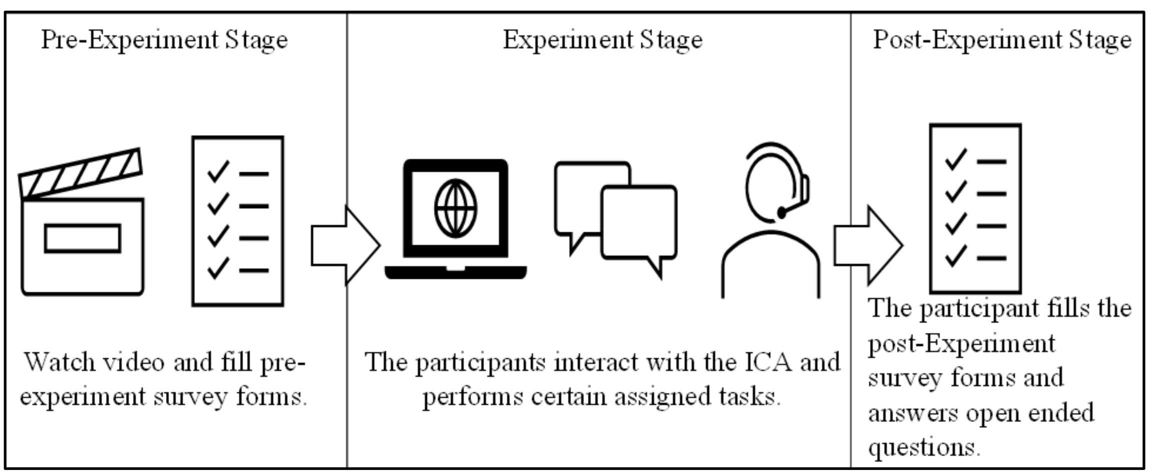

Figure 4.1: The Three Stages of the Experiment

4.4.2. General Instructions

The participants interacted with ICAs used in a Service Providers' customer service. The participant selected one of the five service providers, ensuring that the provider's ICA worked at the interaction time. If an ICA was unavailable or off-service due to maintenance, to complete the Interaction Scenario, the participants were requested to choose another ICA after noting the time and date of the ICA outage and recording on their response forms that they switched to another ICA.

The study participants could interact with the ICA in four situations. The participants were explicitly cautioned that they should not provide personal details like name, address, credit card information, or even names of their family members to prevent any violation of their privacy and their family's privacy. These instructions were shared to comply with the recommendations of the ethics board of McMaster University and Wilfred Laurier University. Figure 4.2 represents the Stages of participant engagement.

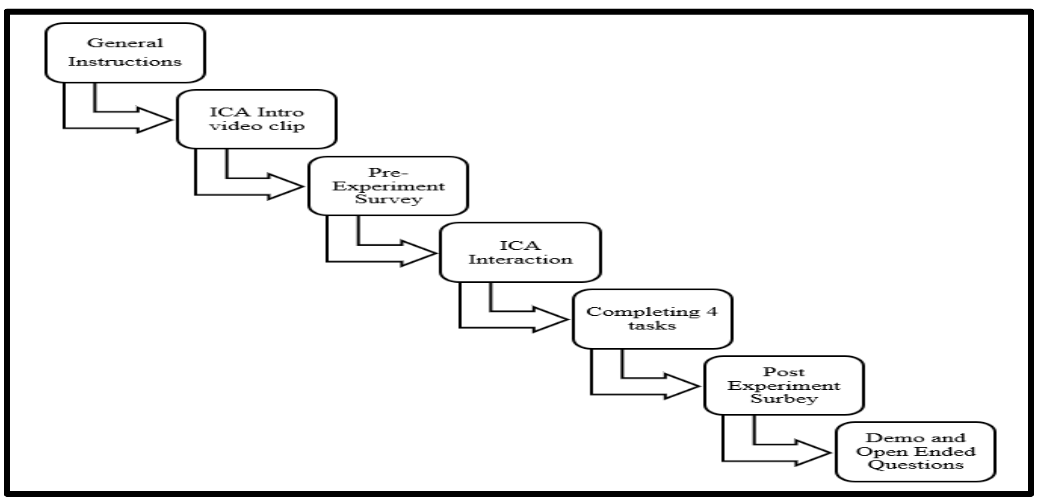

Figure 4.2: The different stages of participant engagement

The experiment settings provided participants with the pertinent information below before sharing a video clip.

1. A chatbot (ICA) is a computer program designed to simulate human conversation with human users, especially over the internet.
2. AI is the simulation of human intelligence in machines (robots, computer software) programmed to think and act like humans.
3. Participants were asked to interact with a chatbot of choice and then respond to the survey questions.
4. Participants briefly narrated the task to be performed with the selected chatbot.
5. The survey provided guiding instructions with specific instructions along with the question. Also, suggested help and explanations usually appeared beneath each specific question.

Participants were requested to watch a 2-minute clip on an ICA and then self-report their responses about their expectations. The video clip showed an ICA working as a help desk virtual assistant. The video demonstrated simple tasks that informed the participants about how ICAs can function and help end users. The video compared an ICA's work to a human agent's work.

The Pre-Experiment Survey required the participants to respond and record their initial attitudes about different ICA capabilities and trust in ICAs. In the Experiment Stage, the participants could interact with any of the five ICAs. If an ICA was unavailable due to maintenance or other related issues, the participants selected another ICA to complete the interaction.

The participants were required to interact with an ICA in English. The interaction gave the participant a transparent, more profound, and tangible experience. Participants were requested to present dialogues generated between the end-user and ICA during the interaction in their own words. Table 4.3 presents the specific experimental tasks, and Table 4.4 represents the choice for participants to select any of the five telecoms ICA.

Table 4.3: Tasks for ICA Interaction

Task	Task Description	Instructions	Examples
1	Asking Price Promotion (Deals)	Ask the ICA if any promotions are available or if the ICA can give you a good deal.	I am a Student/ Senior Citizen, and I am interested in knowing if you can provide me with the Student/ Senior Citizen discount.
2	Reporting and Dealing with Lost Phones (Stolen)	Ask the ICA if any procedures are available to guide a person to report a stolen or lost phone. E.g., if I lost my phone or somebody stole my phone, how can the agent help me solve this problem?	I lost my phone, or somebody stole my phone; how can the agent help me solve this problem?
3	Travelling Abroad and Asking for Service Coverage	Ask the ICA if it can provide roaming services on behalf of the telecom company.	I am travelling to the USA/ Europe/ China. Can I still use the same phone? Is the service available abroad? What is the setting or activation cost for this service?
4	Report Service Problem	Ask the ICA to provide reasons or solutions for service problems, such as static, weak, or poor signals.	I am facing service problems such as lost signals, internet connections, and the quality of voice calls.

Table 4.4: Context List of Telecom ICAs

SR #	Name	ICA	Website URL
1	Fido	ASKJACK	https://www.fido.ca/consumer/content/ask-jack
2	Freedom	Freedom	https://www.freedommobile.ca/en-CA/contact-us
3	Koodo	Koodo Assist	https://www.koodomobile.com/en/help/
4	Rogers	Anna	https://www.rogers.com/consumer/support/contactus
5	Telus	TELUS Assist	https://www.telus.com/en/on/support/article/contact-telus-technical-support OR TELUS Home Assistant on the Google Assistant | TELUS Support

After completing the interaction (task), the participants responded and recorded their attitudes experienced regarding different ICA capabilities and trust in ICAs. Finally, the participant filled out the response to demographic questions.

4.5. Chapter Summary

This chapter discussed the research study's methodology, including the experimental research design, questionnaire, population and sample size estimation, data collection, and data analysis. The items are derived from existing literature with slight modifications to assure the validity and reliability of the measurement model. The experiment required participants to interact with ICAs deployed on Canadian telecom companies' websites.

Chapter 5: Data Collection and Analysis

The preceding chapter outlined the techniques and methods utilized to collect and analyze the data for this investigation. This chapter describes the methods used and the outcomes of the analysis in depth. Section 5.1 offers the results of the pilot study. The preliminary data analysis is discussed in Section 5.2, while Section 5.3 expresses the measurement model's validation. Section 5.3 depicts the structural model analyses. Section 5.4 presents the qualitative feedback from the participants. Finally, Section 5.5 summarizes this chapter.

5.1. Pilot Study Results and Findings

After completing the initial scale development process, I conducted a pilot study to validate the instrument and then conducted a preliminary test of the proposed research model. I tested the model by testing the validity of a set of hypotheses in user attitudes towards ICA usage and intention to use contexts at an individual level of analysis. For my research study, I collected the data with the help of the research firm "Maru Blue." The participants were at least 18 years of age, could read and write English, and were from different geographical areas of Canada. All participants from these segments of society had to interact with an ICA to participate in the survey.

I decided on an online survey because of its advantages over traditional paper-based mail-in surveys: (1) the sample is not restricted to a specific geographical location so that large samples are possible, (2) costs are lower, and (3) faster responses are obtained (Bhattacharjee, 2001). The research firm successfully obtained a total of 100 complete usable responses. Before analysis, I examined all the variables through SPSS programs for data cleaning purposes. Similarly, I checked data entry accuracy, observed no missing values, and completed data screening, but I did remove 11 responses from our analysis due to straight-line responses. A straight-line response occurs when survey respondents provide identical (or nearly identical) responses to items in a battery of questions using the same response scale, which may lower the data quality. (Kim et al., 2019).

My study established preliminary consistency and reliability of reflective multi-item scales with Cronbach's alpha scores and examined Cronbach's alpha estimate for the formative construct. As formative measures examine different facets of the construct, internal consistency or reliability is unimportant. Research suggests that formative measures should not have strong correlations because excessive multicollinearity in the formative measures can destabilize the construct (Petter et al., 2007). I followed the Petter et al. (2007) guidelines; applied the VIF (variance inflation factor) statistic to determine if the formative measures were too highly correlated. The VIF values suggested that multicollinearity was a concern since all of the VIFs were more than 3.33 (Diamantopoulos and Siguaw,2006), except the constructs of PPC, PPF, PPRESP, and EXPTRESP. I decided to use the two-stage disjoint method, which led to VIF values of less than 3.3.

My study tested the construct validity (discriminant and convergent validity) with the Smart PLS 3 software (Hair et al., 2017; Cheah et al., 2018). My study observed that all the loadings of items were more significant than 0.40, and there should be no cross-loading of items above 0.40. My study assessed the reliability using the internal consistency approach by analyzing the composite reliability values. All variables demonstrated composite reliability with values higher than 0.7 (Wong, 2010). I decided that wherever the reliability of indicators (squares of outer loadings) was less than 0.7, but composite reliability and AVE for the variable are acceptable, then the indicators will be retained since they imply additional information (Wong, 2010; Wong, 2019; Sarstedt et al., 2019).

The measurement model of the PLS analysis provides indices for assessing convergent validity and discriminant validity of the scale. Fornell and Larcker (1981) recommend that convergent validity is contingent on meeting three criteria:

1. All item factor loadings should be significant and greater than 0.70.
2. The average variance extracted (AVE), that is, the amount of variance captured by a latent variable relative to the amount caused by measurement error, should be greater than .50 (or the square root of AVE > 0.707); and
3. The composite reliability index for each construct should be greater than .80.

Based on these criteria, my studies' PLS results indicate that our data set carries a satisfactory level of convergent validity. Furthermore, the square root of AVE was greater than 0.707 for each construct. The composite reliabilities of all reflective constructs also met the minimum criterion of 0.80. Since the measures of formative constructs are generally not highly correlated, typical factor analysis, which focuses on common variance and is the method used for determining construct validity with reflective constructs, is not viable for formative constructs (Rossiter,2002). The overall model fit was good.

The two-stage formative model approach appears to be more reliable and valid. I retained all items without modification, which retains content validity. The final study should avoid vague questions and vague items.

My pilot study was valuable because it satisfied the recommended guidelines for both measurement and structural models. My pilot study allowed me to reduce the final study model, and I decided not to consider the pre- and post-experiment attitude. Also, I decided not to measure the construct of confirmation. I decided to measure confirmation (CONF) as the difference between the constructs of Perceived Performance (PP) and Expectations (EXPT) for all the six ICA capabilities of Conversation ability (C), Friendliness (F), Intelligence (I), Responsiveness (RESP), Task Performance (TP) and Trust (TT). I also decided to modify and expand my research model by incorporating the Task Technology Fit theory.

5.2. Full-scale Data Collection and Reliability Analysis

My study initially examined valid responses, outliers, and missing values to determine the precision of the data used for data analysis. My study also examined the demographics and backgrounds of the participants.

5.2.1. Two-Stage Data Screening Process

The valid responses were categorized using a two-stage screening procedure. In the initial step, participants answered a context-related question. Then after the interaction, another question, the screening question "ICA" selection, was added to the survey's questionnaire. Participants were required to select a response (to a trap question) that reflected the degree to which they had paid attention to the survey questions. My study excluded participants' responses who did not match the two questions from the dataset of permissible responses. Responses were also vetted depending on the time respondents spent completing the survey. My study discarded the responses of those participants who completed the survey in less than fourteen (14) minutes. These "113" individuals had, coincidentally, selected the same or nearly identical response for each item question. The multivariate outliers stage eliminated these responses.

5.2.2. Common Method Bias

Common method variance (CMV) is a possible source of error in IS-associated behavioural research (Bagozzi, 2011). While there are numerous possible sources of CMV, method bias is a significant source of measurement error (Podsakoff et al., 2003). CMV ensues when data from exogenous and endogenous constructs are collected simultaneously from the same respondent (Podsakoff and Organ, 1986).

Researchers have found that Common Method Bias (CMB) can arise when CMV levels are too high. To further reduce the likelihood of CMB, the questionnaire's design included a variation in the scale points and anchor labels for scales across constructs (Podsakoff et al., 2012). As a causal factor, CMV biases result when the method meaningfully distorts substantively driven causal effects (Fuller et al., 2016). While these measures may not entirely protect the study from CMV, they will significantly decrease the likelihood of a significant CMB effect on the results (Straub et al., 2004). Also, CMV is just one of the many causes of inaccuracy that potentially lead to attenuated trustworthiness of reported results (Tehseen et al., 2017).

My study is in line with commonly accepted researchers' point of view that the threshold of less than 50% of the variance shows that there is no problem with common method bias in the dataset (Podsakoff and Organ 1986; Eichhorn 2014; Fuller et al., 2016; Hew et al. 2018; Leong et al. 2020). According to Harman's approach, if the value of a single construct is higher than 50% of the variance, then CMB exists in the data (Harman, 1976). Our results indicated that the percent of the variance of a single construct was 44.175%, below 50% of the variance, indicating there is no CMB.

5.2.3. Outliers

A Mahalanobis distance analysis was applied to observe multivariate outliers. The Mahalanobis distance is "the multivariate 'distance' between each case and the multivariate mean (also known as the centroid) of the group" (Meyers et al. 2006). Meyers et al. (2006) explain that Mahalanobis distance uses the chi-square distribution (alpha = 0.001) to evaluate each case. If a case meets this criterion, it should be deemed an outlier for several variables.

Because of this evaluation, my study detected 2 multivariate outliers and deleted them from the dataset. Thus, 380 suitable cases remained in the collection of acceptable responses. The final step of the data screening procedure was locating missing values in the dataset. The evaluation revealed no missing values in the final dataset of approved responses.

5.2.4. Demographic Analysis

Age: Demographic analyses revealed that respondents represented various age groups. Less than 20 years (n=2, 0.53%), between 21 and 40 (n=182, 47.89 %), between 41 and 60 (n=153, 40.26%), and 61 and older (n=43, 11.32 %).

Gender: Respondents identified themselves as Females (n = 177, 46.6%), Males (n = 202, 53.2%), and one individual did not answer (n=1, 0.21 %).

Education: Response revealed High school education (n=57, 15.00%), college graduates (n=233, 61.32%), postgraduate degree (n=85, 22.36%), and no answer (n=5, 1.32%).

Language Proficiency: Participants identified themselves as Native English speakers (n=309, 81.32%), non-native English speakers (n=68, 17.89%) and no answer (n=3, 0.79 % percent).

Occupation: A thorough inquiry elicited and elaborated on the respondents' occupations. The data revealed that most respondents (n = 216, 56.84%) were employed full-time, with the remainder working part-time for a few hours each week (n = 164, 43.16%).

5.3. Validation of the Measurement Model

In order to validate the research model, my study verified the measurement model. In this respect, my study assesses each construct's construct validity and reliability in the proposed study model. In this study, there were two distinct construct types: reflective and second-order formative, with reliability and validity tests varying by construct type. This chapter includes detailed analyses of the reliability and validity of this study's many types of constructs. My study first evaluates the Measurement Model.

PLS-SEM was used to validate both the pilot and final study models. One of the advantages of using SEM is that this causal modelling technique combines measurement and structural models. The measurement model provides an opportunity to conduct, i.e., confirmatory factor analysis and simultaneously test hypothesized relationships between constructs of interest (Meyers et al., 2006). Since my research study is exploratory, I chose PLS-SEM over other SEM techniques (Chin et al., 2020; Gefen et al., 2000). The SEM technique makes no normal distributional data assumptions and is thus suitable for non-normalized data (Chin et al., 2020; Venkatesh and Agarwal, 2006).

SmartPLS version 3.3.9 was used for data analysis and model validation, evaluated in two stages: the measurement evaluation and the structural evaluation, represented by Tables 5.1 and 5.2 that follow. Table 5.1 shows the tests used to evaluate the research model's reflective constructs.

Table 5.1 Measurement Model

Summary of Test-Measurement Model		
Analysis	**Test**	**Note**
Reliability of Measurement Instruments	Cronbach's Alpha	**Acceptance criterion:** Value > 0.70 (Nunnally and Bernstein, 1994)
	Composite Reliability	**Acceptance criterion:** Value > 0.60 (Bagozzi and Yi, 1988)
Convergent and Discriminant Validity	Item Cross-Loading	**Acceptance criterion:** The loading on the corresponding construct (i.e., theoretical construct) should be larger than the loading on other constructs by at least 0.10 (Chin, 2010; Gefen and Straub, 2005)
	Fornell-Larcker Criterion (1981)	**Acceptance criterion:** The square root of the Average Variance Extracted (AVE) of a construct must be larger than the correlation between that construct and any other construct in the model (Barclay et al., 1995)
Multicollinearity	Bivariate Correlations	**Acceptance criteria:** Bivariate correlations greater than 0.8 can indicate traces of multicollinearity (Meyers et al. 2006)
	VIF	**Acceptance criteria:** Variance Inflation Factors (VIFs) greater than 3.3 may indicate potential multicollinearity issues (Petter et al., 2007)

Since my research model is a reflective formative model, the measurement model evaluated the reliability and validity of lower-order reflective constructs and higher-order formative constructs (Chin, 2010). My research study used Hair et al. (2017) guidelines for Smart PLS-based IS research studies. It validates the measurement model's formative constructs using SmartPLS's bootstrapping technique to determine the significance of each indicator's weight (relative importance) and loading (absolute importance). My research follows a complete bootstrap with a minimum bootstrap sample size of five thousand iterations. The bootstrapping step is in line with the fact that the number of cases should equal the initial sample's total number of cases. For the analysis of the significance of the indicators for the dataset, the study uses critical t-values for a two-tailed test of 1.65 (significance level: 10%), 1.96 (significance level: 5%), and 2.58 (significance level: 1%) respectively. My study follows the guideline that if the weight and loadings are insignificant, remove the indicator unless the theoretical support warrants its retention; otherwise justified for inclusion. Tests for multicollinearity formative and reflective constructs were performed similarly (Hair et al., 2021). The formative constructs that determine the degree of correlation between the formative measurements were also validated. My research measured Variance Inflation Factor (VIF) statistics as per the guidelines of Petter et al. (2007). Table 5.2 presents the structural model criteria.

Table 5.2 Structural Model

Summary of Test-Measurement Model		
Analysis	**Calculation**	**Note**
Path Coefficients Significance	Obtained from SmartPLS	A bootstrap approach was employed to evaluate the significance of path coefficients (Chin 1998)
R^2 for Endogenous Variables	Obtained from SmartPLS	Although no specific acceptable threshold value for R^2 exists, a sufficiently high R2 value is preferred. Adequate explanatory power is sought-after (Gefen et al., 2000; Urbach and Ahlemann, 2010)
Effect Sizes	Obtained from SmartPLS	The magnitude of the effect sizes of each path used the following values: $f2$ small (.02), $f2$ medium (.15), and $f2$ large (.35) (Chin, 2010)
Goodness of Fit (GoF) index: GOF index=	GoF = $\sqrt{\overline{\text{communality}} \times \overline{R2}}$	Absolute GoF can be used to assess the PLS model regarding overall (both measurement and structural levels) prediction performance The suggested baseline values of GoF_{small} (.10), GoF_{medium} (.25), and GoF_{large} (.36) evaluated the fit of the model (Tenenhaus et al., 2005; Wetzels et al., 2009)

A series of post-hoc analyses determined the effects of the study's control variables, including demographic variables, context, PAIE (Previous AI Experience – see Table 4.1 Section 14g) and CRME (Customer Relationship Management Experience – see Table 4.1 Section 14h). This Chapter discusses and presents all the pertinent analyses. My study ran the PLS Algorithm to test the measurement model for convergent validity. My study presents the Factor Loadings (F.L) for each Reflective Construct (R.C) at the pre-experiment stage (Expectations), experiment and post-experiment stage (Perceived Performance). My study provides a comprehensive overview of the procedures used to validate the measurement model for the reflective constructs in the proposed research model.

5.3.1.1. Reliability Analysis

Reliability refers to the degree to which the items on the measurement scale consistently measure the variable (Straub et al. 2004). Cronbach's alpha (Cronbach, 1951) and composite reliability are two methodologies suggested in the current literature for testing the reliability of a measurement scale. Table 5.3 below shows the factor loadings for all the reflective constructs at the different stages.

Table 5.3: Factor Loadings of the Reflective Constructs

PRE-EXPERIMENT	
R.C	F. L
EXPTC1	0.890
EXPTC2	0.920
EXPTC3	0.885
EXPTF1	0.845
EXPTF2	0.874
EXPTF3	0.862
EXPTI1	0.871
EXPTI2	0.913
EXPTI3	0.920
EXPTI4	0.862
EXPTRESP1	0.909
EXPTRESP2	0.930
EXPTRESP3	0.931
EXPTTT1	0.885
EXPTTT2	0.866
EXPTE3	0.907
EXPTTT4	0.870
EXPTP1	0.837
EXPTP2	0.923
EXPTP3	0.887
EXPTP4	0.857

POST-EXPERIMENT	
R.C	F. L
PPCON1	0.871
PPCON2	0.905
PPCON3	0.858
PPCON4	0.850
PPCON5	0.914
PPFR1	0.824
PPFR2	0.887
PPFR3	0.888
PPFR4	0.700
PPFR5	0.622
PPINT1	0.866
PPINT2	0.902
PPINT3	0.885
PPINT4	0.853
PPINT5	0.848
PPINT6	0.701
PPINT7	0.846
PPRESP1	0.920
PPRESP2	0.943
PPRESP3	0.925
PPTT1	0.861
PPTT2	0.805
PPTT3	0.863
PPTT4	0.846

POST-EXPERIMENT	
R.C	F. L
CONFC1	0.886
CONFC2	0.911
CONFC3	0.878
CONFF1	0.769
CONFF2	0.800
CONFF3	0.827
CONFI1	0.861
CONFI2	0.899
CONFI3	0.876
CONFI4	0.847
CONFRESP1	0.884
CONFRESP2	0.888
CONFRESP3	0.882
CONFTT1	0.806
CONFTT2	0.796
CONFTT3	0.848
CONFTT4	0.822
CONFTP1	0.832
CONFTP2	0.829
CONFTP3	0.863
CONFTP4	0.739
BI1	0.965
BI2	0.953
BI3	0.953
SATF1	0.858
SATF2	0.863
SATF3	0.694

PPTT5	0.768
PPTT6	0.831
PPTP1	0.890
PPTP2	0.867
PPTP3	0.935
PPTP4	0.887

SATF4	0.881
SATF5	0.763
SATF6	0.908
SATF7	0.804
FFA1	0.790
FFA2	0.946
FFA3	0.949
FFC1	0.847
FFC2	0.935
FFC3	0.943
FFT1	0.913
FFT2	0.930
FFT3	0.911
POAF1	0.951
POAF2	0.954
POAF3	0.961

The results indicate that the sixty-four reflective indicators have outer loadings greater than the threshold value of 0.70 (Hulland, 1999; Nunnally, 1978; Nunnally and Bernstein, 1994). My study removed reflective constructs, which indicated cross-loadings having considerable loadings on the construct other than the parent construct. It negatively impacted the Discriminant Validity (Hair et al., 2011) and amplified structural analysis results. My study, therefore, dropped the constructs of EXPTC3, EXPTI3, PPC2, PPC3, PPI2, PPI3, PPI6, PPI7, PPTP5, PPTP6, PPTTT2, PPTTT6, PPTTT7 and SATF1 from the data analysis.

Cronbach's alpha (ɑ) and composite reliability assess the internal consistency of a measurement scale's items (Raykov, 1997). Current research indicates that the lowest acceptable range for "ɑ" is more than 0.7 (Kline 2000; Nunnally 1978). Moreover, composite reliability exceeding 0.6 is acceptable (Bagozzi and Yi 1988). Table 5.3 shows that all item loadings exceeded the recommended value of 0.6 (Chin et al.2008). My study assesses this measurement through factor loadings, composite reliability, and average variance extracted (AVE).

5.3.1.2. Convergent Validity for Reflective Constructs

My study assessed convergent validity by determining how each measure correlates positively with alternative construct measures. This validity is valuable for establishing the strength of the relationship between two specific measures and the validity of the construct's measurement (Anderson and Garbing, 1988; Fornell and Larcker, 1981).

5.3.1.3. Statistical Significance

The second test confirmed each indicator's statistical significance (Fornell and Larcker, 1981; Henseler et al., 2016). For this study, each indicator was statistically significant at $p<0.001$.

5.3.1.4. Average Variance Extracted (AVE)

The third test was the extracted average variance (AVE) (Fornell and Larcker, 1981; Henseler et al., 2016; Mallin and Munoz, 2013). Each of the constructs had an AVE score of at least.50 (Bagozzi and Yi, 1988; Hair et al., 2012), Given the acceptable composite reliability of these variables, it is appropriate to include them in the study (Gaskin, 2017).

Based on these three tests, my study determined that each reflective first-order construct had adequate convergent validity for this study. My study defined convergent validity as the degree to which a measure (indicator) correlates positively with other measures of the same construct (Hair et al., 2017). Because different indicators reflect the same reflective construct, they should converge so that each indicator correlates with its theoretically defined reflective construct (Gefen and Straub, 2005). These researchers indicate that the outer factor loadings (indicator reliability) and the average variance extracted (AVE) should establish convergent validity. AVE estimation is meaningless for single-item constructs (Hair et al., 2017). AVE values greater than 0.5 indicate sufficient convergent validity for multi-item reflective constructs.

As illustrated in Table 5.4, all of the reflective constructs in the study model met the criteria for AVE and factor loadings were above the recommended levels (Table 5.3), thus establishing the convergent validity for the reflective construct measures.

My research uses Cronbach's alpha (α) and composite reliability (CR) to examine the constructs' reliability (CR). The Cronbach’s alpha values for the constructs were higher than the 0.7 thresholds; similarly, the CR values for all the constructs were higher than 0.7 (Wasko and Faraj,2005). This guideline is in line with the fact that researchers feel that composite reliability is a reliable measure instead of Cronbach Alpha. Convergent validity was acceptable because the average variance extracted (AVE) was over 0.5. The results for reliability and validity, along with Mean and Standard Deviation (SD) values, are presented in Table 5.4. Composite Reliability (CR) values, which depict the degree to which the construct indicators indicate the latent construct, exceeded the recommended value of 0.7, while Average Variance Extracted (AVE), which reflects the overall amount of variance in the indicators, accounted for by the latent construct, exceeded the recommended value of 0.5 (Hair et al., 2013). Due to certain time constraints, the end-user may not have clearly understood specific item questions, leading to inconsistent self-reported responses. Table 5.4 shows the Mean, Standard Deviation (SD); Cronbach’s alpha (α); Composite reliability (C.R); Average variance extracted (AVE) values.

Table 5.4: α, CR and AVE Values

ITEMS	MEAN	SD	α	AVE	C.R	SQRT (AVE)
BI	4.787	0.091	0.960	0.926	0.974	0.962
CONF	-0.317	0.142	0.963	0.576	0.966	0.759
CONFC	-0.416	0.046	0.902	0.837	0.939	0.915
CONFF	-0.133	0.188	0.801	0.715	0.883	0.846
CONFI	-0.422	0.046	0.917	0.802	0.942	0.896
CONFRESP	-0.065	0.007	0.916	0.856	0.947	0.925
CONFTP	-0.366	0.467	0.870	0.721	0.912	0.849
CONFTT	-0.213	0.037	0.896	0.762	0.928	0.873

EXPTC	5.238	0.261	0.900	0.833	0.937	0.913
EXPT	5.320	0.249	0.972	0.647	0.975	0.804
EXPTF	5.416	0.286	0.862	0.783	0.916	0.885
EXPTI	5.007	0.304	0.928	0.822	0.949	0.907
EXPTRESP	5.873	0.041	0.936	0.887	0.959	0.942
EXPTTP	5.161	0.391	0.916	0.799	0.941	0.894
EXPTTT	5.550	0.099	0.928	0.822	0.949	0.907
FFA	5.460	0.197	0.903	0.839	0.940	0.916
FFC	5.080	0.119	0.912	0.851	0.945	0.922
FFT	5.902	0.029	0.941	0.894	0.962	0.946
PP	5.040	0.233	0.980	0.981	0.650	0.990
POAF	5.062	0.050	0.960	0.974	0.927	0.987
PPC	4.888	0.235	0.947	0.960	0.827	0.980
PPF	5.369	0.273	0.895	0.928	0.764	0.963
PPI	4.670	0.346	0.951	0.960	0.774	0.980
PPRESP	5.808	0.035	0.953	0.970	0.914	0.985
PPTP	4.795	0.314	0.938	0.956	0.843	0.978
PPTT	5.214	0.272	0.928	0.946	0.778	0.973
SATF	4.640	0.347	0.942	0.953	0.745	0.976

Discriminant Validity for Reflective Constructs: Reflective constructs should display discriminant validity. Discriminant validity contributes to construct validation by demonstrating the measure's empirical uniqueness. It determines whether all indicators about a latent variable are distinct from indicators of other latent variables (Hair et al., 2010).

The degree to which a construct is genuinely distinct from the other constructs in the model is discriminant validity (Chin, 2010). My study used three criteria to determine discriminant validity: cross-loadings, the Fornell-Larcker criterion, and the Heterotrait-Monotrait correlations (Hair et al., 2017; Tehseen et al., 2017). The Fornell Larcker criterion assessed discriminant validity, and the table shows that the square root of AVE for the construct was greater than the inter-construct correlation. Hence Discriminant Validity is established with the help of the Fornell Larcker Criterion, as illustrated in Table 5.6.

Cross-loadings: The outer loading of an indicator on the associated construct should be greater than any of its cross-loadings on another construct in the cross-loading approach (Hair et al., 2017). I summarize and present the cross-loadings of the indicators on the constructs in Table 5.6. The reported correlation coefficients indicate that the items were highly correlated within their theoretical construct and poorly loaded on the other constructs. The Fornell-Larcker criterion discriminant validity was not an issue in this study, as shown in Table 5.6. I examined the outer indicator loading to determine whether there were any significant cross-loadings onto other constructs (Chin, 1998; Grégoire and Fisher, 2006; Henseler et al., 2016). This study established that significant cross-loadings exist. Due to the higher number of reflective constructs, my study divides the actual cross-loading table and presents it in two tables.

Table 5.5: Cross Loadings

	BI	CONFC	CONFF	CONFI	CONFRESP	CONFTP	CONFTT
BI1	**0.965**	0.337	0.115	0.309	0.138	0.344	0.256
BI2	**0.953**	0.322	0.126	0.267	0.141	0.355	0.252
BI3	**0.954**	0.301	0.143	0.307	0.140	0.331	0.217
CONFC1	0.301	**0.896**	0.404	0.645	0.407	0.665	0.528
CONFC2	0.308	**0.912**	0.451	0.684	0.381	0.641	0.558
CONFC3	0.286	**0.866**	0.450	0.690	0.346	0.643	0.453
CONFF1	0.066	0.393	**0.769**	0.442	0.263	0.363	0.379
CONFF2	0.008	0.329	**0.800**	0.326	0.309	0.269	0.401
CONFF3	0.236	0.439	**0.826**	0.455	0.397	0.379	0.470
CONFI1	0.246	0.648	0.436	**0.870**	0.405	0.650	0.533
CONFI2	0.272	0.686	0.448	**0.900**	0.430	0.696	0.527
CONFI3	0.288	0.641	0.454	**0.867**	0.385	0.633	0.582
CONFI4	0.270	0.644	0.446	**0.846**	0.382	0.695	0.541
CONFRESP1	0.183	0.435	0.338	0.456	**0.884**	0.467	0.517
CONFRESP2	0.073	0.332	0.340	0.351	**0.888**	0.419	0.478
CONFRESP3	0.132	0.362	0.401	0.415	**0.882**	0.451	0.506
CONFTP1	0.327	0.630	0.367	0.620	0.434	**0.831**	0.566
CONFTP2	0.358	0.616	0.343	0.654	0.404	**0.829**	0.497
CONFTP3	0.290	0.614	0.324	0.667	0.422	**0.863**	0.476
CONFTP4	0.179	0.510	0.353	0.565	0.385	**0.739**	0.597
CONFTT1	0.243	0.575	0.433	0.591	0.452	0.575	**0.810**
CONFTT2	0.127	0.410	0.407	0.432	0.503	0.471	**0.785**
CONFTT3	0.222	0.442	0.430	0.525	0.462	0.541	**0.851**
CONFTT4	0.225	0.458	0.440	0.488	0.441	0.526	**0.825**

	FFA	FFC	FFT	POAF
FFA1	**0.790**	0.533	0.654	0.547
FFA2	**0.946**	0.664	0.486	0.763
FFA3	**0.949**	0.676	0.507	0.783
FFC1	0.569	**0.847**	0.413	0.648
FFC2	0.669	**0.935**	0.380	0.771
FFC3	0.665	**0.943**	0.352	0.783
FFT1	0.558	0.384	**0.913**	0.378
FFT2	0.509	0.350	**0.930**	0.333
FFT3	0.560	0.403	**0.911**	0.440
POAF1	0.743	0.759	0.422	**0.951**
POAF2	0.742	0.780	0.367	**0.954**
POAF3	0.774	0.784	0.427	**0.961**

	EXPTC	EXPTF	EXPTI	EXPTRESP	EXPTP	EXPTT
EXPTC1	**0.935**	0.646	0.671	0.564	0.661	0.595
EXPTC2	**0.937**	0.661	0.713	0.507	0.682	0.595
EXPTF1	0.655	**0.845**	0.669	0.408	0.635	0.577
EXPTF2	0.558	**0.874**	0.568	0.485	0.530	0.592
EXPTF3	0.590	**0.862**	0.576	0.635	0.510	0.625
EXPTI1	0.644	0.646	**0.927**	0.497	0.741	0.629
EXPTI2	0.726	0.654	**0.924**	0.552	0.772	0.684
EXPTRESP1	0.572	0.543	0.592	**0.909**	0.587	0.641
EXPTRESP2	0.531	0.550	0.490	**0.930**	0.509	0.600
EXPTRESP3	0.483	0.539	0.487	**0.931**	0.485	0.593
EXPTTP1	0.655	0.574	0.664	0.594	**0.836**	0.695
EXPTTP2	0.655	0.567	0.760	0.515	**0.923**	0.676
EXPTTP3	0.652	0.640	0.727	0.583	**0.887**	0.715
EXPTTP4	0.558	0.498	0.710	0.320	**0.858**	0.587
EXPTT1	0.586	0.623	0.661	0.561	0.717	**0.886**
EXPTT2	0.553	0.585	0.601	0.652	0.642	**0.864**
EXPTT3	0.538	0.606	0.594	0.623	0.636	**0.907**
EXPTT4	0.565	0.632	0.642	0.509	0.685	**0.871**

	PPC	PPF	PPI	PPRESP	PPTP	PPTT	SATF
PPC1	**0.904**	0.521	0.637	0.424	0.723	0.598	0.616
PPC4	**0.876**	0.636	0.654	0.401	0.652	0.630	0.641
PPC5	**0.930**	0.606	0.737	0.420	0.760	0.657	0.705
PPF1	0.518	**0.824**	0.539	0.303	0.451	0.515	0.541
PPF2	0.460	**0.887**	0.339	0.482	0.370	0.580	0.478
PPF3	0.610	**0.888**	0.440	0.523	0.518	0.704	0.552
PPF4	0.608	**0.700**	0.734	0.223	0.624	0.565	0.698
PPF5	0.365	**0.622**	0.191	0.462	0.219	0.468	0.293
PPI1	0.703	0.537	**0.895**	0.262	0.740	0.624	0.701
PPI4	0.666	0.486	**0.907**	0.203	0.770	0.557	0.776
PPI5	0.643	0.483	**0.900**	0.253	0.741	0.542	0.726
PPRESP1	0.503	0.461	0.318	**0.920**	0.468	0.604	0.444
PPRESP2	0.371	0.462	0.200	**0.943**	0.356	0.538	0.369
PPRESP3	0.408	0.487	0.225	**0.925**	0.345	0.525	0.381
PPTP1	0.710	0.488	0.682	0.463	**0.890**	0.679	0.671
PPTP2	0.656	0.482	0.829	0.272	**0.868**	0.573	0.771
PPTP3	0.744	0.503	0.771	0.377	**0.935**	0.637	0.726
PPTP4	0.719	0.499	0.702	0.389	**0.887**	0.662	0.660
PPTT1	0.659	0.630	0.644	0.497	0.698	**0.894**	0.681
PPTT3	0.631	0.667	0.491	0.585	0.592	**0.885**	0.603
PPTT4	0.549	0.603	0.565	0.503	0.599	**0.874**	0.654
SATF2	0.670	0.532	0.797	0.280	0.735	0.575	**0.856**
SATF3	0.466	0.633	0.451	0.439	0.443	0.596	**0.714**
SATF4	0.664	0.534	0.808	0.308	0.770	0.589	**0.882**
SATF5	0.490	0.493	0.538	0.418	0.519	0.610	**0.784**
SATF6	0.690	0.503	0.789	0.340	0.789	0.629	**0.901**
SATF7	0.569	0.549	0.595	0.395	0.601	0.655	**0.824**

I dropped factors loading highly on other constructs and their parent constructs. After removing these factors, I carried out the Fornell-Larcker test, and my measurement model met the Fornell-Larcker criterion. Once satisfied, cross-loading and the Fornell-Larcker criterion helped establish both Convergent and Discriminant Validity for the measurement model.

Fornell-Larcker criterion: The second approach to examining discriminant validity is the Fornell-Larcker criterion, which is considered a more conservative approach (Hair et al., 2017). Table 5.6 presents the Fornell-Larcker (1981) criterion results for this study.

Table 5.6: Fornell Larcker Matrix

	BI	CONF_CO	CONF_FRI	CONF_INT	CONF_RES	CONF_TP	CONF_TRU	EXPFRIE	EXPRESP	EXPTASKP	EXPTINT	EXPTRUST	EXPT_CONV	FFA	FFC	FFT	POAF	PPCONV	PPFRIE	PPINT	PPRESP	PPTASKPE	PPTRUST	SATF
BI	**0.963**																							
CONF_CONV	0.375	**0.915**																						
CONF_FRIE	0.212	0.624	**0.846**																					
CONF_INT	0.344	0.806	0.636	**0.895**																				
CONF_RESP	0.204	0.558	0.588	0.574	**0.925**																			
CONF_TP	0.391	0.787	0.582	0.820	0.620	**0.849**																		
CONF_TRUST	0.290	0.691	0.676	0.716	0.678	0.744	**0.873**																	
EXPFRIE	0.384	-0.290	-0.423	-0.315	-0.249	-0.249	-0.313	**0.885**																
EXPRESP	0.258	-0.287	-0.242	-0.351	-0.437	-0.323	-0.333	0.668	**0.942**															
EXPTASKPERF	0.427	-0.283	-0.266	-0.340	-0.311	-0.409	-0.375	0.711	0.641	**0.894**														
EXPTINT	0.411	-0.302	-0.291	-0.455	-0.306	-0.319	-0.350	0.752	0.634	0.846	**0.939**													
EXPTRUST	0.388	-0.231	-0.217	-0.288	-0.266	-0.292	-0.461	0.757	0.736	0.801	0.761	**0.907**												
EXPT_CONV	0.328	-0.480	-0.300	-0.368	-0.297	-0.334	-0.349	0.759	0.652	0.761	0.782	0.706	**0.947**											
FFA	0.700	0.368	0.328	0.351	0.268	0.381	0.358	0.378	0.383	0.363	0.340	0.422	0.321	**0.916**										
FFC	0.721	0.447	0.301	0.426	0.252	0.451	0.335	0.360	0.292	0.385	0.370	0.400	0.307	0.752	**0.922**									
FFT	0.430	0.225	0.287	0.153	0.302	0.208	0.261	0.346	0.509	0.248	0.257	0.411	0.258	0.697	0.545	**0.945**								
POAF	0.816	0.440	0.301	0.424	0.277	0.465	0.340	0.366	0.262	0.438	0.401	0.426	0.320	0.825	0.847	0.550	**0.963**							
PPCONV	0.673	0.582	0.408	0.522	0.365	0.534	0.439	0.375	0.263	0.380	0.371	0.380	0.356	0.678	0.755	0.481	0.751	**0.930**						
PPFRIE	0.577	0.380	0.586	0.375	0.363	0.367	0.392	0.468	0.355	0.382	0.390	0.465	0.382	0.662	0.632	0.592	0.644	0.758	**0.843**					
PPINT	0.722	0.519	0.359	0.565	0.294	0.536	0.386	0.338	0.170	0.441	0.413	0.372	0.301	0.614	0.730	0.326	0.782	0.822	0.690	**0.902**				
PPRESP	0.431	0.288	0.359	0.246	0.587	0.317	0.366	0.357	0.471	0.271	0.270	0.401	0.295	0.608	0.509	0.754	0.507	0.593	0.675	0.441	**0.956**			
PPTASKPERF	0.744	0.546	0.359	0.532	0.361	0.656	0.435	0.346	0.220	0.420	0.383	0.376	0.303	0.688	0.771	0.425	0.826	0.849	0.685	0.893	0.550	**0.918**		
PPTRUST	0.705	0.488	0.436	0.461	0.408	0.491	0.520	0.413	0.348	0.427	0.406	0.500	0.347	0.761	0.750	0.607	0.796	0.833	0.813	0.797	0.713	0.848	**0.877**	
SATF	0.778	0.407	0.288	0.398	0.254	0.423	0.294	0.411	0.262	0.465	0.441	0.464	0.353	0.695	0.754	0.463	0.833	0.746	0.677	0.824	0.484	0.801	0.787	**0.865**

Fornell-Larcker criteria showing discriminant validity results for this study were established and matched by observing the square root of the first-order reflective construct's AVE on the diagonal. The square root of AVE is also available in the last column of Table 5.4. This method establishes discriminant validity by examining if the square root of each latent variable's AVE is larger than the latent variable correlations. The cross-loading report and the construct correlation matrix provided evidence supporting our reflective constructs. The square root of the AVE measured the discriminant validity (Fornell and Larcker, 1981).

Heterotrait-Monotrait ratio (HTMT): My study also examined the Heterotrait-Monotrait ratio (HTMT) correlations to confirm further the discriminant validity of the constructs used in this study. Table 5.7 summarizes my study's HTMT results.

Table 5.7: Heterotrait Monotrait Test

	BI	CONFIRM	EXPECT	FFA	FFC	FFT	PERC_ PERF	POAF
BI								
EXPECT	0.439	0.447						
FFA	0.745	0.423	0.448					
FFC	0.768	0.460	0.428	0.826				
FFT	0.451	0.289	0.383	0.769	0.590			
PP	0.756	0.602	0.486	0.804	0.830	0.608		
POAF	0.850	0.457	0.447	0.879	0.903	0.576	0.845	
SATF	0.840	0.447	0.484	0.771	0.839	0.505	0.875	0.897

HTMT is a relatively new criterion and is the most conservative test available for determining discriminant validity (Hair et al., 2017). The HTMT technique determines the accurate correlation between two reliable latent variables, with a value greater than 0.9 indicating a lack of discriminant validity (Henseler et al., 2015). The context of the ICA is unique, and the identified six ICA capabilities engendered responses from the participants that showed an overlap among the constructs of Intelligence, Conversation ability, and Task Performance. Researchers have used Social Intelligence to describe this overlap (Chaves and Gerosa, 2021). The participants could also distinguish the other three capabilities of Friendliness, Responsiveness and Trust. The three tests validated the measurement model. Table 5.8 summarizes the three relevant tests.

Table 5.8: Summary of Measurement Model Test Results

TEST	FINDINGS	RESULT
Cross Loadings	Items are highly correlated with their own theoretical construct and poorly correlated with the other constructs.	Cross-loadings established discriminant validity.
Fornell Larcker	The latent variable's AVE is larger than the latent variable correlations	Fornell Larcker criterion establishes discriminant validity.
Heterotrait Monotrait	HTMT should be less than 0.900	HTMT establishes discriminant validity.

The previous discussion on VIF completes our reporting for Lower Order Constructs (LOC); I now focus on reporting Higher-Order Constructs (HOC).

Higher-Order Constructs (HOC) Formative Measurement Model Assessment

The exogenous variable in this study is a reflective-formative second-order construct, "Expectations." Similarly, my study has two endogenous variables of "Perceived Performance (Experience)" and "Confirmation" as reflective-formative second-order constructs. Hair et al. (2017) propose that the researcher analyze formative measurements for models involving formative constructs after securing the reliability and validity of the reflective constructs. Researchers have also recommended that internal consistency is inconsequential for formative constructs, as these are multidimensional constructs with indicators or dimensions that do not generally co-vary (Chin 2010; Hair et al. 2017).

The process for evaluating the measurement quality of a second-order model is identical to that used to evaluate the measurement quality of first-order factors (Amaro and Duarte, 2016). Since the interactive use of an ICA is a second-order reflective-formative construct, the formative assessment of this construct occurs during the second stage by calculating the Lower Order Constructs (LOCs) latent scores and using them as manifest variables for the Higher-Order Construct (HOC). To this end, I analyzed the relationships between these latent LOCs and the HOC (Becker et al., 2012).

I followed the guidelines Chin (2010) provided for quality criteria, so the first-order constructs served as indicators (represented by the latent variable score calculated from the initial stage) for the second-order reflective-formative construct. Table 5.9 presents the formative constructs.

Table 5.9: Outer weights of Formative Constructs

OUTER WEIGHT					
HOC	**LOC -> HOC**	**Weights**	**T Values**	**P Values**	**DECISION**
CONFM	CONFC -> CONF	0.026	0.413	0.679	Insignificant
	CONFF -> CONF	0.189	2.045	0.041	Significant
	CONFI -> CONF	0.157	2.454	0.014	Significant
	CONFRESP -> CONF	-0.265	2.549	0.011	Significant
	CONFTP -> CONF	0.733	6.666	0.000	Significant
	CONFTT -> CONF	0.197	1.725	0.085	Significant
EXPT	EXPTF-> EXPT	0.265	2.454	0.014	Significant
	EXPTRESP -> EXPT	-0.343	2.682	0.007	Significant
	EXPTTP -> EXPT	0.612	4.639	0.000	Significant
	EXPTI -> EXPT	0.124	1.464	0.143	Insignificant
	EXPTTT -> EXPT	0.369	2.698	0.007	Significant
	EXPTC -> EXPT	-0.052	0.577	0.564	Insignificant
PP	PPC -> PP	0.030	0.582	0.561	Insignificant
	PPF -> PP	0.206	2.024	0.043	Significant
	PPI -> PP	0.077	1.568	0.117	Insignificant
	PPRESP -> PP	-0.264	2.911	0.004	Significant
	PPTP -> PP	0.716	5.098	0.000	Significant
	PPTTT -> PP	0.210	1.627	0.104	Insignificant

My study then considered the outer loadings to decide which insignificant LOC loadings are ignorable. The rule suggests that if the insignificant outer weights have a significant outer loading, the LOC can be retained and used in the analysis. Table 5.10 presents the Outer Loadings of Formative Constructs.

Table 5.10: Outer Loadings of Formative Constructs

OUTER LOADINGS					
HOC	**LOC -> HOC**	**Loading**	**T Values**	**P Values**	**DECISION**
CONF	CONFC -> CONF	0.771	25.550	0.000	Significant
	CONFF -> CONF	0.588	7.603	0.000	Significant
	CONFI -> CONF	0.837	33.366	0.000	Significant
	CONFRESP -> CONF	0.377	5.303	0.000	Significant
	CONFTP -> CONF	0.946	28.598	0.000	Significant
	CONFTT -> CONF	0.734	12.750	0.000	Significant
EXPT	EXPTF -> EXPT	0.766	14.571	0.000	Significant
	EXPTRESP -> EXPT	0.448	5.335	0.000	Significant
	EXPTTP -> EXPT	0.933	29.398	0.000	Significant
	EXPTI -> EXPT	0.840	22.832	0.000	Significant
	EXPTTT -> EXPT	0.846	16.757	0.000	Significant
	EXPTC -> EXPT	0.703	13.331	0.000	Significant
PP	PPCONV -> PP	0.811	24.986	0.000	Significant
	PPFRIE -> PP	0.681	7.368	0.000	Significant
	PPINT -> PP	0.876	37.300	0.000	Significant
	PPRESP -> PP	0.302	2.914	0.004	Significant
	PPTP -> PP	0.956	33.955	0.000	Significant
	PPTTT -> PP	0.780	10.221	0.000	Significant

My research revealed that the CONFC, EXPTI, EXPTC, PPTI, PPCT, and PPTT constructs had insignificant outer weights but statistically significant outer loadings at p = 0.001. Thus, all the outer weights were deemed suitable for the analysis and retained.

5.4. Structural Model Evaluation

My research bases its model on the Expectations Confirmation Theory (Oliver,1977) and the Task Technology Fit Model (Goodhue and Thompson, 1995). Figure 5.1 presents the research model for which my study evaluates the structural model.

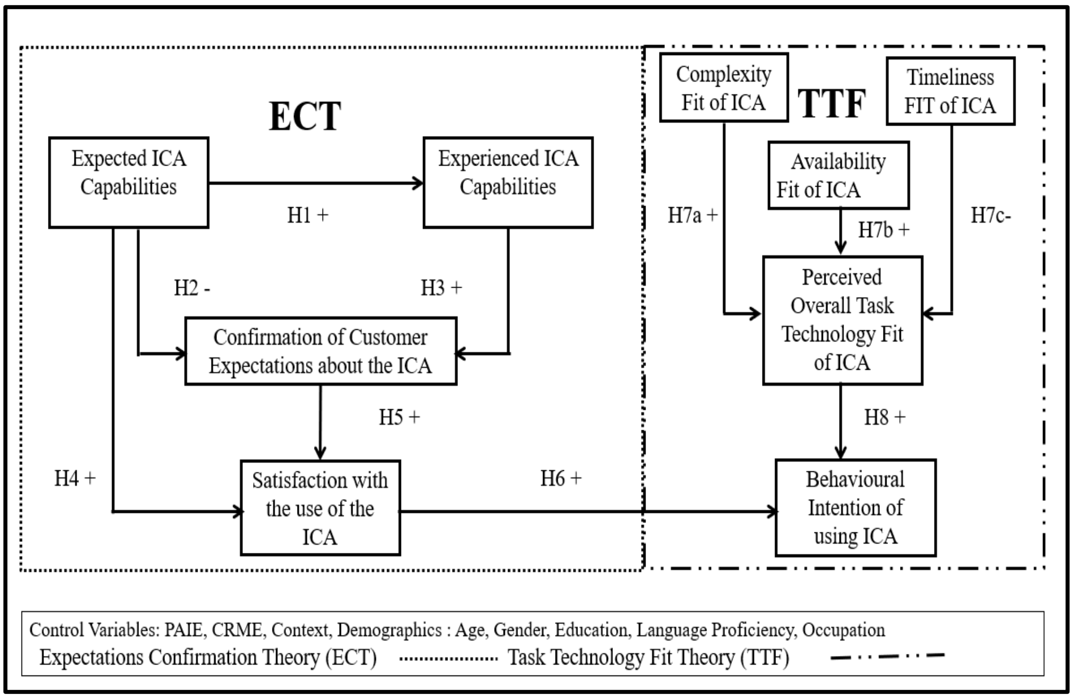

Figure 5.1: Expectations, Experience, and Behavioural Intention of Using ICAs

The evaluation of the structural model follows the confirmation of the validity and reliability measurement model study. Hair et al. (2017) suggest several steps for structural model evaluation. My study presents these steps as follows:

Step 1 Evaluation of Collinearity: My study first assesses the structural model for collinearity issues, and for this purpose, I analyzed the three formative constructs of Expectations, Perceived Performance and Confirmation. My analysis follows the guideline for formative models, that the indicators form the construct collectively, with each indicator contributing new information to the construct (Jarvis et al., 2003). Figure 5.2 shows the six steps required for structural analysis.

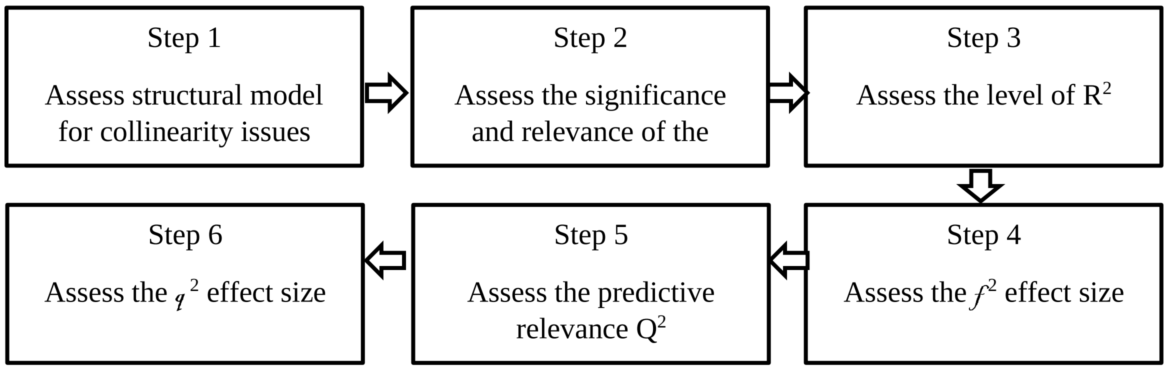

Figure 5.2: Steps for Structural Analysis

My study ensured that indicators were not highly correlated, as multicollinearity in "formative indicators" can result in erroneous results of incorrect weight estimation and statistical significance (Hair et al.,2017). My study examined collinearity by calculating the variance inflation factor (VIF).

The VIF measures how much collinearity affects the standard error. According to Hair et al. (2011), in the context of PLS-SEM, a Variation Inflation Factor (VIF) value of 5 or greater and a tolerance level of less than 0.2 in the predictor constructs indicates a collinearity problem. The six first-order reflective constructs of PPC, PPF, PPI, PPRESP, PPTP, and PPTT, form the second-order formative construct of PP. These first-order reflective constructs combine to form the second-order formative construct of PP. Similarly, the six first-order reflective constructs of CONFC, CONFF, CONFI, CONFRESP, CONFTP, and CONFTT, make the construct of CONF. Also, EXPTC, EXPTF, EXPTI, EXPTRESP, EXPTTP, and EXPTTT form the second-order formative construct of EXPT, in line with ECT theory. Table 5.11 shows VIF values.

Table 5.11: VIF Values for LOC constructs

HOC	LOC	VIF
CONF	CONFC	2.733
	CONFF	1.556
	CONFI	3.260
	CONFRESP	1.578
	CONFTP	3.152
	CONFTT	2.249
EXPT	EXPTF	2.640
	EXPTRESP	1.956
	EXPTTP	3.975
	EXPTI	3.841
	EXPTTT	3.233
	EXPTC	2.797
PP	PPC	3.446
	PPF	2.393
	PPI	3.970
	PPRESP	1.775
	PPTP	4.733
	PPTT	3.397

Table 5.11 presents the second-order formative constructs of EXPT, PP and CONF, along with their respective VIF values of the six first-order reflective constructs. My study observed that the VIF values were less than the threshold value of 5. This observation revealed that collinearity did not reach critical levels in the lower-level reflective constructs forming part of the Higher-Order formative construct. Thus, the model indicated the absence of multicollinearity. My study used the outer VIF values to evaluate the measurement (outer) model. This evaluation was necessary for the interpretation of the formative constructs. It evaluated the collinearity among the indicators of a construct. These values should be high for reflective indicators and often not assessed (Becker, 2020).

5.4.2. Step 2: Significance and Relevance of the Structural Model

My study examined the estimates for hypothesized relationships between constructs in this step of the structural model evaluation. For this purpose, my study considered the path coefficients and related t-statistics obtained via a bootstrapping procedure (Hair et al., 2017). I then ran the path model using computed second-order variable scores. I used a maximum of 5000 iterations and a path weighting scheme (Vinzi et al., 2010).

My study lists the t-values, p-values, and path coefficients obtained from the bootstrapping procedure in Table 5.14. The significance of the path coefficients was determined using t-values and p-values for a two-tailed test (Hair et al., 2011).

5.4.3. Two-Stage Approach

Since the primary goal of my research was to estimate the higher-order constructs, I used a separate two-stage approach, which has the benefit of letting us test a simpler model (Becker et al., 2012). Following the advice of Sarstedt et al. (2019), the disjoint two-stage approach was made in two parts because we made a second-order path model. Also, the importance-performance map analysis illustrated how well the analyzed antecedents worked. The rationale for using the two-stage disjoint approach is that I have an unequal number of indicators specific to each dimension of HOC; thus, adopting a two-stage approach would help us carry out model estimation and analysis. In the first stage of this method, reflective variables determine the latent scores of the LOC, which then identify as the manifest variables for the HOC in the second stage. (Hair et al., 2018). This approach is practical when the number of indicators is unequal across the LOCs.

5.4.4. Coefficient of Determination

My study then hypothesized the structural model in the research framework and assessed the structural model based on R^2, $Q^{2,}$ and the significance of paths. My study ran the bootstrap analysis because I had constructed second (2nd) order higher-order formative constructs. My study observed that the presence of lower-order constructs in the Higher-Order Expectations, Perceived Performance and Confirmation should be used as the Latent Variables, which were attached to obtain the LV dataset. My study then used this LV dataset to rerun the Bootstrap step to find the more pertinent value of R^2. I copied the LV values for the higher-order constructs from the Smart PLS3 output to the Excel spreadsheet, and after saving it in .csv format, I attached this new data set to rerun the bootstrap. Table 5.12 shows the resulting R^2 values.

Table 5.12: Formative Constructs R^2 and Adjusted R^2

	R Square	R Square Adjusted
BI	0.744	0.735
EXPECTATIONS	0.201	0.183
EXPERIENCED	0.329	0.314
POAF	0.821	0.815
SATF	0.676	0.672

Also, I changed the direction of Lower Order Constructs from reflective to formative for Conversation, Friendliness, Intelligence, Response, Task Performance, and Trust at time t_1 and time t_2 to show that they form the Expectations, Perceived Performance and Confirmation Constructs.

My study presents a realistic and representative value of R^2. I determined the model's goodness by the strength of each structural path determined by the R^2 value for the dependent variable (Briones Penavlver et al., 2018); the value for R^2 should be equal to or over 0.1 (Falk and Miller, 1992). The results in Table 5.12 show that all R^2 values are over 0.1. Hence, my study was able to establish the predictive capability of Q^2.

5.4.5. Predictive Relevance

Predictive Relevance "Q^2" establishes the predictive relevance of the endogenous constructs. A Q^2 value above 0 shows that the model has predictive relevance. It is the predictive relevance of the structural model for predicting the indicators of endogenous constructs, using blindfolding Q^2, based on a value of 0.02, 0.15, and 0.35 for weak, moderate, and strong predictive relevance, respectively (Hair et al., 2017). The results show significance in predicting the constructs, as captured in Table 5.13.

Table 5.13: Predictive Relevance "Q^2" Values

	SSO	SSE	Q^2 (=1-SSE/SSO)	SIGNIFICANCE
BI	1140.000	442.311	0.612	Strong
CONF	2280.000	1046.090	0.541	Strong
PP	2280.000	1862.119	0.183	Moderate
POAF	1140.000	357.935	0.686	Strong
SATF	2280.000	1206.290	0.471	Strong

5.4.6. Effect Size

The final step for evaluating my research's structural model was to measure the effect size f^2 of each path in the model. The effect size f^2 quantifies the exogenous construct's contribution to the R^2 value of the endogenous construct in the model. (Chin, 1998). My study also used the criterion of f^2. Accordingly, the effect size f^2 quantifies the exogenous construct's contribution to the R2 value of the endogenous construct in the model. My study analyzed the R^2 of the endogenous constructs and the f^2 effect size of the predictor constructs to determine the model's explanatory power. My study establishes whether f^2 is substantial, moderate, or weak. The value of f^2 would also show that R^2 is substantially moderate or weak. My research utilizes the following criteria to interpret the effect size:

1. For small effect size, $0.02 < f^2 \leq 0.15$
2. For medium effect size, $0.15 < f^2 \leq 0.35$

3. For large effect size $f^2 > 0.35$ (Chin, 1998; Cohen, 1988).

My model reveals a very large effect of Perceived Performance (Experience) on Confirmation, indicating that if I remove the Perceived Performance construct, Confirmation would be significantly affected. Based on accepted guidelines, if the f^2 effect size is greater than 0.020, it has a small effect, so removing that exogenous variable will have a more negligible effect on the r2square value for the endogenous variable.

Similarly, a value of f^2=0.150 reflects the medium effect, and a value of f^2, more significant than 0.350, represents a large effect, according to researchers (Chin,1998; Cohen, 1988). I also depict the disjoint two-stage structural model in Figure 5.3 and illustrate the bootstrapping results. In contrast, Table 5.15 summarizes their interpretation of the study hypotheses and demonstrates that all direct structural model relationships were significant, confirming this study's H1 to H8.

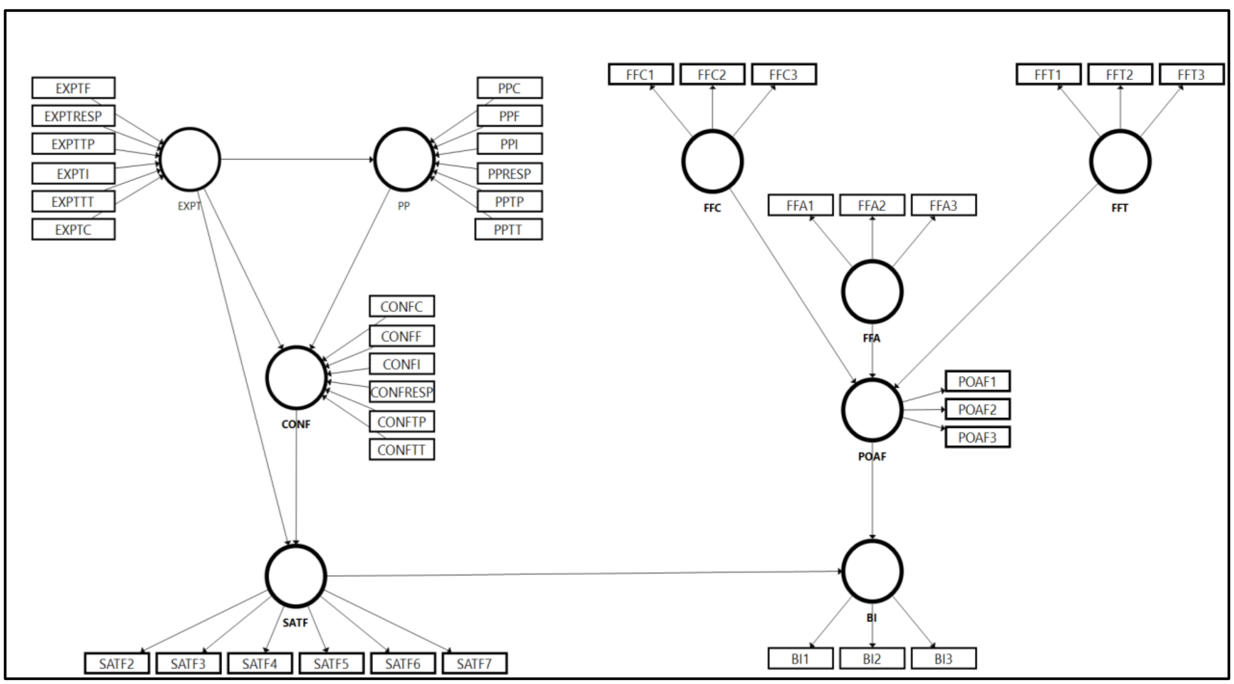

Figure 5.3: The Disjoint Two-Stage Model

My research also depicts the importance of VIF, and Table 5.14 illustrates the relationships and presents the f^2 values.

Table 5.14: VIF and Effect Sizes f^2 values

SR #	DEPENDENT VARIABLE	INDEPENDENT VARIABLE	VIF <5	f^2	Effect Size
1.	SATF	CONF	1.172	1.373	Large
2.	SATF	EXPT	1.172	1.814	Large
3.	CONF	EXPT	1.352	41.390	Large
4.	PP	EXPT	1.000	0.352	Moderate
5.	POAF	FFA	2.501	0.366	Large
6.	POAF	FFC	1.960	0.539	Large
7.	POAF	FFT	1.544	0.012	Small
8.	CONF	PP	1.352	54.713	Large
9.	BI	POAF	3.046	0.327	Moderate
10.	BI	SATF	3.046	0.078	Small

The analysis reveals that the independent variables, Expectation and Perceived Performance have very large effects of 41.390 and 54.713, respectively, on the dependent variable of Confirmation. Similarly, the model shows that Perceived Overall Fit (POAF) has a moderate effect of 0.327 on Behavior Intention (BI).

The effect of Satisfaction (SATF) on Behavior Intention (BI) is 0.078, and the Fit for Timeliness (FFT) on Perceived Overall Fit (POAF) is 0.012. My study also observed large effects present in the model, with the effect of Fit For Availability (FFA) and Fit For Complexity Fit (FFC) on Perceived Overall Fit (POAF) being 0.366 and 0.539, respectively. Lastly, f^2 values also reveal the large effects of Expectations on Satisfaction, being 1.814.

5.4.7. Hypothesis Testing

My study also measured the significance of the path coefficients. The standardized path coefficients indicate the strength of the relationship between independent and dependent variables (Chin, 1998). Figure 5.4 shows the path coefficients and regression coefficients for different pathways. Similarly, Table 5.15 presents the path coefficients.

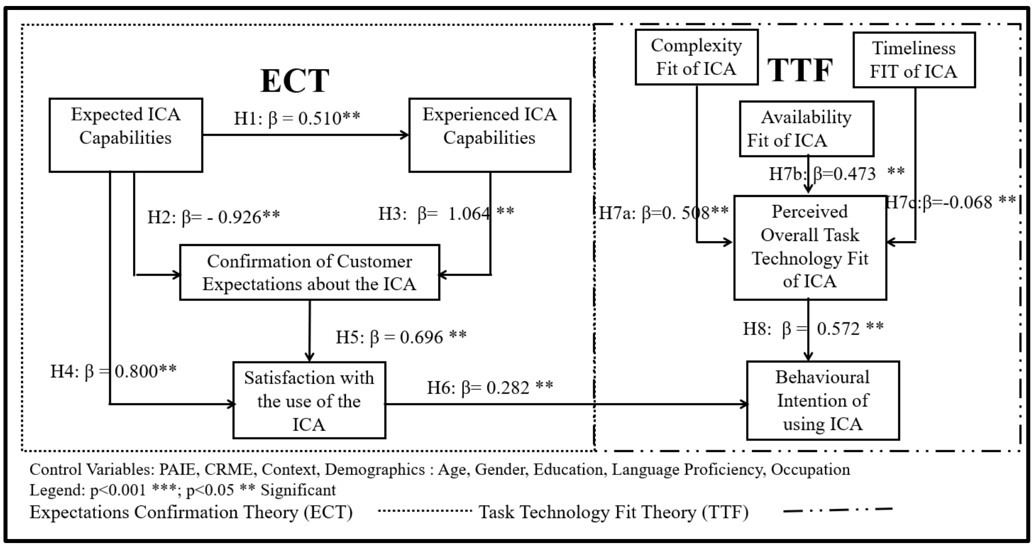

Figure 5.4: The Research Model with "β" values

Table 5.15: Path Coefficients

Paths		Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values
EXPT -> PP	H1	0.510	0.516	0.072	7.081	0.000
EXPT -> CONF	H2	-0.926	-0.928	0.096	9.602	0.000
PP -> CONF	H3	1.064	1.079	0.062	17.193	0.000
EXPT -> SATF	H4	0.800	0.793	0.039	20.476	0.000
CONF -> SATF	H5	0.696	0.682	0.045	15.315	0.000
SATF -> BI	H6	0.282	0.285	0.058	4.840	0.000
FFC -> POAF	H7a	0.508	0.511	0.049	10.283	0.000
FFA -> POAF	H7b	0.473	0.470	0.055	8.582	0.000
FFT -> POAF	H7c	-0.068	-0.067	0.029	2.325	0.020
POAF -> BI	H8	0.572	0.570	0.060	9.545	0.000

Perceived Performance of the ICA capabilities (Experience is influenced significantly by the Expectations of the ICA capabilities ($\beta=0.510$, $p<0.001$). Similarly, the Expectations about the ICA capabilities had an impact on the confirmation of expectations about the ICA capabilities significant on Experience ($\beta=-0.926$, $p<0.001$). Also, Perceived Performance (Experience) about the ICA capabilities has a significant impact on the Confirmation of the ICA capabilities Experience ($\beta=1.064$, $p<0.001$). Thus, H1, H2, and H3 are all supported.

Expectations about ICA capabilities significantly influenced satisfaction with ICA capabilities ($\beta=0.800$, $p<0.001$), and confirmation about the ICA capabilities substantially influenced Satisfaction with the use of ICA ($\beta=0.696$, $p<0.001$). Also, Satisfaction with the use of ICA significantly influences the BI of using ICA ($\beta=0.282$, $p<0.001$). Therefore, Hypotheses H4, H5 and H6 are all supported.

My study observed specific facts about the task technology fit aspects of the model. Fit For Complexity Fit (FFC) aspect of the Task Technology Fit impacts the Perceived Overall Fit (POAF) effectively ($\beta=0.508$, $p<0.001$). Also, the Fit For Availability (FFA) aspect of the Task Technology Fit impacts the Perceived Overall Fit (POAF) effectively ($\beta=0.473$, $p<0.001$). Also, as hypothesized, the Fit For Timeliness (FFT) aspect of the Task Technology Fit does impact the Perceived Overall Fit (POAF) in a potent manner ($\beta=-0.068$, $p<0.05$). Therefore, Hypotheses H7a, H7b, and H7c are all supported. Finally, Perceived Overall Fit significantly influences Behavioural intention to use ($\beta=0.572$, $p<0.001$) and provides support for hypothesis (H8). My study shows a summary of the hypotheses test results in Table 5.16.

Table 5.16: Summary of Hypothesis Tests

	Hypotheses	Path	Supported
H1	Expected ICA Capability has a positive impact on the Experienced ICA Capability.	EXPT -> PP	Yes
H2	Expected ICA Capability has a negative impact on the Confirmation of Expectations about the ICA Capability.	EXPT -> CONF	Yes
H3	Perceived Performance about the ICA Capability has a positive impact on the Confirmation of Expectations about the ICA Capability.	PP -> CONF	Yes
H4	Confirmation of Expectations about the ICA Capability positively impacts satisfaction with the use of the ICA.	CONF-> SATF	Yes
H5	Perceived Performance about the ICA Capability positively impacts satisfaction with the use of the ICA.	PP -> SATF	Yes
H6	Satisfaction with the use of the ICA has a positive impact on the Behavior Intention To Use the ICA.	SATF -> BI	Yes
H7a	Fit For Complexity negatively impacts Perceived Overall Task Technology Fit	FFC -> POAF	Yes
H7b	Availability for Fit has a positive effect on Perceived Overall Task Technology Fit	FFA-> POAF	Yes
H7c	Timeliness for Fit has a negative effect on Perceived Overall Task Technology Fit	FFT -> POAF	Yes
H8	Perceived Overall Task Technology Complexity positively impacts the Behavior Intention To Use the ICA.	POAF -> BI	Yes

Research revealed that all the relationships were significant, and the results supported the hypotheses at $p<0.001$ except for the relationship between FFT and POAF, which is significant at $p<0.05$. Next, my study measures the significance of the path coefficients. The standardized path coefficients indicate the strength of the relationship between independent and dependent variables (Chin,1998). Eight of the eight hypotheses—H1 to H8 are strongly supported.

Relationship Between Expectations and Perceived Performance of the ICA (H1)

The relationship represented by H1 is significant ($\beta=0.782$, $p<0.001$). This aspect corresponds to the fact that, by large, perceived performance is positively related to expectation. Ling et al. (2021) discovered that social behaviours in ICA similar to human agents, such as self-disclosure and reciprocation, can increase user satisfaction and delight. Araujo (2018) discovered that humanlike signals in ICA interaction enhance users' perceptions of ICA being like a human service agent, improve end-users' perception of the ICA, and may improve the emotional connection with the firm hosting the chatbot. Schuetzler et al. (2018) discovered that differences in the conversational content of chatbots influence users' perceptions of humanness in the ICA and, consequently, user interaction with ICA and customer behaviour. Diederich et al. (2019) discovered that a conversational agent that adapts its responses to the user's mood is more humanistic and socially responsive, resulting in a more satisfying service interaction. Research also suggests that humanlike design signals in chatbots, particularly message interactivity, may influence users' perceptions of human qualities and social presence. That consequently increases perceived expertise and friendliness in the chatbot (Go and Sundar, 2019). These factors improve the relationship between user satisfaction and behavioural intention to use the ICA.

The humanlike capabilities of ICA can create expectations similar to human service agents for the ICA deployed for customer service. These expectations suggest that the end-user will have similar service requirements to the deployed ICAs. General expectations for successful ICA customer service involve the efficient and effective resolution of user problems or requests (Dixon et al., 2010). However, efficiency and effectiveness may not be sufficient for an optimal user experience. Business organizations aim to provide customer service that generates positive emotions in users, seeking to please, engage and possibly surprise by going beyond users' expectations (Berry et al., 2002). A customer planning to receive customer service from an ICA may not have a fair expectation about the ICA's capabilities. Expectations about the ICA capabilities can vary from showing disappointment about the Inflexible free-text interaction, which the end-users perceive to be annoying or providing informal content or conversation style that may counter expectations for professionalism in customer service (Haugeland et al., 2022). End-users with lower expectations about the ICA performance would be easily satisfied and impressed.

End-users with higher expectations will not be easily impressed by limited ICA capabilities. Thus, customer expectations about ICA may indirectly impact customer satisfaction through perceived performance (Eren, 2021). Moreover, the impact of customer expectations on the Perceived Performance of the ICA is significant at (β=0.510, $p<0.001$), as shown in Table 5.17.

Table 5.17: Result of Hypothesis H1

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
EXPT -> PP	H1	0.510	0.516	0.072	7.081	0.000

Relationship Between Expectations and Confirmation (H2)

Customer expectations validation measures the Satisfaction of customer expectations. In the service industry, when the service provider delivers the predicted advantages leads to accomplished customer expectations (Bhattacherjee, 2001). According to ECT, there is a positive association between consumer expectations and post-experience Confirmation of customer expectations (Chou et al., 2010). Confirmation of customer expectations occurs when the perceived performance of a product or service corresponds with pre-purchase expectations or a favourable performance rating (Kim, 2012).

The cognitive process of confirming client expectations involves comparing pre-purchase expectations with post-purchase judgments. The confirmation process, which is the customer's evaluation of the performance of a product or service, is based on the congruence between pre-purchase consumer expectations and actual performance (Kim, 2012). Post-usage confirmation impacts usage intention (Lankton et al., 2014). In the world of technology, user experience expresses the degree to which users' expectations for a product or service are satisfied (Huang, 2019). In this study, when an ICA service delivers the benefits, advantages, and utility anticipated by customers, it leads to accomplishing the customer expectations are confirmed. My study considers customer expectations about the ICA technology or service's qualities and attributes.

Similarly, in recent times, ICA studies have identified various attributes and found that reliability, assurance, and interactivity can enhance post-use Confirmation, increasing ICA use (Li et al., 2021). Since the data points begin with high y-values on the y-axis and decrease to low y-values, the variables are negatively correlated. Also, Expectations about the ICA capabilities influence Satisfaction with the use of the ICA. The relationship between Expected ICA capabilities and Confirmed ICA capabilities is significant and supported at (β=-0.926, $p<0.001$) and is reported in Table 5.18.

Table 5.18: Result of Hypothesis H2

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
EXPT -> CONF	H2	-0.926	-0.928	0.096	9.602	0.000

Relationship Between Perceived Performance and Confirmation (H3)

ECT is a procedural model intended to describe actions based on perception or user intention based on real user experience, including performance, conformity, Satisfaction, and original expectation. The ECT asserts that expectations and perceived performance contribute to post-purchase or post-service satisfaction. The negative or positive dissonance between performance and expectations measures Satisfaction (Oliver,1980). Consequently, the ECT is a valuable hypothesis for explaining post-purchase pleasure and the repurchase decision-making process. Recent research has demonstrated that the greater the perceived performance and the confirmation of consumer expectations for technology products, the greater the likelihood of accomplishing these expectations (Chen and Wu, 2018). Especially for technology-based services, a product's perceived performance directly affects the Confirmation of client expectations regarding the product (Brill et al., 2019). My study observed that the perceived performance and Confirmation of customer expectations for ICA technology demonstrated that the greater the perceived performance, the greater the Confirmation of realizing expectations. H3 takes a closer look at Perceived Performance, the relationship between Perceived Performance for ICA Capabilities and Confirmation for ICA capabilities is significant, and H3 supports (β=1.064, $p<0.001$). Table 5.19 reports the results of Hypothesis 3.

Table 5.19: Result of Hypothesis H3

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
PP -> CONF	H3	1.064	1.079	0.062	17.193	0.000

Relationship Between Expectations and Satisfaction (H4)

After considering the influence of expectations on the perceived performance of the ICA's capabilities, my study observed that customer expectations favourably impacted satisfaction with the use of the ICA. As ICA is in the early stage of the service life cycle, several people experienced ICA in Canada for customer service; this situation may have added to the satisfaction towards the ICA. There is evidence that higher comparison standards are associated with either lower perceived performance and lower customer satisfaction or only customer satisfaction. If the realized performance of a product or service is high, customers are more likely to be satisfied regardless of their pre-purchase expectations (LaTour and Peat, 1979). Customer satisfaction is a global evaluation of how well a service meets customer expectations (Anderson and Sullivan, 1993). According to ECT, a product's perceived performance directly affects customer satisfaction (Gupta and Stewart, 1996). Perceived usefulness, a component of perceived performance, is one of the primary predictors of consumer satisfaction with technology solutions like mobile banking (Susanto et al., 2016; Yuan et al., 2016). Customer Satisfaction is reliant upon perceived performance and directly tied to perceived performance (Mou et al., 2017).

In my study, the participants could develop a reasonably clear perception of the ICA performance while interacting with the ICA. They could identify if they were satisfied or not with the ICA performance. Thus if the participants found the ICA lacking in Conversation ability, friendliness, intelligence, responsiveness, task performance or trust, they would express their dissatisfaction or unhappiness. Thus, the relationship between Expectations and Satisfaction is a significant one. Table 5.20 presents the results for hypothesis H4.

Table 5.20: Result of Hypothesis H4

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
EXPT -> SATF	H4	0.800	0.793	0.039	20.476	0.000

Relationship Between Confirmation of ICA Capabilities and Satisfaction (H5)

Customer satisfaction is an emotional or affective state related to and evolving from a cognitive evaluation of the customer's expectation-performance incongruity or Confirmation (Bhattacherjee, 2001). ECT investigates customer satisfaction by concentrating on pre-use customer expectations and post-use performance (Rahi and Ghani, 2018). Negative confirmation occurs when customer expectations are unaccomplished, while positive confirmation happens when the perceived performance exceeds the customer's pre-experience expectations; hence, verifying customer expectations impacts customer satisfaction positively (Jamal and Naser, 2002; Wu, 2013).

Corroborating customer expectations is evidence of customer satisfaction, and recent research reveals the correlation between confirming customer expectations and customer satisfaction (Kim, 2018; Dai et al., 2020). Likewise, the accomplishment of the customer's prior usage after the interaction and receiving ICA service confirms the customer's initial expectations.

Positive Confirmation occurs when the perceived performance exceeds the customer's pre-experiment expectations; hence, verifying customer expectations impacts customer satisfaction positively. Also, the relationship between Confirmation about the ICA capabilities and Satisfaction with the use of ICA is strongly positive, as suggested by (β=0.696, $p<0.001$). Therefore, H5 is supported. Table 5.21 below represents the result for Hypothesis H5

Table 5.21: Result of Hypothesis H5

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
CONF -> SATF	H5	0.696	0.682	0.045	15.315	0.000

Relationships Between Satisfaction and Behavioural intention (H6)

The results indicate that the ICA capabilities impacted the customers' user satisfaction with ICA deployed for customer service. These ICA capabilities impacted user satisfaction and, in turn, impacted the behavioural intention to use the ICA. Researchers have suggested that user satisfaction affects users' behavioural intention to use IS (Lee and Lehto, 2013). Researchers have recently investigated the relationship between ICAs deployed for different purposes and concluded the same (Huang and Chueh, 2021). Thus, my study observed a significant relationship between satisfaction and behavioural intention. Satisfaction impacts behavioural intention to utilize the ICA (β=0.282, $p<0.001$). That shows end-users perceived that the ICA technology fits the complex tasks and was available to complete the assigned tasks. Thus, H6 is supported, as represented in Table 5.22.

Table 5.22: Result of Hypothesis H6

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
SATF -> BI	H6	0.282	0.285	0.058	4.840	0.000

Relationship Between Fit For Complexity, Fit For Availability, Fit For Timeliness and Perceived Overall Fit (H7)

The Task Technology Fit theory is a popular IS theory (Goodhue, 1995; Goodhue and Thompson, 1994), elucidates the concept of analyzing the compatibility between the technological characteristics of a specific IS and the required tasks to support it. TTF theory aims to determine the compatibility between the technology and the task requirements and the effect on utilization (Goodhue and Thompson, 1994). Thus, according to TTF, task features and technical characteristics determine the task-technology fit, which influences the application of technology (Goodhue, 1995; Goodhue and Thompson, 1994).

My study identified three technology characteristics of Fit For Complexity (FFC), Fit For Availability (FFA) and Fit For Timeliness (FFT) and based on these three characteristics, my study presented three hypotheses. These hypotheses contextualized for ICA service fit show that FFC, FFA and FFT all three impact the POAF significantly at (β=0.508, $p<0.001$), (β=0.473, $p<0.001$) and (β=-0.068, $p<0.05$), respectively. Therefore, H7a, H7b and H7c are all supported.

My study indicates that the end-users found the ICA of their choice to fit the complex tasks, and the ICA was available to provide some guidance, if not the solution to the task presented to the ICA. However, the participants found the ICA to be ineffective regarding timeliness. This observation is unique as the ICA provided a quick response, but that response was often neither accurate nor relevant. Thus, Hypotheses 7a, 7b and 7c are significant and represented in Table 5.23.

Table 5.23: Result of Hypotheses 7a, 7b and 7c

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
FFC -> POAF	H7a	0.508	0.511	0.049	10.283	0.000
FFA -> POAF	H7b	0.473	0.470	0.055	8.582	0.000
FFT -> POAF	H7c	-0.068	-0.067	0.029	2.325	0.020

Relationship Between Perceived Overall Fit and Behavioural intention (H8)

As per established TTF literature, the relationships among task, technology, behavioural intention, and usage are critical. This stream of research suggests that the relationship between task complexity and interaction with ICA technology system use is contingent on user perceptions of the ICA system's capabilities and their belief that the ICA will provide task-relevant information and perform the task. My study's theoretical model specifies that aligning the technology characteristics of ICA systems to tasks on hand by the ICA would help customers to achieve improved efficacy.

Although POAF influenced customer behavioural intention to use the ICA, it is critical to emphasize that the participants in the study thought that the ICA system contributed to their receiving customer services from ICA. Also, participants were more likely to expend effort to use and more satisfied with the information if they perceived it to help complete their specific information needs and task performed by the ICA. My study includes the specific ICA technological features in the hypotheses. For instance, the model can assist designers in comprehending which characteristics, Fit For Availability, Fit For Complexity and Fit For Timeliness, will improve the Perceived Overall Fit of the ICA technology for the customer service tasks. Based on hypotheses 7a, 7b and 7c, Fit For Complexity has immense relative significance in the context of customer services. Thus, the Perceived Overall Fit significantly impacts Behavioural Intention to use the ICA ($\beta=0.572$, $p<0.001$). Table 5.24 represents the result of hypothesis H8.

Table 5.24: Result of Hypothesis H8

Paths		β	Sample Mean	Standard Deviation	T Statistics	P Values
POAF -> BI	H8	0.572	0.570	0.060	9.545	0.000

5.4.8. Post Hoc Analysis

I performed the Post Hoc Analysis to pursue possible meaningful objectives that I had not initially planned. My research included context, demographic, CRME, and PAIE constructs in our survey questionnaire as control variables. My study tested these variables for their probable influence on the endogenous constructs in the research model. Context variable refers to the five companies from the Canadian Telecom sector where Context 1, Context 2, Context 3, Context 4, and Context 5 represent Rogers, Freedom, Telus, Fido, and Koodo, respectively. Also, the demographic questions included Age, Gender, Education, English Language Proficiency, and Profession. I included these seven control variables in the PLS model by simultaneously linking one control variable to each endogenous variable.

My study analyzed the paths for significance and strength and showed the results in Table. The construct of Age positively influenced CCD at $p<0.05$, while Language Proficiency does not have any positive influence on the endogenous constructs. Table 5.25 below shows all significant and not significant relationships.

Table 5.25: Post Hoc Analyses for Control Variables

Control Variable	Endogenous Construct	Path Coefficient	T-Values	P-Values	Significance
AGE	AGE -> BI	-0.009	0.306	0.760	n.s.
	AGE -> CONF	0.017	1.385	0.166	p<0.05
	AGE -> EXPT	0.056	1.003	0.316	n.s.
	AGE -> FFA	-0.017	0.322	0.747	n.s.
	AGE -> FFC	-0.090	1.735	0.083	p<0.010
	AGE -> FFT	0.005	0.095	0.924	n.s.
	AGE -> PP	-0.126	2.079	0.038	p<0.05
	AGE -> POAF	-0.023	0.944	0.345	n.s.
	AGE -> SATF	-0.037	1.166	0.244	n.s.
CONTEXT	CONTEXT -> BI	0.000	0.013	0.990	n.s.
	CONTEXT -> CONF	-0.004	0.408	0.684	n.s.
	CONTEXT -> EXPT	-0.015	0.285	0.776	n.s.
	CONTEXT -> FFA	-0.136	2.891	0.004	p<0.05
	CONTEXT -> FFC	-0.179	3.772	0.000	P<0.001
	CONTEXT -> FFT	-0.070	1.345	0.179	n.s.
	CONTEXT -> PP	-0.186	4.056	0.000	p<0.001
	CONTEXT -> POAF	-0.026	1.037	0.300	n.s.
	CONTEXT -> SATF	-0.065	2.390	0.017	P<0.05
GENDER	GENDER -> BI	-0.020	0.664	0.507	n.s.
	GENDER -> CONF	-0.004	0.550	0.582	p<0.1
	GENDER -> EXPT	0.039	0.718	0.473	
	GENDER -> FFA	-0.046	0.905	0.366	n.s.
	GENDER -> FFC	0.027	0.522	0.602	n.s.
	GENDER -> FFT	-0.073	1.411	0.158	n.s.
	GENDER -> PP	0.023	0.470	0.639	n.s.
	GENDER -> POAF	0.020	0.803	0.422	n.s.
	GENDER -> SATF	-0.004	0.123	0.902	n.s.
EDUCATION	EDUCATION -> BI	-0.022	0.693	0.488	n.s.
	EDUCATION -> CONF	0.000	0.001	0.999	n.s.
	EDUCATION -> EXPT	0.032	0.485	0.628	n.s.
	EDUCATION -> FFA	-0.093	1.649	0.099	P<0.010
	EDUCATION -> FFC	-0.032	0.570	0.569	n.s.
	EDUCATION -> FFT	0.007	0.140	0.889	n.s.
	EDUCATION -> PP	-0.084	1.615	0.106	n.s.
	EDUCATION -> POAF	-0.036	1.367	0.172	n.s.
	EDUCATION -> SATF	0.008	0.272	0.786	n.s.
ENGLISH PROFICIENCY	LANG.PROF -> BI	-0.035	1.509	0.131	n.s.
	LANG.PROF -> CONF	0.001	0.063	0.949	n.s.
	LANG.PROF -> EXPT	0.090	1.677	0.094	P<0.010

	LANG.PROF-> FFA	-0.027	0.509	0.611	n.s.
	LANG.PROF -> FFC	0.008	0.171	0.864	n.s.
	LANG.PROF -> FFT	-0.103	1.774	0.076	P<0.010
	LANG.PROF -> PP	0.027	0.592	0.554	n.s.
	LANG.PROF -> POAF	0.029	1.174	0.241	n.s.
	LANG.PROF -> SATF	-0.031	0.974	0.330	n.s.
PROFESSION	PROFESSION -> BI	0.074	3.077	0.002	p<0.05
	PROFESSION -> CONF	-0.007	0.661	0.509	n.s.
	PROFESSION-> EXPT	-0.002	0.038	0.970	n.s.
	PROFESSION-> FFA	0.025	0.510	0.610	n.s.
	PROFESSION -> FFC	-0.022	0.403	0.687	n.s.
	PROFESSION-> FFT	0.029	0.553	0.580	n.s.
	PROFESSION -> PP	-0.061	1.150	0.250	n.s.
	PROFESSION -> POAF	-0.026	0.986	0.324	n.s.
	PROFESSION -> SATF	-0.013	0.464	0.642	n.s.
CRME	CRME -> BI	0.092	2.709	0.007	p<0.05
	CRME -> CONF	-0.008	0.369	0.712	n.s
	CRME -> EXPT	0.270	2.795	0.005	p<0.05
	CRME -> FFA	0.269	5.041	0.000	P<0.001
	CRME -> FFC	0.191	3.199	0.001	p<0.001
	CRME -> FFT	0.324	6.205	0.000	p<0.001
	CRME -> PP	0.054	0.600	0.549	n.s.
	CRME -> POAF	-0.042	1.349	0.177	n.s.
	CRME -> SATF	-0.039	0.705	0.481	n.s.
PAIE	PAIE -> BI	0.116	3.639	0.000	p<0.001
	PAIE -> CONF	-0.013	1.047	0.295	n.s.
	PAIE -> EXPT	0.253	4.719	0.000	p<0.001
	PAIE -> FFA	0.192	3.766	0.000	p<0.001
	PAIE -> FFC	0.255	5.040	0.000	p<0.001
	PAIE -> FFT	0.050	1.001	0.317	n.s.
	PAIE -> PP	0.139	2.673	0.008	p<0.05
	PAIE -> POAF	0.020	0.762	0.446	n.s.
	PAIE -> SATF	0.039	1.329	0.184	n.s.
EE	EE -> BI	0.075	1.996	0.046	p<0.05
	EE -> CONFIRM	-0.012	0.798	0.425	n.s.
	EE -> EXPT	0.201	3.307	0.001	p<0.05
	EE -> FFA	0.322	5.999	0.000	p<0.001
	EE -> FFC	0.278	4.959	0.000	p<0.001
	EE -> FFT	0.280	6.017	0.000	p<0.001
	EE -> PP	0.210	4.134	0.000	p<0.001
	EE -> POAF	0.009	0.267	0.789	n.s.
	EE -> SATF	0.103	2.903	0.004	p<0.05

The post hoc analysis reveals the Importance of control variables. We see that nearly all these variables have a minimum of one or two significant relationships with our proposed model constructs. Future research might consider using CRME, PAIE and EE variables to study the integrated ECT-TTF model.

5.5. Qualitative Feedback for Model Validation and Explanation

My study used open-ended questions to collect qualitative feedback. I did not correct the participants' tone, sentiments, spelling, or grammar. Open-ended questions as a part of the survey item responses after interacting with an ICA make the participant feedback priceless.

ICAs utilize natural language (Jain et al., 2018). Recently, both academia and industry have focused on ICA technologies. ICAs help to humanize machines by facilitating faster and more natural access to information. However, researchers have criticized ICAs as an intriguing but ineffective technology (Kasilingam, 2020). This criticism carries value as ICAs frequently fail to provide the promised service. My study examined participant perceptions of the ICA.

Qualitative Feedback was necessary for model validation and asked questions related to participants' attitudes toward ICA capabilities and satisfaction with the use of the ICA. The end-user ICA interaction was a necessary extension of the concept of usability. Usability is critical in interactive software systems, so adding it to ICA development is necessary to improve the user experience (Ren et al., 2019). Usability is the degree to which a program achieves quantified goals with efficiency, effectiveness, and satisfaction (ISO 9241, 1998; Rapp et al., 2021). That allowed my study to explore how the ICA performed concerning different tasks while engaging (interacting) with the end-users. This background to my study of open-ended questions helped me identify the expectations, confirmation, perceived performance (experience), satisfaction, overall fit and behavioural intention of the end-users towards the ICA.

5.5.1. End-User Satisfaction and Dissatisfaction with ICA Capabilities:

Studies have highlighted ICA end-users negative attitudes toward customer service disclosure (Mozafari et al., 2021). My study provides the positive and negative attitudes engendered by the ICA capabilities after participants' interaction with an ICA. Table 5.26 captures the effect of ICA capabilities on end-user attitudes.

Table 5.26. Effect of ICA Capabilities on Customer Attitudes

ICA Capability	Positive Attitudes	Negative Attitudes	Important Observation
Conversation Ability	(ID # 1641) It was polite, and free of language barriers (tone, accent etc.)	(ID # 2046) I would frankly only use the chatbot to direct me to a live agent. I dislike waiting on hold, but the chatbot feels more like a glorified search-engine that tries to guess what you want. It's not really a "conversation."	(ID # 90) The bot replied very quickly (much quicker than a human could - instantly, in fact), and it asked follow-up questions to narrow down what I meant.
Friendliness	(ID # 1157) I asked if there was an outage in my area, and it referred me to reporting an outage. It gave me box options and I clicked on Text and gave me some technically suggestions. I think this completed the task well enough. It was very friendly and sympathetic again.	(ID # 1690) For the task related to a lost phone and a weak connection signal, I don't feel the chatbots answer was helpful in the slightest. Had it been a real interaction, I would have had to find the info myself on the website and would have been annoyed at the lack of understanding of the chatbot. It also did Segway (segue) from question to question or and it took a	(ID # 2118) The chatbot is too polite and very straight-to-the-point in its answers. It does not mimic the conversational nature of a Customer Service Representative. The chatbot shows no empathy towards a customer's frustrations.

		while for it to realize that I was asking a different question. Usually chatbots say something like "was this answer helpful/is there anything else I can help you with?" but this ------ (NAME OF ICA WITHHELD) one did not.	
Intelligence	(ID #270) "She gave me step by step information to report my lost phone and also provided more information about service. This was helpful and straight forward."	(ID # 107) The chatbot I interacted with provided my wrong or no information for 3 of my 4 questions. It did not seem to understand my questions and just spewed links and info for related topics but not the exact topic I needed. It seemed very rigid and did not grasp the breadth of the question. This has been my experience with chatbots in the past as well. It's almost easier for you to search the site yourself than having to navigate the complexities of the chatbot.	(ID # 299) Chatbots were able to provide an answer regardless if it is correct or not. It does show great AI intelligence
Responsiveness	(ID # 531) Speed and completeness. For all of my questions the response was immediate, probably faster than a human could look things up. I was surprised by how thorough and complete the chatbot was in rooting out the problem with my cell service that I presented to it.	(ID # 170) Very specific questions. Like a lost phone. Or pricing for a plan. In other words, a narrow search whereby I would anticipate a narrow return (or at least limited anticipated variability of info return). Note, I used the term "search". I perceive chatbot tech, or at least the one I tried just now, as really an advanced rule-based type of search. There is no AI here. No responsiveness to nuance or voice tone or cadence or emotion. It's really quite flat.	(ID # 107) The chatbot was able to answer this question in certain terms and linked me to the information I would need to activate this service before I travelled. This was a good answer and would be enough information for me to move to the next step.

Task Performance	(ID # 219) I asked the chatbot about not being able to send and receive text messages. The chatbot adequately responded that there are several cases why this might be. It took me through a number of things to try, and when none of the options worked, finally offered to schedule a call back with an agent. This is definitely the task the chatbot performed the best on and I could see it would resolve any small issue that may be causing service interruptions without having to talk directly to an agent.	(ID # 43) I asked ------ (Name of ICA withheld) if I could use my phone on a trip to Europe, but, since I had identified myself as an existing ------ (Name of ICA withheld) customer, it would not answer the question unless I entered my phone number. I didn't want to do that, so I reworded the question. It just kept telling me "that doesn't look like a phone number" (as if I didn't already know that). Very maddening, especially since I was asking a general service question, not anything specific to my account. I call this one a fail.	(ID # 619) The chatbot responds much more quickly than a human could due to the constraints of typing speed and is able to present several options, including detailed explanations and links, almost instantaneously. It also recognizes when it can't complete a task and refers you to a human agent for issues outside its capabilities.
Trust	(ID #272) I would use the chatbot in situations I believe that are general issues and not specific ones that might apply specific to me. For example, I could ask about general network connectivity issues to see if is aware of any network outages, but if I suspect I have a damaged SIM card from an overheated phone I may need a human to help walk me through the next steps.	(ID # 2065) I would use for simplified things where you don't feel that you need a human -last payment, due dates, promotions, amount due I wouldn't use it for address changes, credit info, personal information and banking access because I still trust humans more.	(ID # 511) Having to type a lot of details and being unable to have a discussion, with a person about your issues. I don't always trust that the answers, I'm given would specifically apply to my particular issues.

Participants were able to provide candid feedback about the sources of satisfaction and dissatisfaction -based on the notion that they think the ICA reflected impressive service and led to a feeling of satisfaction or lousy service, leading to dissatisfaction. Table 5.27 illustrates sources of satisfaction and dissatisfaction.

Table 5.27: Sources of Satisfaction and Dissatisfaction

ASSIGNED TASK	SOURCES OF SATISFACTION	SOURCES OF DISSATISFACTION
INFORMATION RETRIEVAL	(ID # 53) The chatbot gave information quickly and easily, enquiring as to whether I was already travelling or planning to travel, and giving me information such as what number to text to find out of my destination is eligible. I found Anna very helpful in this respect.	(ID # 125) I asked what it could do to help fix the problem of many of my calls cutting off. After I provided a postal code it checked the area for outages, then recommended I restart the phone. It then walked me through some more steps. The chatbot was not really that useful in this case, as the problem I was presenting was not about service outages, but dropped calls.
PROBLEM SOLUTION	(ID # 219) I asked the chatbot about not being able to send and receive text messages. The chatbot adequately responded that there are several cases why this might be. It took me through a number of things to try, and when none of the options worked, finally offered to schedule a call back with an agent. This is definitely the task the chatbot performed the best on and I could see it would resolve any small issue that may be causing service interruptions without having to talk directly to an agent.	(ID # 396) It provided a simple solution for a basic issue but there is no way to explain the full issue. It ended up offering that I can talk to an agent.

COWORKING WITH HUMAN AGENT	(ID # 617) I told chatbot (NAME WITHHELD) that I am travelling to Scotland in December and want to use my phone. The chatbot provided information and links to the Rogers Roaming information and invited me to sign up for the service. It is only available for 15 days, so I asked the chatbot if I could extend the service. A dialogue box asking if I would like to speak to an agent popped open. The chatbot was able to help me to a certain point - then referred me to a live agent when it could no longer answer my questions.	(ID # 1781) The problem I reported elicited a rather canned-sounding response of "We're working quickly to resolve a Wireless network issue in your area", particularly since I don't actually have any outage or issue with my connection. It then asked if I wanted to check network coverage at any other address but if I really did have a network issue that needed resolution, this would not have solved it. I would expect to be redirected elsewhere, either for more information or to speak to a representative but the chat script doesn't seen to parse any option like that.
FUNCTIONALITY	(ID # 1781) The chatbot is much faster in terms of response and can direct me quickly to the information I need based on any key words I entered that outline my reason for interacting with it. I think whatever algorithm powers it is quite good at mimicking interaction with humans in this day and age so it doesn't feel like an unnatural exercise of speaking to a robot. Other than for really complex and isolated scenarios, it's a great way to get help for common customer issues.	(ID # 170) Very specific questions. Like a lost phone. Or pricing for a plan. In other words, a narrow search whereby I would anticipate a narrow return (or at least limited anticipated variability of info return). Note, I used the term "search". I perceive chatbot tech, or at least the one I tried just now, as really an advanced rule-based type of search. There is no AI here. No responsiveness to nuance or voice tone or cadence or emotion. It's really quite flat.
ICA EFFECTIVENESS	(ID # 53) I think firstly, the chatbots ability to ask questions that help narrow down the enquiry to assure they are providing the correct help is very impressive. Secondly, the speed at which this chatbot responded was practically instantaneous. No need to wait on hold to speak to someone and then wait while	(ID # 2124) In three of four questions, the chatbot did not understand the question. In all cases, it did not provide appropriate answers to what I thought were very simple questions. All my "simple" questions made the chatbot refer me to a human. I should have started there first.

	they look something up or transfer you to someone else. Altogether very efficient.	

5.5.2. Participant Understanding of Fit of ICA Capabilities with Task at Hand

My study also examined end-user perceptions of ICA fit with assigned tasks. This question helped to show the different aspects of ICA fit (for example, the complexity of tasks, availability, and timeliness).

5.5.2.1. ICA Fit for Complexity

Most participants found the ICAs suitable for more straightforward tasks but unsuitable for complex tasks, as quoted below:

> (ID # 49) Finding solutions which are straight forward are its strengths, perhaps being too polite is a weakness but I can live with that.

> (ID # 53) Any general frequent questions are probably excellent for chatbot, and as previously stated any odd questions should probably be left to human customer service.

> (ID # 74) Chatbot can do routine tasks or straight forward FAQ style questions. It doesn't do well with more complex or specific scenarios.

5.5.2.2. Fit For Task Variability

Participants often found ICAs provided quick responses and the ability to provide adequate help for simple tasks, yet the same ICAs could not respond to complex tasks. These participants were of the view that:

> (ID # 86) It's very good at providing relevant information in response to people's questions (again, it's just looking for keywords), but it's not great at doing actual tasks.

> (ID # 90) It is well-suited for finding information on the website and linking you to it, but not well-suited for answering specific questions in detail or clarifying information on the website.

> (ID # 119) To me, it seems like little more than an elaborate "search" feature -- it just picks up on specific keywords, so if you can choose appropriate keywords, you can often find the specific info you need yourself. however, for details such as local service interruptions that may not be searchable, it might be able to access the needed information.

> (ID # 211) The chatbot fits for general questions without additional qualifiers/adjectives. The chatbot does not fit well for specific or complex product/service questions.

5.5.2.3. Fit For Timeliness:

Many participants were impressed with the timely response of the ICAs. This service fit aspect of the ICAs invoked strong reactions from participants who felt they might not use ICA again due to irrelevant quick responses.

> (ID # 219) Chatbots can definitely fit well in helping a customer quickly and effectively for small issues or in finding information but doesn't fit well for more specific inquiries that require a more in depth look into an account or information.

> (ID # 327) It has really quick responses…..all incorrect and not even on the topic I raised with it, but it's random and incorrect answers were really quick.

5.5.2.4. Fit For Responsiveness:

Some participants also found that sometimes their ICAs could provide the information, but their results were disappointing when completing a task. Participants were often disappointed by incorrect responses and found the responses random.

> (ID # 341) It (ICA) does not fit well with tasks that require a higher level of interpretation and personalization.

> (ID # 352) it depends and varies from each chatbot and the brand that they represent. some are good with inquiries and solving issues while others are not.

> (ID # 426) The chatbot fits most generic questions very well but the more specific you get, the more generic answers you receive, which doesn't help anyone. So it would do well with things like providing numbers and pages that have info, but would do poorly at tasks involving assisting customers with service problems.

> (ID # 607) Again, it works well for straightforward/general questions like what to do when you lost a device, but it doesn't work well for something really specific where the information isn't readily available on the website somewhere – like very specific questions about roaming

> (ID # 782) Can fit well with easy tasks, often based on keywords (like "promotion" or "deal"), but also with the initial troubleshooting of problems (like going through a flow chart to determine what is wrong and attempt to fix it).

5.5.2.5. Perceived Overall Fit

Participants could usually spot limitations in ICA capabilities, especially when handling specific questions or tasks. They believed ICAs could handle tasks or queries that would engender multiple responses or solutions. Few participants found their ICAs to be of no value. In contrast, others were generous enough to suggest that participants were at fault in phrasing their queries which led to poor, inaccurate or no response from the ICA.

> (ID # 815) The chat bot does well with very specific key words that it can search using its algorithm. It does not do well with specific, complicated questions that require some brain work for a human to decipher.

> (ID # 890) For very general information, the chatbot is great at sending customers the right links. If a customer has very specific needs, the links given lead to a maze of searching for the answer. Generally, if I'm contacting support I want answers.

> (ID # 1034) I hate Chatbox, doesn't fit well with anything

> (ID # 1157) Chatbots would be good for searching for information on the website. Or just gathering information for a human, especially if the wait time is longer. But real issues like mentioned before, losing phone, tech support I would prefer to talk to a human.

> (ID # 1453) things like lost phone but not lost signal. Even lost internet connection it made me feel like it was something wrong on my end not a problem on their end

Some participants pointed out specific characteristics of the ICAs that allowed them to reduce waiting time in receiving customer services from human agents. These participants also identified task and technology characteristics for which the fit needs improvement for complex tasks or tasks requiring the ICA to display intelligence and task performance.

> (ID # 1492) Chatbot is mainly for people with no patience to read carefully or understanding of their own needs and are impatient with live agent responses. However, if there is "real" problem a live agent is needed.

> (ID # 1543) Chatbot fits well getting general information. But technical issues like weak signals, service outages or having problems with phone calling out I would need to speak to a real human technical support agent. So as long it's not a technical issue then I would use chatbot. But I would probably only use chatbot for general information.

> (ID # 1624) The chatbot fit the task of searching through already-publicly-available information and providing it to me quickly. However, it was unable to provide me information beyond what I would otherwise be able to find on my own, which is why I would normally be contacting customer service in the first place.

> (ID # 1639) it is a good attempt but does not replace live human interaction and interpretation.

5.5.2.6. Fit For Availability

Interactions with ICAs helped to provide some participants with an experience that would help them with the ICA's availability for specific basic and generic tasks like information search. However, they felt the ICA was unavailable for other, more specific tasks. Some participants felt the ICA could respond to anything if the request made to the ICA were correct. Their perspectives about ICA availability suggest:

> (ID # 1708) It fits well with finding out any type of information without having to go searching for it. It's like talking to a person at a kiosk without having to go to one.

> (ID # 2057) I am fairly sure there is nothing the chatbot cannot do. It is all a matter of phrasing the questions the proper way.

Participants could usually identify the variety of tasks their ICA could perform. Various participants explained the capabilities of the ICA with the following comments.

> (ID # 2120) Chatbots are programs built to automatically engage with received messages. Chatbots can be programmed to respond the same way each time, to respond differently to messages containing certain keywords and even to use machine learning to adapt their responses to fit the situation

> (ID # 2275) Chatbot is suitable for finding information like recipes, maps, directions, weather, alerts, those type of things. It would also be beneficial for appointment making and reminder calls to save human time. Chatbot services are not well suited when people require specific information with pending, fluid, or nuanced answers where relationality is essential

> (ID # 2403) When chatting with the chatbot I found it was an easy and pleasant conversation. The chatbot was able to access my file and was able to fully assist me without needing to transfer me to a live agent or have one call me back everything worked perfectly.

In general, participant sentiments collected through this qualitative feedback, suggest that the participants found the ICA ill-equipped to provide a solution to complex tasks but were adequate for more straightforward tasks. Also, they found it very useful that the ICAs were available beyond regular office hours. However, some had reservations about timely ICA responses since they often had to rephrase their queries to invoke relevant information or replies from their ICA. Thus, the Fit aspect is evident from their comments in general and supports Hypothesis 7a, 7b and 7c, respectively. Their comments also tend to endorse the fit for complexity, availability and timeliness, thus influencing the overall fit for ICAs.

5.5.3. Behavioural intention for ICA usage with end-user satisfaction and Fit perspective

My study also asked the participants questions that prompted them to identify virtues and vices that encouraged them to use an ICA or prevented them from using an ICA.

5.5.3.1. ICA Acceptance: Simple tasks with no waiting times

Participants understood that ICAs were more suitable for performing simple tasks, essential customer services, and serving end-users, avoiding painful waiting times for human service agents. For instance, participants ID # (86,107,219,300 and 607) are of the view:

> (ID # 86) If there's a very long wait for a person to help me, and I have a very simple and specific question, I would use the chatbot. If there was a person readily available or if my question was too complicated, I would not use the chatbot.
>
> (ID # 107) I would use it for the most basic of customer service questions. It did not have the capacity to answer more complex issues with any substance.
>
> (ID # 219) I would definitely use chatbot for finding technical help for small issues and service interruptions. I wouldn't use it for issues with billing or anything related to my own account as I don't think it can effectively handle that type of stuff like a human agent can.
>
> (ID # 300) For simple inquiries or troubleshooting when I don't want to wait for an agent, I would probably use the chatbot. For anything beyond that (tech support, plans that chatbot can't find instantly, questions about service) I would prefer a live agent.
>
> (ID # 607) I would like to use it only in cases such as reporting a lost/stolen device where I could get a clear, easy answer very quickly with step by step instructions. In that case, it does an even better job than a human. Other cases that are more complex, where the answer might not be so straightforward or readily available or very specific to what I'm asking instead of something generic/general, I would not use (Name of the ICA withheld).

5.5.3.2. ICA Avoidance: Preference for Human Service Agent

Participants also felt that ICAs have minimal knowledge and capability. Participants pointed out that they were better off receiving services from human customer agents and, thus, less inclined to use ICAs. Participants ID # (215, 2046,2124,2204, and 2296) present the perspective.

> (ID # 215) I would always prefer to speak to a real person. For the most part, the Chatbox was a waste of time and I felt more frustrated. If I had a real problem and I was forced to deal with a Chatbox, I would be angry.
>
> (ID # 2046) I would frankly only use the chatbot to direct me to a live agent. I dislike waiting on hold, but the chatbot feels more like a glorified search-engine that tries to guess what you want. It's not really a "conversation."
>
> (ID # 2124) Only if there were no other alternative offered and I required a relatively immediate answer. However, based on this exercise, I doubt that I would get a suitable answer.
>
> (ID # 2204) I would always prefer to speak with a human. With this and other chatbots in the past I find it frustrating to now be able to get an answer to my questions.
>
> (ID # 2296) when I need a quick easy answer, but a human advisor still does a better job of finding answers

5.5.3.3. Important Scenarios for ICA Usage

Some participants indicated intentions to use ICAs in non-stressful environments. Also, customers seeking quick solutions instead of consulting the website's FAQ section or contacting the Call Center found ICAs suitable for use. Participants ID # (710, 782, 1458, 1486, and 1642) present the following views:

> (ID # 710) I wouldn't use chatbox in stressful situations phone stolen etc. I would use it if I were browsing for information in general and was in no rush/ under no stress

(ID # 782) When I have a problem or question, maybe even in lieu of looking up FAQ or browsing different pages myself. Would avoid if I had a bad experience with that chatbot previously, or if I had already tried it and it hadn't been able to help with my issue.

(ID # 1458) I would use the chatbot for simple questions or problems where I don't want to be on hold forever. I would use the chatbot after office hours. For really complex technical troubleshooting where I would have trouble easily describing the problem in one sentence, I would prefer dealing with a human technician.

(ID # 1486) The chatbot is good for quick responses - particularly when a human customer service agent was not available.

(ID # 1642) Most simple things would be chatbot not Call Center. Promotions, information. I don't think I would use it for a lost phone myself, I would probably do that through my account (where possible) or call in, I wouldn't have the patience at the time to deal with a chatbot (in a panic). Disputing a charge would also be something I couldn't use a chatbot for.

5.5.3.4. Intention to use

Some participants expressed their intention to use ICAs, usually due to their quick response or ability to complete non-complex tasks or simple queries. Many participants also indicated that they would not use an ICA while recording their grievances against poor customer services or decisions related to financial transactions. Participants (ID # 1781,1808, and 1814) present the following views:

(ID # 1781) I generally prefer the use of chatbots because it's a faster way to get help into my issues. While live chat with agents is really good for specific cases, there is sometimes a very long wait before an agent is available. For generic day-to-day questions, chatbot is my preferred way to get instant help. I don't prefer calling or emailing as those options usually take up too much of my precious time.

(ID # 1808) If my problem or question is simple enough, the chatbot can help me easily. For more complex issues, it might have to redirect me to an actual person.

> (ID # 1814) If I had a simple question, I would like to use the chatbot. If I needed to troubleshoot a problem, I would like to speak with a live agent to walk me through the steps

5.5.3.5. Trust Deficit

Some participants were able to distinguish between the service zones suitable for ICAs and human agents. Participants believed that for non-financial transactions, they would be happy to use an ICA, but for financial and banking issues, they would still trust human service agents more. Participants (ID # 511, 2057, and 2065) are of the view:

> (ID # 511) Having to type a lot of details and being unable to have a discussion, with a person about your issues. I don't always trust that the answers, I'm given would specifically apply to my particular issues.

> (ID # 2057) If I wanted to purchase something I would prefer an (human) agent. If I had questions about my service, etc., I would be more than happy to use a chatbot.

> (ID # 2065) I would use for simplified things where you don't feel that you need a human -last payment, due dates, promotions, amount due I wouldn't use it for address changes, credit info, personal information and banking access because I still trust humans more

As voiced by the participants, the above sentiments validate hypotheses H6 and H8. The qualitative feedback verified Hypothesis 6, that if the end-user is satisfied, he or she would likely express an intention to use an ICA. Finally, many participants indicated that they felt an ICA was more suitable for simple tasks, like generic information generic tasks. Thus, participants exhibited behavioural intentions to use ICAs for simple or generic tasks. Finally, qualitative participant statements supported H8.

5.6. Chapter Summary

The fifth chapter comprehensively analyzed my research by describing the methods and outcomes in depth. Section 5.1 described the preliminary data analysis, while Sections 5.2 and 5.3 using smart PLS3, examined my research model. Section 5.2 described the validation of the measurement model concerning validity and dependability. Section 5.3 depicted the structural model analyses and proved that all the hypothesized relationships were significant. This section also showed saturation analysis and post hoc analysis. Section 5.4 presented qualitative participant feedback. Accordingly, Section 5.5 provided the related qualitative study's outcomes and a summary.

Chapter 6: Discussion and Conclusion

Chapter 6 provides a detailed explanation of the hypothesized relationships discussed earlier in chapter 3. Similarly, it expands the results from Chapter 5 to match the ICA context and provides the study's contributions in the subsequent sections. Section 6.1 highlights significant discoveries from the research study based on the results presented in Chapter 5. Section 6.2 discusses the theoretical implications. Likewise, Section 6.3 discusses the managerial and practical implications of the study's findings. Correspondingly, Section 6.4 discusses the limitations of the study and possible strategies to overcome the limitations of my study. Section 6.5 then suggests potential directions of the research. In conclusion, Section 6.6 wraps up the discussion.

6.1. Discussion

My study is one of the first empirical studies on ICA that integrates ECT and TTF. My research effectively assessed customer attitudes and satisfaction with ICA capabilities by integrating these theories. Since this study focused on commercial ICAs deployed on Canadian telecom sector websites, it is unique and more aligned with the general topic of ICAs deployed for customer services business requirements.

My research examined how customer attitudes and satisfaction based on their ICA experience influence their behaviour and intent to utilize ICA. The study revealed that end-user interaction with ICAs influences the end-users' beliefs and attitudes. The quantitative data supported the hypothesis that user expectations about ICAs would affect their experience and attitude prior to the experiment. The analysis examined the results to see if there was support for the posit relationships. Similarly, qualitative feedback from the participants suggested that improving customer attitude and satisfaction with ICA performance may improve end-user engagement with ICAs and positively influence the business value associated with commercially deployed ICAs. Participants were ready and eager to point out ICA's strengths and weaknesses. Participants were vocal about the circumstances suitable for using ICAs, including task complexity and judged ICAs suitable for usage, but only to a limited extent. My study investigated if the deployed ICA technology was deemed fit by the end users in terms of service complexity, availability, and timeliness. In addition, whether the ICAs possessed the necessary AI capabilities and could complete the assigned tasks. My study also presents the theoretical, methodological, and managerial contributions in subsequent sections of this chapter.

My study developed and tested a conceptual framework incorporating task-technology fit (TTF) into expectation-confirmation theory (ECT) to investigate ICA capabilities that increase end-user intention to use them. My empirical findings support the proposed model, demonstrating that ECT can explain and predict end-user decisions to use ICAs. My study also concluded that task-technology fit is a good model of end-user preference to use ICA systems.

6.1.1. Experiment Setting

My research environment included Expectation Creation, Interaction, and Post-Interaction, with a research strategy to collect data simultaneously for three instances: expectation formation, interaction with ICAs (exposure to ICA services), and post-interaction evaluation. The interaction was the primary focus of my study, which also investigates whether the fit between ICA technology and assigned tasks can influence customer expectations. This strategy catered to the challenges of locating the same participants and replicating customer usage patterns with a deployed ICA. Shorter time frames allow participants to recall positive outcomes as a suitable proxy that aligns with a real-world business customer visiting a website for ICA services. This condition augments my view that a customer's attitude can be changed quickly. My research emphasizes that businesses adhering to this strategy will find their deployed ICAs more beneficial to customers, employees, and the organization.

ECT's premise is simple: end-users anticipate using an ICA with an expectation that the ICA can complete their task. Accomplished expectations will make the end-user happy; otherwise, they will be unhappy. Oliver's (1977, 1980) ECT theory displays exquisite minimalism, which makes it a critical clarifying theory. My study explores task completion with the help of the task-technology fit (TTF) theory, which indicates that technology is more likely to be utilized if its capabilities align with the user's tasks (Goodhue and Thompson, 1995). Goodhue and Thompson (1995) discovered that TTF was a significant predictor of user reports of improved job performance and effectiveness due to system use. Zigurs and Buckland (1998) also presented a group-level analogue to the individual model of Goodhue and Thompson (1995). My research observed that all the fundamental ECT and TTF hypotheses were strongly supported.

6.1.2. Operationalization of Confirmation Construct

ICA performance and initial expectations for the six ICA capabilities form the basis of my study and determine the end-user confirmation dimensions. For my study, I operationalized the CONF (Confirmation) construct as the difference between the measured Expectations and Perceived Performance scores. This operationalization uses the research works of Spreng and Page (2003). Interestingly these researchers define methods of measuring Confirmation as the difference between the customer's expected (or desired, ideal) level of product (or service) performance and their perception of actual performance after actual product use (LaTour and Peat, 1979; Oliver and Bearden, 1985; Swan and Trawick, 1981; Myers, 1988; Tse and

Wilton,1988; Parasuraman et al., 1994; Kettinger and Lee, 1995; Jiang et al., 2000a; Spreng and Page, 2003).

Algebraically, this difference is represented as (Pi- Ei), where Pi is the perceived performance on attribute "i" and Ei is the expected or desired performance standard. All six ICA attributes have Pi and Ei distinctions. Each attribute is evaluated on two scales (expectations and performance) rather than three (expectations, performance, and a direct confirmation). Based on Spreng and Page (2003), my operationalization of the confirmation construct for ICA use requires subjects to complete a pre-experience questionnaire, a service experience, and a post-experience questionnaire.

In their study, Spreng and Page (2003) operationalized "disconfirmation" as the difference between measured values of expectations and perceived performance. In their work, expectations and perceived performance to before and after consumption. In my research, I operationalized confirmation using the same strategy. My research results reflect that, following the findings of Parasuraman et al. (1994), difference scores can effectively operationalize confirmation in marketing practices when it is essential to measure a standard through people's perceptions of performance. Since my research is related to customer service provided by ICAs, it gives me the confidence to apply this operationalization strategy.

Thus, the constructs of expectations, perceived performance and confirmation are all essential determinants of satisfaction with ICAs. Satisfaction contributes considerably to usage intention in ICAs, which is a significant finding consistent with the seminal work of Oliver (1980). Also, the findings from my study demonstrate that expectations and confirmation dimensions directly impact end-user satisfaction and behavioural intention to use an ICA.

6.1.3. Human Customer Services vs ICA Customer Service Features

End-users believe using ICA systems is satisfactory (or a source of satisfaction) if the ICA's AI capabilities can imitate human service agents' capability. As a result, it is critical for ICA systems to improve their AI capabilities and performance to increase end-user satisfaction. The six ICA capabilities (C, F, I, R, TP and TT) attempt to mirror the capabilities displayed by a human service agent. These six capabilities for the ICA influence the end-user experience. An end-user may view the ICA as providing a service comparable to that of a human service agent. My study has ignored the hedonic or social presence quality of these ICAs.

6.1.4. Significant Findings

Researchers have studied ICA satisfaction in health care issues, education, and customer services. To benchmark my study's effectiveness, I considered only the ICAs deployed by businesses for customer services. Several researchers have recently studied customer satisfaction with ICAs (Lee and Park, 2022; Yun and Park, 2022; Eren, 2021; Ashfaq et al., 2020). Researchers have studied behavioural intentions for ICA (Jiang et al., 2022; Kasilingam, 2020; Cheng and Jiang,2020). Even though this study differs from previous studies in many ways, the findings support previous studies on the expectation effect and recent interpretations of the disconfirmation effect. My research revealed that an ICA elicits positive and negative emotions depending on whether the ICA accomplishes the customer's expectations or whether the ICA is qualified to perform the task assigned by the customer. My research revealed that ICAs could interact, engage, and retain end-users by interacting and engaging with them (Prentice and Nguyen,2020). Participants impersonating ICA customers have revealed the limitations of ICA capabilities, suggesting that an effectively designed ICA would engage the end-users for short-, medium-, or long-term interactions (Nißen et al., 2022).

My study participants found that ICAs redirected or deleted issues to human agents either too quickly or slowly, causing dissatisfaction. 90% of customer inquiries are resolved in ten messages or less (Rajnerowicz, 2022). This finding may prompt businesses to improve ICA's utility and value.

6.1.5. ICA Capabilities

The response of the participants shows that the six ICA capabilities substantially impact the customers' overall expectations of the ICA capabilities, indicating that they expect the ICA to be conversational, friendly, intelligent, responsive, task performer and trustworthy. The results also reveal that when interacting with the ICA, the end-users found the six capabilities evident and confirmed that these capabilities contribute to the Confirmation of the ICA capabilities. Results also show that after completing their interactions with an ICA, my participants found the six ICA capabilities to play an essential role in the overall perceived performance of ICA capabilities.

6.1.6. ECT Lens

Expectations-confirmation theory posits that expectations, coupled with perceived performance, lead to satisfaction. Our results show that an ICA can outperform expectations (positive disconfirmation), thus resulting in satisfaction. This observation is in line with extant research literature (Oliver, 1980; Spreng et al., 1996). Customers' expectations about ICA impact the Perceived Performance of the ICA. Thus H1 is supported.

Similarly, customers' initial expectations about ICA capabilities show a strong relationship with confirmation and display a favourable impact on satisfaction; this finding is consistent with those of Eren (2021), Cheng and Jian (2020), Chung et al. (2020), Sanny et al., (2020) and Ashfaq et al. (2020). The study's results validate the ECT extant literature that expectations about ICA capabilities and Perceived Performance of ICA capabilities influence confirmation about the ICA capabilities, as shown by Hypotheses H2 and H3.

The findings of our study further substantiate that customer satisfaction is positively influenced by chatbot expectation and confirmation about ICA capabilities, as shown by Hypotheses H4 and H5. The study's results also extend the ECT extant literature that Satisfaction with ICA capabilities strongly impacts behavioural intentions for ICA. Suppose the customer is unsatisfied with ICA's performance. In that case, usage intention will be negative. If a customer is more satisfied with ICA's performance, he or she will be more interested in using the ICA, as shown by Hypothesis 6.

These findings have exceptional significance for business organizations deploying these ICAs for customer service. If the customers seeking service from ICAs have a realistic expectation about the capabilities of the ICA, the customers would be able to confirm ICA capabilities and have a favourable view of the perceived performance of ICA capabilities. This view can lead to satisfaction with the deployed ICA.

Businesses often do not provide their customers with realistic expectations, leading to customers staying away from using their ICAs and eventually removing these ICAs from active deployment. Figure 6.1 shows the different forms of ECT used in the extant literature. The value of R^2 for BI is more or less flat as it is not part of the ECT theory, whereas SATF shows an increase for different path models. The highest value of R^2 for SATF is 0.758 for the path model from Perceived Performance -> Satisfaction. However, this parsimonious model does not focus on the Expectations and Confirmation part and thereby theoretically undermines the proper theoretical foundations. Figure 6.1 shows the R^2 value for different path models

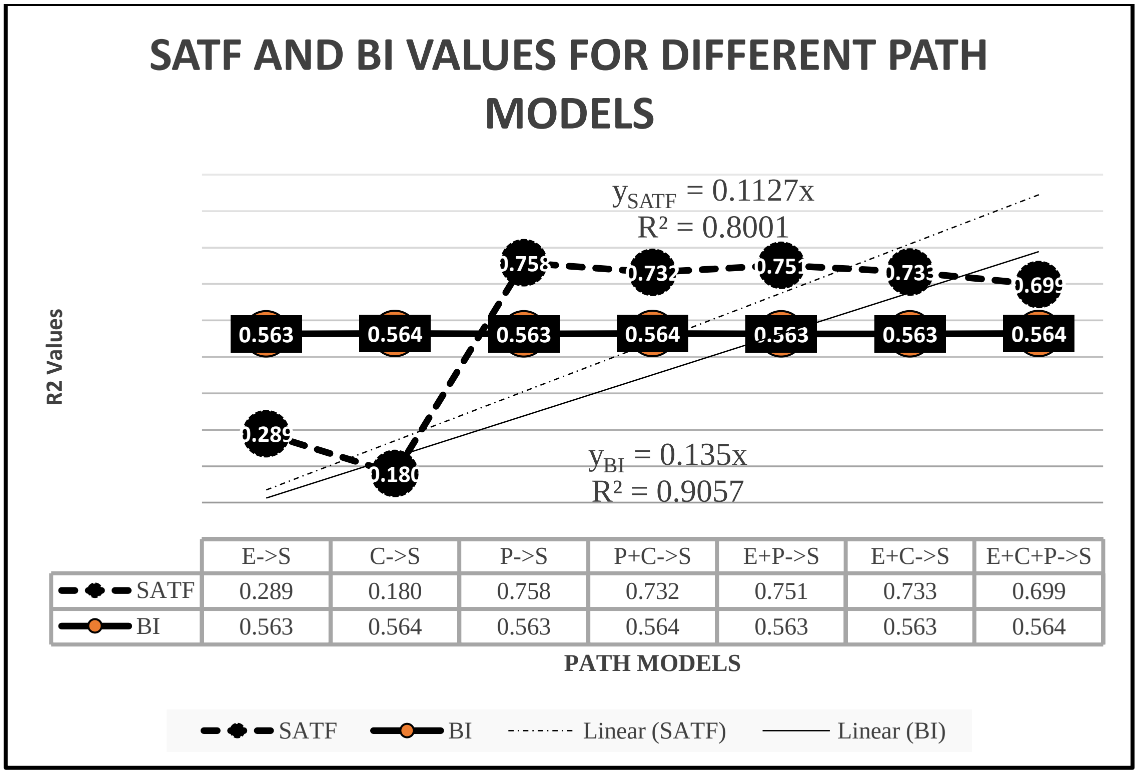

Figure 6.1: R^2 Values for SATF and BI Constructs

Measured against this, the complete model of Expectations ->Confirmation ->Perceived Performance -> Satisfaction holds theoretical and practical relevance and shows that Expectations and Perceived Performance are both confirmed to contribute to Satisfaction.

6.1.7. TTF Lens

ICAs are trained and deployed on business websites to provide customer service but are they fit for the purpose? For this objective, my study envisioned using the Task Technology Fit Theory (Goodhue and Thompson, 1994). Behavioural intentions for ICAs studied with a TTF perspective (Wang et al., 2021) include expanding the Perceived Overall Fit aspect, a relatively under-explored area in the ICA domain. The service fit of my model explored three aspects: first, a strong relationship between ICA Fit For Complexity (FFC) and Perceived Overall Fit for ICA.

Secondly a strong relationship between ICA Fit For Availability (FFA) and Perceived Overall Fit for ICA. Thirdly, a strong relationship between ICA Fit For Timeliness (FFT) and Perceived Overall Fit for ICA. These conditions are necessary because, in my study, the ICAs performed four tasks of varying complexity. These tasks allowed my study to understand the Perceived Overall Fit (POAF) for ICA fit in terms of the three relevant aspects of FFC, FFA and FFT.

Similarly, POAF strongly correlates with BI for ICAs. This perspective aligns with the established view of task technology fit (TTF) theory. TTF, highlighted in different studies, suggests that an IS or a technology may permit diverse tasks, performances and implementations; hence, a system's capability to perfectly serve numerous tasks will differ (Chen et al., 2015; Goodhue, 2006).

My study found evidence for the three additional hypotheses in my pre- and post-interaction model. The findings indicate that variables from the task-technology fit hypothesis are essential in explaining user intentions to interact with ICAs. Thus, Hypotheses H7a, H7b, H7c and H8 are all supported.

With the help of FFC, FFA, and FFT, the ICA service suggested that the Perceived Overall Fit (POAF) is essential for explaining usage intention. FFC, FFA and FFT indicate adequate criterion-related validity for a formative construct of POAF. Table 6.1 shows the results for the POAF construct

Table 6.1: POAF Construct

Paths	β	T Statistics	P Values	Decision
FFA -> POAF	0.473	8.582	0.000	Supported at p <0.001
FFC -> POAF	0.508	10.283	0.000	Supported at p <0.001
FFT -> POAF	-0.068	2.325	0.020	Supported at p <0.05
POAF -> BI	0.572	9.545	0.000	Supported at p <0.001

6.1.8. Coefficient of Determination R^2 Values

The POAF construct, combined with previous variables from the ECT part of the model, explains up to 75.6% of the variation in behavioural intention. This high value dramatically improves the ability of our model to explain variance in the behavioural intention-dependent variable. The critical theoretical implication of this study is that we propose an extension of customer behaviour theory with a fit aspect from IS to explain the possible behaviour of a customer to use an ICA. The table below presents the values of critical constructs, which show how the Coefficient of Determination R^2 for the dependent construct of BI improves from 56.6 percent to 67.1 percent as a result of the POAF construct. Table 6.2 shows the value of different constructs under individual and combined theories of ECT and TTF.

Table 6.2: R^2 Values for individual and combined theories of ECT and TTF

THEORY	COEFFICIENT OF DETERMINATION (R^2)	CONSTRUCTS				
		BI	PP	CONF	SATF	POAF
ECT ONLY	R Square	0.564	0.260	0.985	0.699	Not Applicable
TTF ONLY	R Square	0.645	Not Applicable		Not Applicable	0.756
ECT AND TTF	R Square	0.671	0.260	0.985	0.699	0.756

Researchers believe that when there is a well-researched customer satisfaction model that controls for the most critical known effects like quality and expectations, the value of R^2 should be greater than 60% (Larsen et al., 2009). My study registers an R^2 value of 69.9% for SATF and 67.1% for BI.

In previous research like that of Eren (2021), the R^2 values were 0.104, 0.142 and 0.617 for confirming customer expectations, perceived performance and customer satisfaction for chatbot use, respectively. In other words, the related variables explain 10.4% of the confirmation of customer expectations, 14.2% of the perceived performance, and 61.7% of customer satisfaction.

Similarly, in another paper by Nguyen et al. (2021), Confirmation, Performance Satisfaction and System Satisfaction had R^2 values of 42.45%, 68.95% and 57.41%, respectively. My study showcases R^2 values for Confirmation, Perceived Performance, Satisfaction, Perceived Overall Fit and Behavioural Intention as 98.5%, 26%, 69.9%, 75.6% and 67.1%, respectively. Table 6.3 represents a comparison between my studies and previous studies.

Table 6.3: Comparison of R^2 values for different studies

RESEARCH STUDY	THEORY	R Square VALUES FOR CONSTRUCTS				
		BI	PP	CONF	SATF	POAF
Eren, 2021	ECT ONLY	Not Applicable	14.2%	10.4%	61.7%	Not Applicable
Nguyen et al., 2021	TTF ONLY	Not Applicable	68.95	42.45%	57.41%	Not Applicable
My research study	ECT & TTF	67.1%	26%	98.5%	69.9%	75.6%

My study allowed participants to interact with the ICA, resulting in enhanced interactions between participants and the ICA. This improvement indicates that customer expectations for ICA services influenced perceived performance with the ICA, thereby strongly impacting customer satisfaction. Table 6.3 above represents the R^2 and R^2 values from previous studies' findings (Eren, 2021; Nguyen et al., 2021). Similarly, the customer expectations for ICA also impact the confirmation dimensions for ICA capabilities. This result supports the extant literature. Individuals have clear expectations for ICA that they experience and know well. Expectations correspond to the standards that a service or product should have. Moreover, customer expectations may be affected by other customers' experiences, which can shape satisfaction differently. Figure 6.2 shows the R^2 values for my research model.

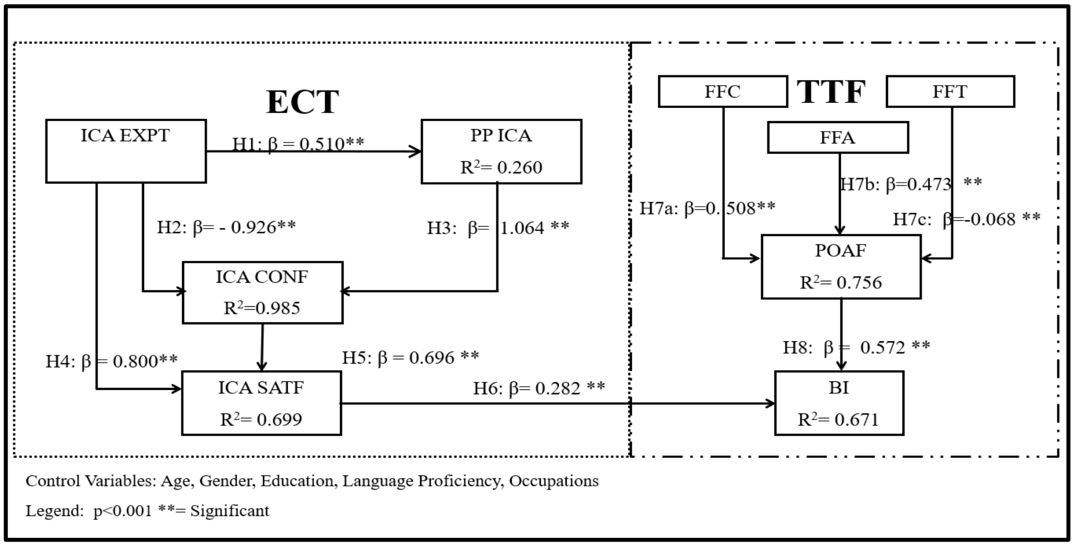

Figure 6.2: R^2 Values for PP, CONF, SATF, POAF and BI Constructs

6.2. Theoretical Contribution

There are several important theoretical contributions.

First, My study is one of the earliest attempts to explore actual ICA end-user satisfaction and BI through the lens of the ECT (Oliver, 1980) and TTF (Goodhue and Thompson, 1994) models. In other words, these two theories (ECT and TTF) are integrated into a new, simplified theoretical framework to investigate end-user satisfaction and BI of ICA usage when evaluating ICA that corresponds to the task at hand.

Second, my study extends these two primary bodies of research literature by incorporating the constructs related to six ICA capabilities of Conversation ability, friendliness, intelligence, responsiveness, task performance and trust at the Expectation, confirmation and perceived performance stages. These constructs were developed and measured to check the effectiveness of the research model. More importantly, my study demonstrates how POAF affects BI in a significant and positive relationship; in other words, the end-users perceive the overall Task-Technology Fit between the ICA technology and the assigned tasks. Thus the end-users display a clear behavioural intention to use ICA appropriately while seeking the provision of information or performance of the task.

Third, although extensive research has been conducted on ICAs recently, no study has adequately evaluated the key AI capabilities affecting user satisfaction and BI toward chatbots. My study sheds new light on the role of AI capabilities from the perspective of customer service elements based on the ECT model (Oliver, 1980).

Fourth, my study investigated ICAs by studying task complexity and experimental effort that will enrich the extant research literature. Thus, the findings related to whether an ICA can help the end-user get the information or service he wants or if he would be better off connecting with a human agent will be a part of human vs AI research on ICAs.

Fifth, by exploring if there is a consistent pattern in how end-users use an ICA, my study provides a theoretical extension to the fact that ICAs can assist a business organization in improving its functionality. This utility assists the business organization's human resources in responding to end-user queries and offering support to the customer service resource.

In addition, the following theoretical contributions are presented in greater detail:

6.2.1. Beyond the initial adoption of the ICA

First, my research is one of the first few studies empirically examining the theoretical foundations for behavioural intention to use an ICA. Researchers have focused on adopting ICAs (chatbots) or continuing to use some survey scales taken directly from the extant IS literature. My research incorporates an experiment that enables participants to engage with the ICA, and thus we can measure changes in their beliefs and attitudes toward the ICA. We also develop measurement scales for constructs we have identified from a detailed literature review. Our survey scales specifically focus on the human agent versus AI agent comparison and form unique concepts researchers have not previously adopted. Researchers have yet to explore this crucial point for AI technologies due to the relative infancy of AI-enabled conversational agents.

6.2.2. AI Capabilities of the ICA

My study has the potential to take on the inconsistency in research as it has the potential to endorse the relevance and significance of core satisfaction concepts in this new technology. End-user satisfaction has long been a strategic focal point of existing marketing and information technology literature. Thus, my second contribution can broaden the research on ECT relationships with these research fields. This study extends the findings of previous research studies (Lankton et al., 2013; Bhattacherjee and Lin, 2015; Guo et al., 2015; Lin et al., 2017; Brill et al., 2019; Ashfaq et al., 2020). These studies link different IS applications, including ICAs and intelligent personal assistants, to the ECT model's end-user satisfaction and related outcomes. My study adds the critical element of ICA capabilities to these research genera.

6.2.3. Integrated ECT and TTF framework

The astronomical evolution of AI and advanced information systems capabilities like computer vision, natural language processing, and speech recognition have profoundly influenced user behaviour. My study observed that individuals face challenges in managing the complex trade-offs of trusting technology innovation and accepting ICA capabilities. My research included perceptions, attitudes, and trust implications that represent essential topics within marketing and Information Systems disciplines. To the best of my knowledge, this study is one of the first attempts to empirically examine the influences of trust and perceptions related to Conversation ability, friendliness, intelligence, responsiveness, and task performance toward user attitudes within the context of ICAs.

6.2.4. Factors affecting ICA Usage

Another critical line of research from my study's findings is determining and evaluating the factors influencing an end user's intention to use an ICA. To that end, my research provided through the experiment how a researcher can study the effects of several variables on whether an ICA end-user finds the ICA to display capabilities of Conversation ability, friendliness, intelligence, responsiveness, task performance and trust. My study collected responses from the participants about issues related to satisfaction with ICA capabilities and the fit between ICA capabilities and assigned tasks.

6.2.5. ICA Capabilities as a second Order Constructs

My study makes significant theoretical contributions by pursuing the stated objectives. First, to the best of my knowledge, this is the first study that has conceptualized and validated the concept of ICA capabilities as a second-order construct. We conceptualize the construct at the two stages of Expectation and Experience. We discovered that the most influential ICA capabilities were responsiveness and friendliness. These findings advance the current literature on ICAs by conceptualizing and validating these constructs.

6.2.6. Extending and Combining ECT and TTF

The empirical evidence from my research study supports all of the study's hypotheses. Based on an integrated ECT and TTF, mediation and moderation methodologies allow my study to explore the impact of ICA capabilities at the Expectation and Experience stages, further extending the research on ECT and TTF. Evidence from extant literature suggests that this is probably the first study to conceptualize or empirically test changes in beliefs and attitudes toward ICA usage. My study contributes to ICA usage research by combining ECT and TTF constructs and building one of the earliest process models for ICA usage. My study is unique and may inspire other researchers to develop chronological models that focus on changing patterns of ICA usage. This approach is different from the usual static ICA usage models based on the theories of TRA, TAM, TPB, and UTUAT (Trivedi, 2019; Behera et al., 2021; Eren, 2021). My study also makes theoretical contributions to Expectations Confirmation Theory and Task Technology Fit research literature. My research results show that Complexity, Availability, and Timeliness impact the Perceived Overall Fit, positively impacting Behavioural Intention to use the ICA. The ICA capabilities of Conversation ability, friendliness, intelligence, responsiveness, task performance, and trust can offer more outstanding customer service than traditional methods for end-users who consult with customer service departments via ICAs instead of human agents. These constructs also contribute to the referent theories by illuminating some empirical inconsistencies while resolving previous empirical inconsistencies. Much of the existing IS literature describes the complex interrelationships between expectations (beliefs), attitudes, satisfaction, and behavioural intention. My study's unique perspective is that more minor changes in beliefs and attitudes stabilize ICA usage and improve the outcomes of using an ICA.

6.2.7. Time Period Study on ICA Usage:

I successfully presented a time-period study on ICA usage, tested our theoretical model in an empirical setting, and provided an example of combining quantitative and qualitative approaches to ICA research. This type of multi-method research is critical for understanding complex temporal behaviours like ICA usage. Our model empirically validated ICA usage contexts, revealing unique aspects. Similarly, the qualitative feedback was analyzed using the Grounded Theory Method, allowing us to refine our theory. These approaches helped us triangulate and validate quantitative results and provide unique insights into complex temporal processes like ICA usage. Even though my study validated the hypothesized model using survey data on the ICA usage contexts, my study recommends incorporating these emerging factors into future long-term ICA usage process models.

6.2.8. Perceived Overall Fit:

Finally, this study provides another essential theoretical contribution regarding Perceived Overall Fit in terms of Fit for Complexity, Fit for Availability and Fit for Timeliness. The findings showed that the perceived overall Fit for the ICA shows a positive relationship with end-user behaviour and intention to use the ICA. My study found that if the ICA is not fit for complex tasks, the end-users were neither happy nor showed any behavioural intention to use the ICA. Customer service features concerning Complexity, Availability, and Timeliness can significantly improve the Behavioural Intention of using the ICA.

6.3. Managerial and Practical Implications

My study highlights several practical implications. ICA systems should be able to handle tasks of varying complexity and be available 24-7. Customer service strategists opting for preemptive ICA-enabled customer service systems must promptly provide relevant, reliable, personalized, precise, and up-to-date information in a helpful format.

6.3.1. Variable Individual Usage

Customers can use ICAs to perform information retrieval and other complex tasks. Research helps practitioners understand ICA end-user motivations and satisfaction. End-users can use ICAs to receive customer service comparable to a human agent. ICA utilization varies according to the user (Kumar et al., 2016). The findings provide practitioners with insightful knowledge regarding ICA drivers and end-user satisfaction. According to researchers, customers want a valid, trouble-free, 24-7 ICA (Ashfaq et al., 2020). ICA creates digital customer-services systems that boost customer interaction, enable unrestricted availability, and offer high adjustability (Chung et al., 2018).

6.3.2. ICA Customer Services

My research provides motivations for IS practitioners working in telecom, airlines, shipping, logistics, retail, online banks, and online brokerages' e-commerce environments. These businesses previously relied on IT assets and services and now rely on ICA-enabled customer service to generate revenue. The limitations of an ICA as a service provider hinder customers' chatbot adoption (Adam et al., 2021). Effective long-term ICA management requires anticipating and understanding belief and attitude changes. Businesses can reduce the likelihood and impact of customer attitude changes by planning proactive interventions. Proactive transactional initiatives like customer orientation and training to use an ICA can help set realistic expectations about the ICA's capabilities, reducing dissatisfaction and the impact of using an ICA instead of a human agent.

6.3.3. Building up Realistic Customer Expectations

My study introduced the ICA in a two-minute video clip, ensuring that the participant (customer) first builds realistic expectations, then engages with the ICA, and then expresses their attitude (positive or negative) and satisfaction or dissatisfaction with it. Given the importance of attitude and satisfaction in later-stage user cognitions and long-term usage, an IS professional can track end-user disconfirmation and satisfaction with ICA usage. My study advocates this as a pragmatic way for professionals to implement a strategic and operational plan. A short movie showcasing ICA's capabilities can encourage customer adoption. Unrealistic expectations, disappointment, and the end of the ICA may result from a poorly implemented informational/training technique.

6.3.4. Identify and Isolate Sources of Dissatisfaction

Businesses should identify dissatisfaction sources to avoid ICA discontinuation and intervene early to encourage ICA usage by the end-user. My study shows that when end-users use ICA for customer services, Conversation ability, friendliness, intelligence, responsiveness, task performance, and trust affect their attitude, satisfaction, and behavioural intentions to use ICA. My inquiry used an introductory video to realistically set end-users' ICA expectations to help participants anticipate ICA capabilities and performance. My research strategy may lead to realistic expectations, user satisfaction, and eventual ICA usage. Incorrect ICA deployment can result in unmet expectations, user dissatisfaction, and discontinuation of use or future non-use of ICA. Telecom companies may benefit from helping users set realistic expectations with a short video clip demonstrating ICA's capabilities. ICA customer service must be effortless and demonstrate its capabilities. Suppose the ICA's interaction with end-users does not show its capabilities. In that case, Big Data Analytics algorithms should update the ICA knowledge base and response rules database daily.

6.3.5. ICA Capabilities

A self-learning function of the ICA governed by an algorithm ensures that the ICA displays its six AI capabilities. ICA's six capabilities mirror the capabilities of the HR agents. Conversation ability means the ICA can have a meaningful conversation with the end user. Friendliness creates an environment where end-users find the ICA respectful and courteous, which builds trust. The ICA must be intelligent when responding to end-user queries and complete the task of providing information in minimal time without deflecting to a human agent. A trustworthy response requires the ICA to provide the end user with the necessary information.

6.3.6. Service Fit

Complexity Fit (FFC), Availability Fit (FFA), and Timelines Fit (FFT) are all crucial for overall service fit (POAF) between ICA technology capabilities and assigned tasks. FFA means users can use the customer service ICA anytime, anywhere, and the ICA should be available 24 hours a day, 7 days a week and respond quickly to end-user queries. FFT shows that an ICA's timely response affects user trust, attitude, and satisfaction. My research found that the model developed in this study shows that the ICA can handle most CRM tasks, ranging from simple to complex.

After evaluating an end-user's need, the ICA should provide a friendly, intelligent, conversational response, including time and trustworthiness information. User queries are similar to FAQs. These include new deals, promotions, service issues, location coverage in and out of Canada, or lost or stolen phones. End-users will not always describe issues, so they will test an ICA's ability to ensure user satisfaction. Conversation ability, friendliness, intelligence, responsiveness, task performance, and trustworthiness can increase end-user willingness to use ICAs.

6.4. Limitations of the Research

There are several significant limitations related to the scope of the study, sample selection, and methodology. Certain limitations to my study may influence the interpretation of the findings.

6.4.1. ICA type

My research study excludes Embodied Conversational Agents and prominent cue features of Embodied Conversational Agents like facial expressions, homophily (Graham,2014) and anthropomorphism (Han, 2021). Commercial products include these features, and scholarly journals have published articles about these cues as an essential source of communication (Go and Sundar, 2019). These features are also available in voice assistants, effectively engaging the customers (Moriuchi,2019). Future studies may use these features for text-based Conversational Agents, either in word phrases or emoticons.

6.4.2. Gaps in Literature Review

There is a possibility that the literature review may have missed important work on textual, vocal, and embodied conversational agents, even though the article selection is up to date. The search is based on IS Scholars Basket of Eight periodicals, IS conferences and articles published in computer science and marketing fields to uncover research outside IS. Future research may include more management, business, and strategy disciplines to increase the scope of comparative research.

6.4.3. Single Study Bias

My research findings are possibly susceptible to single-study bias. My study participants, in particular, were engaged by a single research firm. The participants were well versed in understanding English, educated and adept at using ICA technologies, and came from Canada. Canada is a technologically sophisticated nation. As a result, one future research option is to replicate this study in different populations — that is, in different countries. However, since my study's findings can guide how the ICA usage trend may emerge in less technologically sophisticated countries, this fear is partially mitigated. Given the critical nature of single-study bias, future research may include different contexts. The context can include different technologies and user groups, for instance, embodied or disembodied conversational agents, and user groups, including end-users or employees. Context can help tease apart the strands of universal constructs like perceived trust in driving user behaviour, such as intention to use.

6.4.4. Moderator Variables

Additionally, ICA capability constructs like Conversation ability, friendliness, intelligence, responsiveness, task performance, and trust) play a role in driving user behaviour, such as conditional or unconditional intention to use. Second, while my study investigated control variables, we did not consider critical moderators like the experience of using ICA, intention to use voluntarily, or compulsion (Venkatesh et al., 2003). Future studies should consider how these moderators might fit into the ECT framework.

6.4.5. Actual ICA Usage

Behavioural intention to use ICA was my study's dependent variable, which is a good predictor of behaviour that mediates the effect of other factors on behaviour, e.g., Venkatesh et al. (2003); future research should collect actual usage data to improve the IS continuity model's criterion validity.

6.4.6. Crossover effects

While performing statistical analysis, my research looked into crossover effects with the help of mediation and moderation strategies in this study. However, I did not formally include them in my research design.

6.4.7. Voluntary vs Mandatory Use of the ICA

Covid times brought an interesting situation that a lot of ICA services moved from voluntary to necessary, i.e., ordering of food or delivery due to limited human contact, thereby suggesting that older research related to dependent variables, such as satisfaction, became more relevant (Brown et al., 2002).

Finally, given the increased interest in the intersection of HCI and IS research, future studies should leverage the model presented here to create and test interventions and their impact on IS usage.

6.5. Future Research Directions

Like any other empirical study, my dissertation research study has certain limitations. When analyzing the conclusions of this study, these constraints may present exciting future research opportunities. In the future, the study may include different types of ICAs. Academics and practitioners advocate that ICA should improve performance and increase customer engagement so businesses deploying ICA can improve customer service (Robinson et al., 2020). Researchers have found that ICA immaturity affects usage intention (Rese et al., 2020). AI-enhanced work design and operations can benefit business organizations (Wang et al., 2022). AI reduced order errors and product returns during covid pandemic (Repko,2022).

6.5.1. Fusion of Design Science and Qualitative Research

Future ICA research will likely combine design science and qualitative research to examine comparable variables using DSR to generate design concepts (Strohmann et al., 2018). Researchers will investigate trust between end-user and the ICA interface (Baker et al., 2018). Facial expressions and body language help us understand why embodied ICA does not respond (Diederich et al., 2020), and in future, textual ICAs will use these characteristics in a modified way. The literature review shows that researchers continue to study ICA in IS research with factors influencing customers' attitudes toward ICA, comparing ICA's characteristics to human agents, and a collaborative approach that facilitates ICA and human collaboration (Seeber et al., 2020).

6.5.2. Underexplored Constructs of Satisfaction with ICA

There is a dearth of research on Satisfaction with ICAs. My dissertation can advance the understanding of Satisfaction within the context of ICAs. My dissertation will contribute to the extension of the body of knowledge related to the fields of AI, HCI, IS, cognitive sciences, and psychology. Also, the impact and influence of the proposed study on the established theories of ECT, and TTF, are unique and not available before in the discussion of ICAs.

6.5.3. Uninvestigated Constructs of Task Complexity with ICA

The complexity of the task can influence user satisfaction ratings. My research did not consider the influence of ICA types and task complexity on Satisfaction. My research excluded the essential AI characteristics such as Homophily (Graham, 2014), Perceived Accuracy, Perceived Ambiguity, and infrequent usage, usually found in the extant literature.

These factors may expand the scope of current research and inspire future studies. My research investigated the AI capabilities of ICAs by analyzing user satisfaction in service interactions. My study assists in comprehending ICA user satisfaction. This study investigated empirical evidence regarding user experience and satisfaction in the context of ICA. In the future, researchers could use constructs such as Thoroughness, Anthropomorphism (Humanness), Personalization, Emotional Intelligence (Empathy), and Technostress, Anxiety, and Technophobia to enhance AI-enabled understanding, its impact on AI-enabled customer services, and the workforce's quality of customer service.

Future research will compare and expand the current research on ICAs and Real Human Agents comparison. Similarly, future research will focus comparison of ICAs, chatbots, and virtual agents. This comparison initiative aligns with the value-added maturity model that can assist businesses in ICA enhancement. A laboratory experiment may employ Neuro IS settings. The complexity of AI tasks can facilitate a more profound comprehension of Satisfaction.

6.5.4. Behavioural Intention To Use ICA

The study's participants were current (and ongoing) ICA users, with few never-users. My study’s strategy was not to ask the research firm to recruit former ICA users because it was difficult to find them. Also, including such sample individuals could reduce relationship satisfaction.

Future research should examine existing users' commitment and intention to use ICA and whether end-users intend to reject, accept, or use it conditionally. By understanding commitment type variances and characteristics, managers can avoid ICA performance traps and advocate complementary programs and resources that can be supported. Researchers will ask past ICA users why they stopped using the ICA. Combining information from current and previous users could lead to future managerial decisions, such as strengthening user loyalty, highlighting competition weaknesses, improved ICA capabilities and intentions to use. Managers will need a varied and relevant implementation and communications plan because the antecedents and resources utilized to optimize each type of commitment will likely vary among ICA end-users.

6.5.5. Context Satisfaction

My survey instrument invited respondents to identify any ICA used. We had identified and included only those ICA associated with established and vital telecom sectors, i.e., Fido’s Jack, Freedom’s Freedom, Koodo’s Koodo Assistant, Roger’s Anna, and Telus’s Telus Assistant. These telecom ICA have strong images with established perceptions of trust and respect for individual privacy, at least to its end-users. Additionally, these organizations have not sustained significant losses due to massive data breaches. Thus, the end-users generally have a higher perception of trust for these ICA. Also, in conjunction with perceptions of trust, our research focuses on perceived Conversation ability, friendliness, intelligence, responsiveness, and task performance. Future research would explore if context satisfaction impacted ICA’s expectations, trust, and privacy concerns. Results in Chapter 5 under Post Hoc Analyses suggest the same.

6.5.6. Influence of Change in Attitude

Existing literature demonstrates the importance of end-user participation in achieving improved satisfaction and productivity benefits, with attitude considered a good predictor of adoption intent. My study had the option of using survey scales focusing on general attitudes about various items reflecting manifestations of attitudes towards AI, generated and evaluated by researchers for coverage, fit, clarity of expression, and suitability for a large audience (Schepman and Rodway, 2020). The attitude could affect user perceptions of their ICA mastery. Consequently, it is plausible to assume that such assumptions will substantially impact future ICA satisfaction ratings. After investigating the relative importance of self-efficacy, users' daily routine adopts new technologies like ICAs. These insights will benefit managers in functional areas because they facilitate the acquisition of knowledge in product design, program architecture, and ICA-related content.

6.5.7. ICA Capabilities and Trust

The ICA capabilities of Conversation ability, friendliness, intelligence, responsiveness, task performance, and trust improved our understanding of user behaviour. In the future, we can include technostress, technology anxiety, and fear to see if the negative attributes also play a part in the behavioural intention to use an ICA. This research study incorporated an experiment that allowed the participant to interact with an ICA, and this interaction helped several participants change their trust perception about the ICA. This finding is in line with the fact that trust could be both cognitive (based on rational thinking) and emotional (based on effect; McAllister, 1995), and as these types of trust might differ in their antecedents, we discussed their development separately (Glikson, and Woolley,2020). Therefore, as AI behaviour is not deterministic, scholars must examine how it changes based on human-AI interactions (Rahwan et al., 2019).

6.5.8. Longitudinal Study

My cross-sectional data revealed two distinct time intervals. Extant literature indicates that it is uncommon for a single point to capture numerous connection variables' dynamic and interdependent nature. A study that measures ICA data at a single point cannot accurately predict end users' future behaviour and expectations because it lacks empirical evidence and is, at best, speculative. A single-point-in-time study cannot predict the future direction of both ICAs and AI due to the rapid development of ICA. I chose to evaluate expectations and perceptions of performance at two different times.

Future ICA modifications will likely be the subject of a longitudinal investigation within the ECT framework. My study has created a longitudinal study by measuring data twice before and after interactions with the ICA. This strategy accurately measures the end-experience user's and performance expectations, enabling confirmation or denial. The same strategy can increase the commercial value of ICAs. Future research on new ICA features may lead to the collection of longitudinal data in two settings, resulting in a greater understanding of consumer expectations and satisfaction evolution and its effect on business profitability.

6.6. Conclusion

Marketing and IS researchers have emphasized customer satisfaction for decades. My research contributes to the theoretical underpinnings of ICA customer satisfaction. In light of the dearth of experimental empirical research on ICA acceptance and utilization, this study's exploration and explanation of customer satisfaction will inform future researchers. The research can address customers' infrequent usage by evaluating user attitudes toward ICAs and promoting and regulating the influence of cognitive fit. My research supports the referent theories of the Expectations Confirmation Theory (Oliver, 1977; 1980) and the Task Technology Model through the concept of cognitive fit (Goodhue and Thompson, 1995).

ICA agents assess customer interaction with AI services. My research examined ICA's effects on attitudes by introducing a user-AI causal model. My research also helps end-users understand their satisfaction with ICA, including expectations, task-technology fit, and cognitive fit for problem-solving.

My study included telecom website users who could read, write, and communicate in English with an ICA. Participant feedback can help to improve ICA telecom services and may help businesses that have deployed ICAs for customer service to realize the commercial value of an ICA. End-user satisfaction and acceptance can help a company determine the business value of deployed ICAs. My research examines ICA and problem-solving. Customers use ICAs to get important information and answers and to solve problems. ICAs must be accessible after hours to collect customer data at home or on weekends. The study examines how ICA capabilities affect customer satisfaction and ICA adoption.

Due to limited end-user acceptance, ICA deployment has not yet helped businesses recognize much of their business value. End-users expect an ICA to provide instant information, answer questions correctly, complete the assigned tasks and solve problems completely. In essence, ICA customers want an ICA to be an expert conversationalist, friendly, intelligent, responsive, task performer, and trustworthy human service agent. My research confirmed the integrative role of expectation confirmation and task technology fit in end-user satisfaction while assessing whether the deployed ICA was suited to perform the specified tasks. My study will help practitioners understand the AI capabilities of ICA as drivers of end-user satisfaction and intention to use under the direct effect of overall fit between assigned tasks and ICA technology.

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Appendix A
Sample Email From Recruiting Firm

From: Maru Voice Canada <support@maruvoice.ca>
Sent: Tuesday, May 4, 2021 10:28 AM
To: Rashmi Mukherjee <Rashmi.Mukherjee@maruservices.com>
Subject: New Survey Invitation (Survey Code: %ISSUENAME%)

Hi FIRSTNAMEHERE,

We're interested in your opinion - don't miss this opportunity to be rewarded.

Start Survey

Reward:
%POINTSMIN(PAC-vlt1-1) % points

Length:
%SURVEYDURATION% minutes

Close date:

Survey code:
%ISSUENAME%

Instructions and Details:

- Some of our surveys are done in partnership with clients and you may be redirected to a client's external website or platform to answer questions. They will have full access to any information or responses you submit on their site or platform.
- If you are redirected to an external site or platform, **please be sure to click the survey's final "Next" or "Finish" button to receive your points**.
- You will return to the Maru Voice Canada site at the end of any survey.
- Some surveys may require you to answer all questions in one session. You will not be able to go back to these surveys at a later time and complete it.

If you are unable to click the button above, please copy and paste the full URL below into your browser to get started: [no survey ID specified]

Thank you,
Your Maru Voice Canada Team

Do you have questions about Maru Voice Canada? We want to hear from you. Reach out to our Support team by visiting our community support page.

To help us assist you faster, please include this survey code in your message:
%ISSUENAME%

McMaster University

Online Survey: Wording For Preamble And Closing Statements

1. The "Preamble" Statement:

This survey is administered by Maarif Sohail and Dr. Yufei Yuan, DeGroote School of Business, McMaster University. The purpose of the survey is to examine Users' Attitude Towards Chatbot (Artificially Intelligent Conversational Agents, ICA) or simply Conversational Artificial Intelligence. We hope to learn how adults use conversational Artificial Intelligence and how it influences their attitude with conversational AI. We hope to find out if the use of online social networking has an impact on social isolation/loneliness.

To learn more about the survey and the researcher's study, including any associated risks or harms, how confidentiality and anonymity will be handled, withdrawal procedures, promised incentives, and how to obtain information about the survey's results. Please visit the survey's website by clicking the button "Letter of Information."

Letter of Information

This survey should take approximately 30 minutes to complete. People filling out this survey must be 18 years of age or older, English speaking, and living in Canada.

This survey is part of a study that has been reviewed and cleared by the McMaster Research Ethics Board (MREB). The MREB protocol number associated with this survey is MREB 5282.

You are free to complete this survey or not. If you have any concerns or questions about your rights as a participant or about the way the study is being conducted, please contact:

McMaster Research Ethics Secretariat
Telephone 1-(905) 525-9140 ext. 23142
C/o Research Office for Administration, Development, and Support (ROADS)
E-mail: ethicsoffice@mcmaster.ca

DATE: 11-09-2020

Letter Of Information / Consent (For Pilot / Actual Study)

A Study of Perceptions, Attitudes, Expectations, Confirmation, Task Complexity, and Experience with Chatbots (Artificially Intelligent Conversational Agents s, ICA)

Principal Investigator:
Dr. Yufei Yuan
DeGroote School of Business
McMaster University
Hamilton, Ontario, Canada
(905) 525-9140 ext. 26392
E-mail: yuanyuef@mcmaster.ca

Student Investigator:
Maarif Sohail
DeGroote School of Business
McMaster University
Hamilton, Ontario, Canada
(905) 525-9140 ext. 26398
E-mail: sohaim9@mcmaster.ca

Purpose of the Study: You are invited to take part in an online research study on perception, attitudes, expectations, confirmation, task complexity, and experience with Chatbots (Artificially Intelligent Conversational Agents s, ICA) also known as Artificial Intelligence Enabled Conversational Agents (AIECA) and at some website places identified as Artificial Intelligence Enabled Virtual Agents (AIEVA). We hope to understand what factors contribute to the satisfaction or dissatisfaction end-users may face when it comes to engaging with Artificial Intelligence enabled virtual agents deployed on websites, specifically dealing in providing answers to questions or problems faced by the end-users.

Procedures involved in the Research: As a participant, you will be asked to interact with one of the ICAs deployed on the Telecom Company websites of your choice. The scenarios present Both the scenarios present an opportunity to the participant (end-user) to interact with any one of the five (5) given Chatbots (ICAs). These ICAs are deployed on commercial websites. After the interaction, the end-user will be asked to answer questions concerning perception, attitudes, expectations, confirmation, task complexity, and experience with ICA. Engagement (interaction) as well as the survey questionnaire completion will take approximately 30 minutes.

Potential Harms, Risks, or Discomforts: The risks involved in participating in this study are minimal. If the end-user feels uncomfortable (uneasy, anxious) while interacting with ICA and any experience, he or she can close the website which carries the ICA, and it will end the interaction. You can also click "skip question" for any questions that make you feel uncomfortable. The participants have the freedom to withdraw from the survey at any point.

Potential Benefits: The information from this study will contribute to our understanding of perception, attitudes, expectations, confirmation, task complexity, and experience with Artificially Intelligent Conversational Agents s (ICA). Also, this study, will contribute to our understanding of the business value of the ICA. Additional possible benefits of participation include increasing awareness about an individual’s perception, attitudes, expectations, confirmation, and experience. This study has the potential to extend theories, create a linkage between academic research and practitioners along with how academic research can help understand and improve business value for businesses. Nonetheless, as each individual is different, there is also the possibility that you may not receive any benefit from this study.

Compensation: The participant will be compensated by MaruBlue, the research firm as outlined in MaruBlue's compensation policy. The participant must complete the survey before he or she can enter his or her e-mail address to receive points as identified by the MaruBlue research firm. Please note that the participant is still eligible for compensation if he or she elects not to answer some of the questions in the survey. Please visit the MaruBlue URL about Incentives and Rewards (https://maruvoicecanada.zendesk.com/hc/en-us/categories/115001577587-Rewards) for further information about the compensation process.

Confidentially: You are participating in this study anonymously. Note, because our interest is in the average responses of the entire group of participants, your responses will not be identified individually in any way. Data will be kept on a locked and password-protected computer that only my faculty supervisor and I will have access to and nobody else. Note, in the publication process; it is possible that a journal will request the data to be available. If this is the case, the data will be shared in aggregate form.

Participation and Withdrawal: Your participation is voluntary; you may decline to continue to participate at any time. If you choose to be a part of this study, you can withdraw for whatever reason, even after "clicking the consent button". or part-way through the survey, up until clicking the "submit" button. Please note that once you submit the questionnaire, your responses will be anonymous; therefore, removing your data will not be possible if you wish to withdraw after submitting your responses.

Information About the Study Results: The results from this study may be used in journal articles, presentations, or books. A summary of the results of this research will be available approximately one year from now; participants who wish to receive information about the findings of this study at that time can email sohaim9@mcmaster.ca or yuanyuf@mcmaster.ca.

Questions About the Study: If you have questions or need more in for about the study itself, contact me at:

sohaim9@mcmaster.ca
905-525-9140 ext. 26398

The study has been reviewed by the McMaster University Research Ethics Board and received ethics clearance. If you have concerns or questions about your rights as a participant or about the way the study is conducted, please contact:

McMaster Research Ethics Secretariat
Telephone: (905) 525-9140 ext. 23142
C/o Research Office for Administrative Development and Support
E-mail: ethicsoffice@mcmaster.ca

CONSENT

I understand the information provided for the study "Users Attitude towards Chatbots (Conversational Artificial Intelligence Agents, ICAs)" as described herein. I have answered to my satisfaction, and by clicking on the "Yes" button below, I understand that I agree to participate in this study. I may withdraw from the study at any time.

Yes "I agree to participate"

No "I do not agree to participate"

McMaster Research Ethics Board

May 12, 2021

Supervisor: Dr. Yufei Yuan
Student Principal Investigator: Mr. Maarif Sohail
Applicant: Mr. Maarif Sohail
Project Title: Attitude Towards Intelligent Conversational Agents
(ICA) MREB#: 5282

Dear Researchers,

Thank you for sending me your response. Your careful attention to addressing and documenting your responses to all of the previous comments is GREATLY appreciated! Your clarifications and revisions address the prior concerns that were raised. As such, I am approving your research protocol for ethics clearance. A certificate of clearance will be issued shortly. However, please note the following conditions associated with your ethics clearance;

As noted in the previous review and your responses, you will also be seeking REB approval from Laurier's research ethics board. Once you have that additional clearance, you may proceed with recruitment and data collection. Additionally, as soon as possible after the Laurier REB has cleared your protocol (but not necessary to delay data collection for this), please submit a For Information Only sub-form and upload the approval to this protocol.

If this project includes planned in-person contact with research participants, then procedures for addressing COVID-19 related risks must be addressed according to the current processes communicated by the Vice-President (Research) and your Associate Dean (Research). All necessary approvals must be secured before in person contact with research participants can take place.

All the best in your research.

Dr. Sue Becker

Dr. Violetta Igneski, MREB Chair,	**Dr. Sue Becker, MREB Vice-Chair,**
Associate Professor,	Professor,
Department of Philosophy, UH-308,	Department of Psychology, Neuroscience and Behaviour, PC-312,
ext. 23462,	ext. 23020,
igneski@mcmaster.ca	beckers@mcmaster.ca

Wilfred Laurier Research Ethics Board

Cc: Sohail Maarif (Co-Investigator) <sohaim9@mcmaster.ca>; REB <reb@wlu.ca>; do-not-replylaurier@researchservicesoffice.com <do-not-reply-laurier@researchservicesoffice.com>

LAURIER
Inspiring Lives.

June 07, 2021
Dear Fang,
REB # 6874
Project, "Users' Attitude Towards Artificially Intelligent Conversational Agents "
REB Clearance Issued: June 07, 2021

REB Expiry / End Date: May 31, 2022

Your project was previously approved by the McMaster University Research Ethics Board (MREB#5282) on May 12, 2021. I have reviewed your proposal on behalf of the University Research Ethics Board at Wilfrid Laurier University and determined that it is ethically sound.

If the research plan and methods should change in a way that may bring into question the project's adherence to acceptable norms, please submit a "Request for Ethics Clearance of a Revision or Modification" form for approval before the changes are put into place.

Note – Minor Revision with Approval: As a part of this approval, please add the WLU REB file number (REB#6874) to participant-facing documents.

Note – University Research Resumption Requirements: REB approvals do not supersede any current university guidelines or measures in place to contain the spread of the novel coronavirus (COVID-19) including restrictions on university laboratory, field, or in-person research activities. If laboratory, field, or in-person research activities are described in this application, you are not permitted to undertake these portions of the project unless you've received prior approval through the university research resumption process. In order to apply to resume in-person research activities with human participants, please submit the appropriate phase 3b (on-campus) or phase 3c (off-site) application form (https://lauriercloud.sharepoint.com/sites/office-of-researchservices/Pages/default.aspx).

If any participants in your research project have a negative experience (either physical, psychological, or emotional) you are required to submit an "Adverse Events Form" to the Research Office within 24 hours of the event.

You must complete the online "Annual/Final Progress Report on Human Research Projects" form annually and upon completion of the project. ROMEO will automatically keeps track of these annual reports for you. When you have a report due within 30 days (and/or an overdue report) it will be listed under the 'My Reminders' quick link on your ROMEO home screen; the number in brackets next to 'My Reminders' will tell you how many reports need to be submitted.

All the best for the successful completion of your project.

(Useful links: ROMEO Login Screen ; REB Students Webpage; REB Connect Webpage)

Yours sincerely,

Jayne Kalmar, PhD
Chair, University Research Ethics Board
Wilfrid Laurier University

Please do not reply directly to this e-mail. Please direct all replies to reb@wlu.ca

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