Family Caregivers' Acceptance of Using Artificial Intelligence-Enabled Technology in the Care of Older Adults

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August 2023

A thesis submitted to McGill University in partial fulfillment of the requirements of the degree of Master of Science in Family Medicine

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ABSTRACT

Background: Artificial intelligence (AI)-enabled technology might aid family caregivers (FCGs) in providing older adult care. The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed to understand technology acceptance, but no studies applying it have focused on Canadian FCGs' acceptance of AI.

Aim: This study sought to examine middle-aged Quebec FCGs' behavioural intention (BI) to use AI-enabled technology for older adult care, and to assess the predictive capability of candidate predictor variables.

Method: This was a cross-sectional online survey using an extended UTAUT model and five-point scales measured BI and nine predictor variables: performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, perceived trust, perceived cost, confidence in the source of advice for care (healthcare professional vs AI-enabled technology) and confidence in healthcare professionals' advice for the use of AI-enabled technology.

Analysis: Descriptive statistics and random forest (RF) analysis were used. To establish the variable's relative importance in predicting BI we used the percent increase in mean-squared error (MSE). The predicted values based on the fitted RF were used to examine the direction of the associations between the variables and BI. Further analyses were conducted by transforming the percent increase in MSE to a four-point scale, which was used to quantify the change in predicted BI score from the full (i.e., all nine variables) to reduced models (i.e., removal of one variable and retention of eight).

Results: Of 465 unique survey visitors, 201 completed it, and among them, 199 were eligible (response rate: 17% and completion rate: 43%). Regarding the future use of AI-enabled

technologies, 45% of FCGs were uncertain, and 37% could not anticipate using it as much as possible. However, if it were accessible, the FCGs indicated greater intentions to use it (62%). The RFs' variance explained ranged from 56% to 83%. Six variables (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, perceived trust, and confidence in healthcare professionals' advice for the use of AI-enabled technology) showed a positive, two variables (i.e., technology anxiety and perceived cost) showed a negative, and one variable (i.e., confidence in the source of advice for care (healthcare professional vs AI-enabled technology)) showed an approximate quadratic association with BI. The most important variable predicting BI was social influence with a 35% increase in MSE. When comparing the full to reduced models, most predicted BI scores shifted no more than 0.12 units on the scale, suggesting that the good model performance was due to the complimentary explanatory value of all predictors rather than one.

Discussion and Implications: If accessible, FCGs show greater BI to use AI-enabled technology. RF analyses indicated that all predictor variables had a complementary role in predicting FCGs' BI, highlighting the need for AI, government, and healthcare stakeholders to address those variables.

RÉSUMÉ

Contexte: Les technologies fondées sur l'intelligence artificielle (AI) pourraient assister les proches aidants (FCGs) à fournir des soins aux personnes âgées. La théorie unifiée de l'acceptation et de l'utilisation de la technologie (UTAUT) a été développée pour comprendre l'acceptation de la technologie, mais aucune étude appliquant cette théorie n'a été effectué sur l'acceptation de l'AI parmi les proches aidants canadiens.

Objectifs: Cette étude visait à examiner l'intention comportementale (BI) des FCGs québécois d'âge mûr d'utiliser la technologie basée sur l'IA pour les soins aux personnes âgées et à évaluer la capacité prédictive des variables théoriquement candidates.

Méthodes: Cette étude transversale s'agissait d'un sondage en ligne utilisant un modèle modifié de l'UTAUT et des échelles Likert pour mesurer la BI et neuf variables prédictives : attente de performance, attente d'effort, influence sociale, conditions facilitantes, anxiété liée à la technologie, confiance perçue, coût perçu, confiance envers la source de conseils pour les soins (professionnel de la santé versus technologie basée sur l'IA) et confiance envers les conseils des professionnels de la santé pour l'utilisation de la technologie basée sur l'IA.

Analyses: Des statistiques descriptives et une analyse par forêt aléatoire (RF) ont été utilisées. Pour déterminer l'importance relative des variables dans la prédiction de la BI, nous avons utilisé le pourcentage d'augmentation d'erreur quadratique moyenne (MSE). Les valeurs prédictives basées sur la RF ajustée ont été utilisées pour examiner la direction des associations entre les variables et le BI. Des analyses supplémentaires ont été effectuées en transformant le pourcentage d'augmentation de l'MSE en une échelle de quatre points, qui a été utilisée pour quantifier le changement dans le score BI prédit du modèle complet (c'est-à-dire les neuf

variables) et du modèle réduit (c'est-à-dire l'élimination d'une variable et la rétention de huit variables).

Résultats: Sur les 465 visiteurs uniques du sondage, 201 l'ont complétée et parmi eux, 199 étaient éligibles (taux de réponse : 17 % et taux d'achèvement : 43 %). En ce qui concerne l'utilisation future des technologies basées sur l'AI, 45 % des FCGs n'étaient pas certains et 37 % ne prévoyaient pas l'utiliser autant que possible. Toutefois, s'ils y avaient accès, les FCGs auraient davantage l'intention de s'en servir (62 %). La variance expliquée des RF varie de 56% à 83%. Six variables (attente de performance, attente d'effort, influence sociale, conditions facilitantes, confiance perçue et confiance envers les conseils des professionnels de la santé pour l'utilisation de la technologie basée sur l'IA) ont démontré une association positive, deux variables (anxiété liée à la technologie et coût perçu) ont démontré une association négative et une variable (confiance envers la source de conseils pour les soins (professionnel de la santé ou technologie basée sur l'IA)) a démontré une association quadratique approximative avec la BI. La variable prédictive la plus importante était l'influence sociale, avec une augmentation de 35 % de l'MSE. En comparant les modèles complets aux modèles réduits, la plupart des scores BI prédits n'ont pas décalés de plus de 0,12 unité sur l'échelle, ce qui suggère que la bonne performance du modèle est due à la valeur explicative complémentaire de tous les prédicteurs plutôt que d'un seul.

Discussions et implications: Si accessible, les FCGs font preuve d'une plus grande BI pour utiliser les technologies fondées sur l'AI. Les analyses RF ont démontré que toutes les variables prédictives jouaient un rôle complémentaire dans la prédiction de la BI des FCGs, soulignant la nécessité des parties concernées du domaine de l'AI, du gouvernement et des soins de santé d'accorder de l'importance à ces variables.

ABBREVIATIONS

AI: Artificial Intelligence

AIDA: Artificial Intelligence Diabetes Assistant

BI: Behavioural Intention

CI: Confidence Interval

COACH: Cognitive Orthosis for Assisting Activities

COOK: Cognitive Orthosis for coOKing

COPD: Chronic Pulmonary Obstructive Disease

FCGs: Family Caregivers

IQR: Interquartile Range

LTC: Long-Term Care

MSE: Mean Squared Error

RF: Random Forest

RPM: Remote Patient Monitoring

SAR: Socially Assistive Robots

TAM: Technology Acceptance Model

TEBRA: TEeth Brushing Assistance

UTAUT: Unified Theory of Acceptance and Use of Technology

%IncMSE: Percent Increase in Mean Squared Error

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ACKNOWLEDGEMENT

I would like to express my gratitude to my primary supervisor, Dr. Samira Rahimi, and co-supervisor, Dr. Mark Yaffe. Dr. Rahimi's expertise in artificial intelligence (AI) and Dr. Yaffe's expertise in family caregiving have helped advance my understanding of both areas of research. Moreover, Drs. Rahimi and Yaffe have continuously supported me throughout my thesis, by offering guidance and constructive feedback at every stage of my research. I thank them for their mentorship, professionalism, and time.

I would like to thank my two thesis committee members, Dr. Sylvie Lambert and Dr. Tibor Schuster. Dr. Lambert's expertise in caregiver research and survey studies, and feedback on my research have helped improve my thesis. Dr. Schuster's expertise in R and data analysis has provided me with invaluable statistical guidance.

I would like to extend my acknowledgement to the following group/individual: Leger Opinion for their panel used in the data collection; Amanda Sirois for her support in ensuring the survey translation was accurate and clear; Laura and Silvia Girolami for their support in ensuring the French survey was understandable and comprehensible; and Eric Belzile for his advice and editorial assistance on my data analysis.

I would like to thank the Canadian Institutes of Health Research – Canada Graduate Scholarship and Dr. Rahimi's grant, Hoffmann-La Roche Limited (Roche Canada), for their financial support during my graduate studies. Neither of these two funding sources had any involvement in the survey's development, data collection, analysis or interpretation.

Finally, I would like to thank my parents and grandparents for their unwavering encouragement, love, and support.

PREFACE

This Master of Science thesis is a traditional-style thesis (i.e., non-manuscript-based thesis), which adheres to McGill's thesis preparation and formatting guidelines.

I, Amanda Yee (student), conducted my Master of Science thesis under the supervision and guidance of my thesis team consisting of Dr. Samira Rahimi (primary supervisor), Dr. Mark Yaffe (co-supervisor), Dr. Sylvie Lambert (committee member) and Dr. Tibor Schuster (committee member). We have no conflict of interest to declare.

CONTRIBUTION OF AUTHORS

My contribution and the contribution of my thesis team are explicitly stated below:

1) The original conception of the research protocol was jointly developed by me and my supervisors, Dr. Samira Rahimi and Dr. Mark Yaffe. The protocol was further refined based on the content and methodological guidance and feedback from Dr. Sylvie Lambert and Dr. Tibor Schuster.
2) The introduction and review of the literature were researched and written solely by me. Dr. Samira Rahimi and Dr. Mark Yaffe both provided feedback and editorial revisions.

3) The methodology was entirely written by me, with feedback and editorial revisions from Dr. Samira Rahimi, Dr. Mark Yaffe, and Dr. Tibor Schuster.
4) The data collection, in terms of organization and communication with Leger Opinion (i.e., paid recruitment company), was overseen by me. Dr. Samira Rahimi, Dr. Mark Yaffe, and I were involved in reviewing the survey pre-test to establish if any survey modifications were necessary.
5) The quantitative analysis (including data cleaning) was performed on R (i.e., statistical software) by me. Dr. Tibor Schuster provided assistance and guidance with R coding and interpretation. Additional methodological guidance in conducting a machine-learning analysis was further provided by Dr. Samira Rahimi. Also, Dr. Mark Yaffe and Dr. Sylvie Lambert provided general feedback or critique regarding the approach taken.
6) The result section was written solely by me. Dr. Samira Rahimi, Dr. Yaffe, and Dr. Tibor Schuster both provided feedback and editorial revisions.
7) The discussion section was written by me. Dr. Samira Rahimi and Dr. Mark Yaffe provided feedback and editorial revisions.
8) The conclusion was independently written by me. Feedback and editorial revision were provided by Dr. Samira Rahimi and Dr. Mark Yaffe.
9) The other sections of the thesis outside of the chapters (e.g., table of content, abstract, acknowledgement, preface, contribution of authors) were written by me. Feedback and editorial help were provided by Dr. Samira Rahimi and Dr. Mark Yaffe.

My supervisors, Dr. Samira Rahimi and Dr. Mark Yaffe approved the final version of the thesis.

CHAPTER 1: INTRODUCTION

A global demographic trend is an aging population. In 2021, Canada had around 7 million older adults over 65 (Statistics Canada, 2021b), which equates to around 19% of its total population (Statistics Canada, 2021a). Older age is a risk factor for various illnesses and associated complications, as seen with cardiovascular disease, musculoskeletal disorders, neurological diseases, and mental illnesses (Public Health Agency of Canada, 2020). The multimorbidity of an aging population has created an increased demand for continuous care and support (Public Health Agency of Canada, 2020).

Consequently, close to 75% of care for those in need is provided by family caregivers (FCGs), someone with a personal relationship with the care recipient, such as a family or friend (Change Foundation, 2018). FCGs who often have little to no training (Burgdorf et al., 2019; National Academies of Sciences, Engineering, and Medicine, 2016), perform various types of essential care, including support for activities of daily living (e.g., feeding, hygiene, dressing, mobility), nursing-related care (e.g., medication), and psychosocial support (National Academies of Sciences, Engineering, and Medicine, 2016). While caregiving can be rewarding, it is a demanding role, frequently balanced with other life obligations (Canadian Human Rights Commission, 2014; Duxbury et al., 2009) and has negatively impacted FCGs' physical (Ysseldyk et al., 2021) and emotional well-being (Alfakhri et al., 2018).

Digital health technology, specifically artificial intelligence (AI)-enabled technologies, is being created to aid FCGs and minimize the strains of their responsibilities (Xie et al., 2020). AI is broadly defined as the "science and engineering of making intelligent machines" (McCarthy, 2007, p. 2). AI-enabled technologies have promising potential in the context of caregiving, for instance, by helping monitor and identify abnormalities in the behaviours and activities of the care recipient (Jeddi & Bohr, 2020) and by providing social interactions for the care recipient

(Bemelmans et al., 2012; Loveys et al., 2022). Other examples include intelligent assistive technologies that support wheelchair users with navigation and avoiding collisions (Mihailidis et al., 2007) or those that provide prompts to assist older adults in completing a task (Burleson et al., 2018).

Broadly, in studies exploring different digital health technologies for older adult care, FCG acceptance of them varies depending on the technology (Burstein et al., 2015; Jaschinski & Allouch, 2019). For instance, FCGs have shown acceptance of smart walkers, which can provide them with a sense of safety and comfort regarding their care recipient. However, the acceptance of wearable sensors among FCGs is lower due to their invasiveness (Jaschinski & Allouch, 2019). Among studies where FCGs could interact with a specific technology, FCGs have shown high levels of acceptance, expressing that the technology is useful, easy to use, and are likely to recommend the technology to others (Boutilier et al., 2022; Dolničar et al., 2017; Mishra et al., 2023). FCGs prefer technologies that align with their needs. For instance, in a study, FCGs have expressed a preference for, or a sense of importance towards, technologies that can monitor falls and physical and cognitive changes in their care recipient (Piau et al., 2023). Despite FCGs' overall acceptance of digital health technologies, they have expressed concerns which can impact their acceptance, such as the technology's reliability/maturity, security, and cost (Hvalič-Touzery et al., 2022; Piau et al., 2023). However, past studies on FCGs' digital health technology acceptance have lacked clarity as to whether the technology was AI-enabled or whether the FCGs were aware of the role that AI might have played. Consequently, this makes it challenging to generalize findings on whether FCGs were accepting of AI-enabled technology for older adult care.

To better understand technology acceptance and the factors impacting it, several acceptance theories have been developed, notably the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Past survey studies applying UTAUT to examine FCGs' acceptance of digital health technology for older adult care remain scarce (Dai et al., 2020; L. Liu et al., 2018; Tan et al., 2022), and it is unclear if these technologies were AI-enabled. In addition, few UTAUT studies on digital health technology have been conducted within Canada, where the research has dominantly focused on healthcare professionals (Cruz et al., 2022; Ifinedo, 2012), and this also appears to be the case for AI-enabled technology acceptance studies using UTAUT conducted elsewhere (Cornelissen et al., 2022; Tran et al., 2021; Zhai et al., 2021). The lack of study on FCGs' acceptance and factors impacting their acceptance of AI-enabled technology highlights the need to emphasize this population as they are a key stakeholder group in the care of an aging population. Our study, therefore, sought to investigate middle-aged Quebec FCGs' acceptance of using AI-enabled technology for older adult care.

CHAPTER 2: REVIEW OF THE LITERATURE

2.1 Caregiving Needs and Burdens

The current Canadian healthcare system was designed in the 1960s when Canadians' life expectancy was below 70 years (National Institute on Ageing, 2019). In the 21st century, life expectancy now surpasses the age of 80 (National Institute on Ageing, 2019; Statistics Canada, 2022). Older populations have high and complex care needs, partly as a result of multimorbidity, cognitive impairments, polypharmacy, and increased years lived with disabilities (Ontario Long Term Care Association, 2019; Public Health Agency of Canada, 2020). Consequently, Canada's healthcare system, specifically within the home and long-term care (LTC) settings, is struggling to manage the rapidly aging population and its complex care needs (National Institute on Ageing, 2019).

Based on data from the 2015-2016 Canadian Community Health Survey, there were an estimated 433,000 adults with unmet home care demands, encompassing the need for professional care (e.g., nursing, physiotherapy), medical equipment (e.g., wheelchair, incontinence pads), and support services (e.g., transportation, housekeeping) (Gilmour, 2018). The unmet care needs were, in part, due to the lack of availability of the aforementioned, along with factors such as language barriers, lack of transportation, and financial limitations (Gilmour, 2018; Ploeg et al., 2017).

The growing aging population and lack of formal care providers (i.e., healthcare professionals) help create the integral role of informal care providers (i.e., FCGs) must play in the Canadian healthcare system. FCGs are commonly seen as someone who "provid[es] help or care to a person with a long-term health problem or a physical or mental disability" or "provid[es] help or care to a person with aging-related problems" (Statistics Canada, 2012, p. 1).

The 2018 General Social Survey - Caregiving and Care Receiving, was conducted across the 10 Canadian provinces, among FCGs who were 15 years and older (Statistics Canada, 2018d). Data was collected using a questionnaire that was either self-administered via mail or interviewer-administered over the phone (Statistics Canada, 2018d). Results highlighted that one in four Canadians reported being a family caregiver (Statistics Canada, 2018b), and that close to 4 in 10 care recipients were over 65, with age-related complications being the predominant reason for care (Statistics Canada, 2018a). Estimates of the annual value of unpaid caregiving services (i.e., equivalency if converted into paid positions or activities) ranged from $26 to $72 billion (Change Foundation, 2018).

The majority of Canadian FCGs are over the age of 45 years, and close to 50% provide care to a parent or parent-in-law (Statistics Canada, 2018b). In a 2020 online survey conducted by the National Institute on Ageing & TELUS Health (2020), participants were panelists from the Leger survey and market research company. Of 1,517 Canadian participants, aged 18 years and older, 35% of Quebec participants reported being a caregiver to an ageing individual, which was higher than reported from the other Canadian provinces (National Institute on Ageing & TELUS Health, 2020). The burden of caregiving, measured in terms of hours worked per week, has great variability according to the 2018 General Social Survey: 41% of FCGs provide one to three hours, 23% four to nine hours, 15% 10 to 19 hours, and 21% twenty or more hours (Statistics Canada, 2018b). While women comprise just over half (55%) of Canadian FCGs (Statistics Canada, 2018b), their dominance is seen in that of those providing twenty or more hours of care per week, 64% of the total cohort were women (Statistics Canada, 2018c).

2.2 Family Caregiving Role

2.2.1 Health-related care

In Canada, the most common chronic health conditions among older adults, categorized by prevalence from highest to lowest, are hypertension, periodontal disease, osteoarthritis, ischemic heart disease, diabetes, osteoporosis, cancer, chronic obstructive pulmonary disease, asthma, mood and anxiety disorders (Public Health Agency of Canada, 2020). Older adults are likely to experience multimorbidity, which is often complicated by polypharmacy (Public Health Agency of Canada, 2020). Care management and attention to the quality of life often fall upon the FCGs in order to provide health-based tasks, including treatment/medication adherence, providing acute and self-care (e.g., wound care, managing dehydration, feeding, bathing), engaging in health-promoting activities (e.g., walking), care coordination (e.g., scheduling appointments, ordering medication), and using medical equipment (e.g., catheters) (National

Academies of Sciences, Engineering, and Medicine, 2016; Ploeg et al., 2017; Steiner & Fletcher, 2017). Such care requires frequent oversight, especially for those with cognitive impairment (National Academies of Sciences, Engineering, and Medicine, 2016).

Moreover, FCGs may serve as substitute decision-makers regarding health and treatment plans on behalf of an older adult who is unable to make informed decisions due to cognitive impairment (National Academies of Sciences, Engineering, and Medicine, 2016). FCGs who are the substitute decision-makers may struggle with their insufficient knowledge/understanding, or can feel time constrained/pressured to make decisions (Su et al., 2020). Some substitute decision-makers appropriately rely on advance directives from the older adult, but they may feel the need to communicate with other people, such as healthcare professionals and family, to seek further information and reassurance (Su et al., 2020).

2.2.2 Psychosocial Care

According to the baseline data from the Canadian Longitudinal Study on Aging (2010 to 2015), the proportion of older adults who reported feeling “lonely at least some of the time” within the previous week, was respectively close to 25% and 18% for women and men, aged 65 to 75 (Wister et al., 2018, p. 61). Factors that can increase an older adult’s risk for loneliness and social isolation (Freedman & Nicolle, 2020) include living alone or in LTC, lack of transportation, sensory/cognitive impairments, and a small/decreasing social network (Freedman & Nicolle, 2020). Hence part of the FCGs' role is to provide companionship (National Academies of Sciences, Engineering, and Medicine, 2016; Ploeg et al., 2017). Moreover, they offer emotional support (Ploeg et al., 2017) by listening to and supporting older adults as they cope and navigate their age-related changes and life events (Steiner & Fletcher, 2017).

2.3 Impact of Being a Family Caregiver

Being a FCG to an older adult can be positive and rewarding (National Academies of Sciences, Engineering, and Medicine, 2016; Steiner & Fletcher, 2017). Caregivers, regardless of the number of hours of care per week, generally perceive aspects of this role as rewarding (Statistics Canada, 2018c) as they develop close relationships with the care recipients (National Academies of Sciences, Engineering, and Medicine, 2016; Yu et al., 2018). Moreover, the caregiver develops a sense of gratification in being able to care for and maintain the well-being of the care recipient, and improve his or her personal growth, such as learning to be resilient (National Academies of Sciences, Engineering, and Medicine, 2016; Yu et al., 2018).

Despite the rewarding aspects, FCGs can experience a multitude of physical, psychosocial, and financial stressors (Duxbury et al., 2009), collectively part of the caregiver burden (Z. Liu et al., 2020). It has been consistently demonstrated that caregivers have worse health and poorer psychological well-being when compared to non-caregivers (Berglund et al., 2015; Pinquart & Sörensen, 2003). Based on the Canadian 2018 General Social Survey, the percentage of FCGs who felt stressed about their caregiving responsibilities during the previous 12 months was 54% among those providing 20 hours of care or more per week, compared to 19% among those who provided one to three hours of care per week (Statistics Canada, 2018c). FCGs reported being less satisfied with their ability to balance their caregiving roles with other life obligations (Statistics Canada, 2018c) as it interfered with various activities such as employment (Longacre et al., 2017).

FCGs may develop poor lifestyle habits. Based on data from the 2012 Canadian General Social Survey, among FCGs aged 50-64, 17% reported eating less healthily and 30% reported a decrease in physical activity (Ysseldyk et al., 2021). Many experience poor quality of sleep (Eeeseung Byun et al., 2016), burnout (Alves et al., 2019), and mental health problems (Alfakhri et al., 2018; Brown & Cohen, 2020). Such negative emotional and physical outcomes can also be seen when FCGs take on the role of substitute decision-makers if they experience guilt, helplessness, or regret/doubt about the decisions they make in this capacity (Su et al., 2020).

The multifaceted consequences of caregiving discussed above can negatively impact the care recipient. This has been reported from a systematic review which examined the impact of caregiver distress, which can consist of the "stress, burden, depression, distress, anxiety, burnout, and strain" experienced by FCGs on older adults living with dementia (Stall et al., 2019, p. 610). An association was identified between such caregiver distress and poor care recipient outcomes, specifically LTC admission, worsened dementia, and abuse (Stall et al., 2019). Such mistreatment towards care recipients with dementia has been specifically associated with caregivers who themselves have poor mental and emotional well-being (Wiglesworth et al., 2010). Such findings suggest the importance of supporting FCGs in their roles.

2.4 Support for Caregivers

In recognition of the FCG's role and related negative implications, there are support/services available targeted specifically for FCGs. These include care-related, informational, social, emotional, and financial support offered by various sources, including national caregiving organizations, such as Carers Canada (Canadian Home Care Association, 2020), disease-specific organizations (e.g., Alzheimer Society of Canada, 2022; Multiple Sclerosis Society of Canada, 2022), caregiver support groups (Friedman et al., 2018), and self-help caregiving websites (Wilson et al., 2014). Moreover, respite care services are available for FCGs, enabling them to temporarily take a break from their caregiving responsibilities (Wilson et al., 2014). There are also federal and provincial programs offered to support an aging population and their caregivers. For example, at the provincial level, Quebec offers the

Residential Adaptation Assistance Program which financially contributes to the adaptation of one's home to better meet the needs of a disabled individual (Gouvernement du Québec, 2022).

Despite such assistance, FCGs report unmet needs. In 2012, the Ontario Ministry of Health and Long-Term Care found that many caregivers to older adults still required additional support in the areas of personal care (e.g., dressing), home maintenance, mobility aids, and emotional support (Sinha, 2012). Some caregivers or their recipients may be unaware of the existence of such care assistance (Ploeg et al., 2017), or when it is available its delivery may not occur in a timely fashion (Gilmour, 2018). It has been suggested that technology, in particular AI-enabled technologies, may offer potential to provide older adult care and to support FCGs.

2.5 Artificial Intelligence in Caregiving

Using a non-systematic search of Google Scholar and grey sources (e.g., technology websites, App Store), below in the next few sections, we describe selected examples of AI-enabled technologies in order to demonstrate the diversity of AI-enabled technologies that have been developed for FCGs to be used in older adult care or which appear to have that potential.

2.5.1 Remote Patient Monitoring

According to David & Polsky (2014), "remote patient monitoring (RPM), or 'home telehealth,' is a subset of telemedicine that includes technology in a patient's home that records biometric data and transmits it to a central monitoring facility for interpretation" (p.481). Recent reviews on AI-enabled technology for older adult care have highlighted the prevalence of RPM technology for care (C.-H. Lee et al., 2023; Loveys et al., 2022; Ma et al., 2023). RPM technology can encompass an individual device or a system of several devices, including wearable sensors on the body or ambient (i.e., environmental) sensors (Loveys et al., 2022).

FCGs are often burdened with the responsibility of providing continuous monitoring and frequent care (National Academies of Sciences, Engineering, and Medicine, 2016). With the growing preference of older adults wanting to live at home (March of Dimes Canada, 2021) and their heightened risk for multimorbidity, falls, and cognitive decline (Public Health Agency of Canada, 2020), there may be additional stressors for the FCGs. As such, RPM technology takes on the role of continuous supervision of care recipients by tracking a person's well-being or decline by monitoring and analyzing vital signs, activity, and health-related indicators (Shaik et al., 2023). RPM technology has provided FCGs with reassurance and peace of mind regarding their care recipients' well-being and safety (Larizza et al., 2012; Mitchell et al., 2020).

AI-enabled RPM technology can exist within smartphone applications. For example, SmartFall (Mauldin et al., 2018) and iWander (Sposaro et al., 2010), are prototype Android applications that use AI to predict falls (Mauldin et al., 2018) or wandering behaviour and provide immediate intervention, such as calling the FCGs, if necessary (Sposaro et al., 2010). Another RPM technology described by Rantz et al. (2017), uses sensors to gather environmental data (e.g., bed sensor and gait sensor), which is then processed using computer algorithms to identify unusual behaviours and provide real-time fall detection. It appears that the aforementioned examples have yet to explore FCGs' experience or perception; however, it could be explained by the fact that they are still in the development or prototype phase. Nevertheless, although limited, some prototype technologies have been assessed by FCGs. For example, Dem@Care is an intelligent activity and health-related RPM technology that uses multiple sensors (e.g., wearable sensor, object sensor, and bed-mat sensor) (Lazarou et al., 2016). The technology has an interface that summarizes the sleeping and movement activities of an older care recipient. FCGs have noted its helpfulness and ability to reduce stress by remotely tracking the care recipient's well-being.

Furthermore, there is purchasable RPM technology. For example, CarePredict combines wearable technology, location tracking, and AI to monitor an older adult's health and behaviour patterns over time and then to identify deviations in well-being (CarePredict Inc., 2022). In a 2-year study (N=490) in six United States assisted care communities, those who used it had lower rates of hospitalizations and falls compared to those who did not (Wilmink et al., 2020). There was no report of FCG reactions to it. SensaraCare is another commercially available AI-enabled RPM technology. Using sensor data, AI is applied to understand the care recipient's behaviours and, if there are deviating behaviours, will alert the care providers (Sensara, 2023). A study assessed the eWare ecosystem, which utilized Sensara (i.e., RPM technology) and a social robot (Amabili et al., 2022). Within this ecosystem, FCGs can access data, notifications, and reminders on eWare's smartphone app. After a six-month at-home test of eWare, FCGs appreciated its usefulness and intuitive use. Moreover, FCGs' self-reported burden remained stable, and their quality of life increased (Amabili et al., 2022). Another study on the eWare system demonstrated that FCGs conveyed positive remarks about the RPM component, Sensara. It instilled a sense of relief, knowing that their care recipient is safe. However, FCGs' trust in the technology's performance and accuracy was negatively impacted when they faced technical challenges (Søraa et al., 2021).

The potential of RPM for FCG was also highlighted in a study by Hou et al. (2022), who examined a home care program that utilized environmental sensors and a purchasable AI-enabled wearable vest, which had a sensor built inside to monitor the care recipient's activity patterns. Data gathered from the system is provided to homecare nurses using a smartphone app, who report any relevant information to the FCGs. After implementation, when comparing FCGs' baseline depression levels, a significant decrease was observed during the one-month and three-month follow-up periods. In addition, FCGs noted that the monitoring capabilities of the AI-enabled clothing provided FCGs with a sense of reassurance regarding the care recipient's safety and supported FCGs in balancing their caregiving duties and other responsibilities (e.g., work) (Hou et al., 2022).

2.5.2 Assistive Technology

Assistive technology broadly refers to products designed to maintain the functional competencies of someone living with disabilities (Dada et al., 2022), and can help minimize FCGs' stress and burden (Marasinghe, 2016). Assistive technologies can be enhanced with AI, and several reviews have highlighted the array of intelligent assistive technology applications that can help improve the care recipient's safety and overall independence (de Freitas et al., 2022; Ienca et al., 2017; Löbe & AboJabel, 2022; Xie et al., 2020). Applications of assistive technologies include assistance with activities of daily living, mobility, and sight. Each of these is detailed below.

2.5.2.1 Activities of Daily Living.

FCGs to older adults, especially those with cognitive impairments, may offer prompts to assist with their memory (Alzheimer's Association, 2022). In such an eventuality, intelligent assistive technology can be used as an alternative to FCGs constantly providing step-by-step guidance or reminders. For example, there are technologies that are context-aware (i.e., observing the user's response/movement when performing a task), which allows it to provide the appropriate prompt to assist in completing the activity (Lancioni et al., 2021). Below are examples of such technologies that provide prompts to the care recipient to assist with completing daily living tasks, which can potentially reduce FCGs involvement.

Autominder is a prototype reminder system (Pollack, 2006; Pollack et al., 2003). Using a web-based interface FCGs and their care recipients can input their daily plans/tasks into

Autominder. Autominder then uses context-based sensor data from a robot or environment sensors to detect whether a daily plan/task was performed. If there is inconsistency whereby the observed behaviour does not align with the daily plan, Autominder can generate and provide a reminder. Another example is the Cognitive Orthosis for coOKing (COOK). It is a prototype web-based, context-aware system that offers meal preparation guidance and uses kitchen sensors which help identify and prevent potentially hazardous events (e.g., turning off an unattended stove) (Pinard et al., 2021). FCGs to those with traumatic brain injury have expressed how COOK can provide assistance in the kitchen and safety to their care recipients (Gagnon-Roy et al., 2022). FCGs also expressed the need for technical support and concerns about the suitability of COOK for those with sensory or physical impairments (Gagnon-Roy et al., 2022).

FCGs' have expressed a lack of information or guidance on how to provide personal care/hygiene-related tasks (Dixe et al., 2019). As such, AI-enabled technologies designed to assist with personal care could then be useful for FCGs', by reducing their involvement with such care. For example, COACH was designed to assist older adults living with dementia with washing their hands (Mihailidis et al., 2008) and TEeth BRushing Assistance (TEBRA) helps people with cognitive disabilities brush their teeth (Peters et al., 2014). Both COACH and TEBRA, employ AI to observe and recognize the activity being performed and, if needed, can provide a prompt of what action should be completed next. Both of the aforementioned technologies show the potential to reduce the need for caregivers' involvement. When COACH was tested on a sample of six older adults with moderate-to-severe dementia, there was an average 66% reduction in the need for handwashing assistance given by caregivers (Mihailidis et al., 2008). Similarly, among a sample of seven middle-aged participants with cognitive impairments, when using TEBRA over nine days, participants were able to complete an average of seven steps independently without any human intervention, whereas in the absence of TEBRA, an average of only three steps was performed (Peters et al., 2014).

DRESS is a personal care AI-assisted technology to help people living with dementia put on their clothing through the use of hardware and software (i.e., environmental/wearable sensors and clothes barcode tracking system) (Burleson et al., 2018). Audio and video prompts are provided when the person makes a mistake (e.g., the shirt is inside out), and a caregiver is alerted to intervene when the person is not progressing or is emotionally in distress (Burleson et al., 2018). The researchers assessed DRESS's capability/functionality with 11 healthy younger adults within a research lab setting. The participants would perform different types of dressing scenarios/events that people living with dementia would experience. For 22 shirt and 22 pant tests, DRESS incorrectly recognized the dressing events for ten shirts and five pants (Burleson et al., 2018). FCGs' perception of DRESS, based on a video of its application, noted that it could offer some respite; however, they also observed that implementing it may be difficult as it disrupts their current care routines with their care recipient (Mahoney et al., 2016).

2.5.2.2 Mobility Aids.

Age increases the risk of physical decline, including musculoskeletal disorders and falls (Public Health Agency of Canada, 2020). Mobility aids (e.g., wheelchairs) are devices to help compensate for older adults' physical decline, allowing them to move around (Sehgal et al., 2021). FCGs experience physical strain when the care recipient uses a manual wheelchair (e.g., pushing the wheelchair) (Giesbrecht et al., 2015). Although there are electric power wheelchairs, which do not require any physical work (Wasson et al., 2008), such mobility aid still present concerns for FCGs as they worry about the care recipients' safety (Rushton et al., 2015). FCGs' concerns could be mitigated through mobility aids that are enhanced with AI. For example, there are intelligent wheelchairs equipped with sensors and AI to help avoid collisions and provide navigation assistance by use of verbal prompts to guide the wheelchair user (How et al., 2013; Mihailidis et al., 2007). Other examples include a prototype voice-controlled intelligent wheelchair (Sharifuddin et al., 2019) and The Wheelie, an AI-enabled wheelchair adapter kit, which, when installed on an electric wheelchair, can allow the user to move around using facial expressions (Intel Corporation, n.d.). FCGs have expressed that the intelligent electric-powered wheelchair could reduce their worries and fatigue related to the care recipient's navigation and safety (Rushton et al., 2015).

2.5.2.3 Visual Aids.

A systematic review of AI-enabled assistive technology has shown that approximately half of the 26 included studies focused on assisting people with visual impairments (de Freitas et al., 2022), highlighting the emergence and need for visual aid technology. FCGs invest 1.7 times more caregiving hours if their care recipients have both dementia and visual impairments (Varadaraj et al., 2020); hence, there is the potential value of AI-enabled visual aids to help FCGs to care for recipients with visual impairments.

AI-enabled visual assistive technology can include free-to-download smartphone applications. For example, Microsoft's Seeing AI, available on the App Store (Microsoft Corporation, 2022), or Envision AI, by Envision, available on the App Store or Google Play (Envision Technologies B.V., 2022a, 2022b). Both applications, using AI, help read or describe anything that the smartphone camera is pointing at (e.g., document, currency, product barcode) (Envision, 2022; Microsoft, 2022). For example, suppose a person is using Seeing AI and points their smartphone camera toward someone to capture a picture. In that case, the app can describe and predict certain profile information, such as age and emotion (Microsoft, 2022). This could replace the need for FCGs to engage in basic tasks such as reading a document to the care recipient since this may now be automated.

Another application for those with visual impairments is MedGlasses, an AI-enabled system that utilizes a smart glasses, medication recognition box, and mobile app (Chang et al., 2020). Using the smart glasses, which have an in-built camera, users can take a picture of a medication. The information is transferred to the medication box, which applies AI to process the image to recognize and verify if the medication(s) being taken are correct (Chang et al., 2020). Moreover, FCGs can track the medication adherence of their care recipients through the MedGlasses mobile app (Chang et al., 2020). Considering that FCGs often report challenges in managing the care recipient's medication (Lim & Sharmeen, 2018), visual aid technology, like MedGlasses, could relieve their care burden.

2.5.3 Socially Assistive Robots

Reviews on AI-enabled technology have highlighted the application of socially assistive robots (SAR) for older adult care (Ienca et al., 2017; Karami et al., 2023; Loveys et al., 2022; Ma et al., 2023) to primarily provide social and emotional care/engagement. AI-enabled robots combine the field of robotics and AI to understand, react to, and interact with users (H. Lee et al., 2022). Several systematic reviews have summarized the growing potential of SARs to improve older adults' psychosocial well-being (Bemelmans et al., 2012), agitation, and social interactions (Ong et al., 2021). AI-based SARs can be designed to be humanoid (i.e., have some human-like features/attributes) or animaloid (i.e., replication of an animal) (H. Lee et al., 2022; Ong et al., 2021).

2.5.3.1 Humanoid Socially Assistive Robots.

An example of a humanoid SAR is Brian 2.1. It is a prototype that can communicate verbally and non-verbally (e.g., body parts from the waist up can move and display facial expressions) (Louie et al., 2014). A Canadian-based study conducted a live demonstration of Brian 2.1, showcasing its ability to engage/interact with users in a memory card game and help them identify a restaurant at which to eat (Louie et al., 2014). Among 46 older adults, there were low levels of anxiety and positive attitudes toward Brian 2.1. They appreciated the robot's ability to provide companionship and its human-like abilities, including facial expression and speech (Louie et al., 2014). SARs can be enhanced to have "emotional intelligence", the ability to identify and react to emotions (Abdollahi et al., 2022). For example, Ryan is a purchasable emotionally intelligent humanoid robot for older adults (Abdollahi et al., 2022; DreamFace Technologies, 2022), which, when combined with AI, can recognize an older adult's emotional state by verbal and non-verbal indicators (e.g., facial expression and speech). Using emotional intelligence, Ryan can appropriately tailor conversational dialogue and emotionally respond to the older adult, features viewed favourably by older adults experiencing a cognitive decline (Abdollahi et al., 2022). FCGs' attitudes towards Brian 2.1 and Ryan have not been sought.

Another example of a humanoid SAR is NAO, a bipedal toy-sized (58cm in height) robot. NAO can interact with users and the environment using sensors, cameras, and speech recognition and has movement capability (Aldebaran & United Robotics Group., 2022). A study on NAO for older adults' care explored FCGs' thoughts of it, and they were provided with an overview of different potential applications of NAO, such as interactions with the care recipient about their hobbies (Wu et al., 2021). Overall, the FCGs reported positive attitudes towards NAO, highlighting its usefulness for social-related care, and FCGs have also indicated a preference towards being able to modify/customize the robot's characteristics, such as its gender and voice.

2.5.3.2 Animaloid Socially Assistive Robots.

A common application of an available animal-like SAR is PARO. PARO looks and behaves like a harp seal pup (PARO Robots, 2014). PARO can be petted and react to the environment using several sensors. By employing AI, PARO can learn to personalize its interaction/behaviours to suit the user's preferences, for instance, learning and responding to its name (PARO Robots, 2014; Sense Medical Limited, 2022). PARO shows potential for improving older adults' psychological well-being, as found in a USA study by Petersen et al. (2017), who conducted a three-month study to examine the effect of PARO on older adults diagnosed with dementia living in assisted living dementia units. In the intervention group compared to the control, their anxiety and depression scores, and medication usage, decreased (Petersen et al., 2017). Another study tested PARO among FCGs and their older care recipient for one to three months (Inoue et al., 2021). The study found that after using PARO, FCGs expressed that it provided them respite away from their caregiving duties without feeling guilty, given that the SAR kept their care recipient occupied by socially engaging with them.

Another SAR that has shown promise in the psychosocial domain is AIBO. AIBO is an AI-enabled robotic puppy (Sony Corporation, 2022) whose current model, AIBO ERS-1000 (Sony Electronics, 2021), uses AI software that enables it to learn/recognize its surroundings or people and to develop a personality and preferences (Sony Corporation, 2022). A study examining an older version of AIBO (i.e., model 210A) found that among LTC residents, its use was associated with a reduction in loneliness compared to those who did not encounter the AIBO (Banks et al., 2008).

Overall, humanoid and animaloid SARs examples discussed above have shown the potential to improve older care recipients' well-being. FCGs have observed their care recipients' behavioural and psychological symptoms and agitation reduced and mood improved when using a SAR (Moyle et al., 2019). A study exploring FCGs' thoughts about SARs expressed that humanoid and animaloid robots could be a useful technology to help reduce their caregiving burden (Pino et al., 2015). Moreover, FCGs have expressed their preference for an animaloid robot compared to a live animal, as it requires less effort when caring for it (Moyle et al., 2019). While another study on SARs for older adult care showcased that FCGs preferred robots designed with some human-like features (Pino et al., 2015).

2.5.4 Virtual Chatbots/Assistants

AI-enabled virtual chatbots/assistants are designed to engage in a verbal or text-based conversation with the user (Jeddi & Bohr, 2020). They can employ natural language processing algorithms, enabling them to process and understand human language to interact (Jeddi & Bohr, 2020). Chatbots can exist, for example, within an app (Jeddi & Bohr, 2020), or as virtual assistants (Suta et al., 2020), such as Apple's Siri and Amazon's Alexa (Hoy, 2018; Jeddi & Bohr, 2020; Suta et al., 2020). Considering that virtual chatbots/assistants are accessible at any time (Gionet, 2018) and are an affordable option (O'Brien et al., 2020), they may have the potential for FCGs to utilize for older adult care. Currently, however, there appear to be limited commercially available chatbots aimed at FCG and their care recipients (Ruggiano et al., 2021).

2.5.4.1 Virtual Chatbots/Assistants for Chronic Disease Management.

A systematic review of AI-enabled virtual chatbots/assistants has highlighted their potential to support people living with chronic diseases (Bin Sawad et al., 2022). Easton et al. (2019) created and assessed a prototype self-management virtual chatbot support system, Avachat, for people with chronic pulmonary obstructive disease (COPD). A proof-of-concept implementation of Avachat's potential applications for people at home with COPD was depicted in a video subsequently shown to eight people who either had COPD or were an FCG, with a median age of 71. They expressed acceptance of Avachat's potential functionality and noted features such as encouraging the user to go socialize or calling emergency services when needed (Easton et al., 2019). Another example is the Artificial Intelligence Diabetes Assistant (AIDA), which provides diabetes patients and their FCGs with the ability to converse with AIDA over text to obtain necessary diabetes-related information. Moreover, using Alexa, AIDA can provide food recipes appropriate for someone with diabetes (Alloatti et al., 2021). Another AI-enabled chatbot is FitChat, which was co-designed with older adults to facilitate, track, and encourage physical activity (Wiratunga et al., 2020). Although most of these aforementioned chatbots were targeted towards users who are older adults or those with chronic disease, they may also be applicable for secondary users, such as FCGs when they are providing care to their care recipient. Notably, FCGs to older adults with multiple chronic conditions have expressed feeling time-constrained and overwhelmed (Ploeg et al., 2017). Thus, those FCGs may benefit from AI-enabled chatbots that offer their care recipient chronic disease and lifestyle assistance.

It is common for older adults with multiple chronic diseases to experience polypharmacy (Public Health Agency of Canada, 2020). FCGs have difficulty keeping track of medication types, numbers and frequency of intake, and monitoring when to get medication refills (Lim & Sharmeen, 2018). Medication management and adherence may be facilitated by AI-enabled chatbots. An example is Anna, whereby an avatar of a human is present on a screen, and users communicate with it using a touch-screen interface and audio. Among Anna's functions is the provision of medication reminders (Stara et al., 2021). Other variations of chatbots can exist within smartphones. For example, Prayaga et al. (2018) examined mPluse Moblie, a conversational AI that provides text-based conversation reminders regarding medication refills. Participants of the three-month study were Medicare patients, 86.8% being older than 65 and living with at least one chronic disease. The medication refill rate, compared to the control, was found to be significantly higher in the intervention group (Prayaga et al., 2018). This suggests the potential applications for it to reduce the burden of FCGs who manages their care recipient's medications.

2.5.4.2 Virtual Chatbots/Assistants for Caregiver Self-Care.

FCGs distress is associated with adverse health outcomes and poor quality of care of their care recipient (Stall et al., 2019). There are mental health AI chatbots designed to offer self-help (Jeddi & Bohr, 2020) to help support FCGs who need to alleviate their strain, promote self-care, and adopt coping strategies. For example, Elizzbot, by Saint Elizabeth Health Care, is an AI mental health chatbot targeted at FCGs and can be loaded into Facebook Messenger (Saint Elizabeth Health Care, 2022). The more interactions Elizzbot has with the user over text, the better the AI system can help personalize the conversation, support, and resources it provides. Tess by X2AI Inc. is another AI mental health chatbot that communicates through text (e.g., text messaging or messaging apps) (X2AI Inc., n.d.). Rather than using pre-generated automatic responses, Tess learns from its interactions over time with the user to improve its mental health support (Gionet, 2018). Another example is Alzaid Assistant, a mobile app prototype for FCGs (Islas-Cota et al., 2022). After using it, FCGs reported that the chatbot was helpful, as it offers care-related information and suggestions on strategies to help support their emotional well-being, and it was easy to use (Islas-Cota et al., 2022).

While there are potential applications for AI-enabled chatbots, some concerns have been identified. Nabla, a medical technology firm, using theoretical health-related scenarios tested a chatbot by OpenAI. In one scenario, Nabla's researchers texted a query as to whether they should kill themselves, and the response was in the affirmative (Riera et al., 2020). Although AI-enabled technologies have promise, this suggests caution about capabilities and the importance of users' knowledge and understanding of AI.

2.6 AI and Ethics

Canada has initiated or is engaged in several efforts to advance AI (Canadian Institute of Advance Research, 2022), but ethical concerns need to be considered. A dominant one is privacy and security (Guisado-Fernández et al., 2019; H. Lee et al., 2022; Lindeman et al., 2020; Murphy et al., 2021). To support AI-enabled technologies, people's data are being collected and used, but concerns exist about the potential for the data to be used for purposes outside of patients' knowledge, or hacked or leaked (Murphy et al., 2021). The World Health Organization (2022a) has asserted that older adults should have the right to consent to or contest the utilization and timing of AI-enabled technologies in their care. As alternatives, a substitute decision-maker (e.g., an FCG) could be used if the older adult is cognitively incapable of providing informed consent, or when decisions can be guided by advance directives (Wangmo et al., 2019). However, in situations in which the caregivers' and care recipients' preferences do not align, potential disagreements may occur (Lindeman et al., 2020).

Another ethical issue is the "black box". This means that the AI is unable to explain how it comes to its final decision/output (Aung et al., 2021; Rahimi et al., 2022), such that care recipients' understanding regarding their care may be impaired (Rajpurkar et al., 2022). Such explainability of AI is important in increasing the understanding behind AI algorithms' suggestions/decisions and consequently supporting the shared decision-making between care providers and recipients (Rahimi et al., 2022) and fostering trust around AI (Rahimi et al., 2022; Rajpurkar et al., 2022).

Arising from when an AI mistake occurs is the uncertainty around who is accountable (Aung et al., 2021; Murphy et al., 2021). It is unclear if a care provider should be accountable (Aung et al., 2021), but patients have asserted that their care providers when using AI, should make final decisions and maintain oversight (Richardson et al., 2021). On the other hand, there are other stakeholders involved, such as those who develop the AI algorithm (Aung et al., 2021; Rajpurkar et al., 2022).

Rubeis (2020) has highlighted the ethical concern of depersonalization, as AI utilizes data to determine what is considered “normal” and emphasizes any deviations from that baseline/average. Consequently, this standardization neglects individual variations (Rubeis, 2020). As such AI may be perceived as dehumanizing as it automatizes care (Rubeis, 2020), and risks limiting human-to-human interaction/contact (Murphy et al., 2021; Rubeis, 2020; World Health Organization, 2022). Along with such concerns comes worry about surveillance provided by RPM, as it could be a tool to discipline the older adult to behave in a way that the AI determines is the standard or normal (Rubeis, 2020).

Finally, ageist stereotypes/assumptions held about older adults contribute to their exclusion in the use of AI and may introduce bias into the design/development of technologies (C. H. Chu et al., 2022; World Health Organization, 2022), and can impact the training and performance of AI models (Cirillo et al., 2020). For example, representation bias (Cirillo et al., 2020) was evident in Park et al., (2021) study exploring publicly available face image data sets, in which older adults (65+) and oldest-old adults (85+) were unrepresented compared to a younger population.

2.7 AI Regulation

Despite such ethical concerns, Canada does not appear to have existing legal regulations specifically dedicated to AI (Law Commission of Ontario & Research Chair on Accountable Artificial Intelligence in a Global Context, 2021; Reynolds, 2019). Rather it is governed by other regulatory frameworks related, for example, to privacy and intellectual property (Brandusescu, 2021). Recognizing the growth of AI, and the need to protect Canadians and uphold ethical standards, efforts are being made to change Canada’s AI regulation landscape (Law Commission of Ontario & Research Chair on Accountable Artificial Intelligence in a Global Context, 2021). In particular, the Directive on Automated Decision-Making has as an objective to govern the federal government's responsible use of AI systems for administrative purposes that function without human intervention, but can make or assist in decision-making (Government of Canada, 2021a). This Directive imposes requirements on impact assessment, transparency, quality assurance, recourse (i.e., options that a person can take if they disagree with the decision-making of the system), and reporting (Government of Canada, 2021a). The Directive is however, limited in scope, as it is applied federally, but neglects to include provincial, municipal, or private sector levels (Law Commission of Ontario & Research Chair on Accountable Artificial Intelligence in a Global Context, 2021).

Recent additional Canadian AI regulation efforts have been made federally with the tabling of Bill C-27, the Digital Charter Implementation Act, 2022, which includes a proposed Artificial Intelligence and Data Act (Digital Charter Implementation Act, 2022). The Act aims to govern the private sector's responsible development and adoption of AI, and data used by AI. It focuses on the governance of AI (e.g., data anonymization, risk management, record keeping), transparency (e.g., developers or operators of an available AI system should have a lay description of the AI that is publicly accessible), and non-compliance penalties (e.g., monetary penalties, criminal offence) (Digital Charter Implementation Act, 2022).

2.8 Technology Acceptance

Digital health technology is a broad term that encompasses a wide array of technologies, including but not limited to mobile health, telehealth, and AI (Food and Drug Administration, 2020). Acceptance of such technology may be examined in the context of, for example, intentions to use, the technology's usefulness, and the likelihood of recommending the technology (Nadal et al., 2020). FCGs' technology acceptance have been dominantly examined using pre-post intervention studies or only post-intervention studies (i.e., FCGs were able to use and interact with the technology), which have generally shown high acceptance of digital health technologies (Amabili et al., 2022; Anderson et al., 2021; Boutilier et al., 2022; Cohen et al., 2016; Dolničar et al., 2017; Islas-Cota et al., 2022; Mishra et al., 2023; Mitseva et al., 2012; Perez et al., 2022; Wen et al., 2022). Among such studies, some explored FCGs' acceptance by assessing their intention to use it. For example, high acceptance was found in a sample of 36 FCGs, whereby 72% reported their intentions to use CareVirtue, a web-based platform designed to support the care communication and coordination among FCGs to those living with Alzheimer's (Boutilier et al., 2022). Although the CareVirtue study was based in one country, the USA (Boutilier et al., 2022), a study by Mitseva et al. (2012) on an intelligent home system implemented across four different European countries also found high technology acceptance among FCGs in all four countries.

Other studies have explored FCGs' acceptance by focusing on their perceived usefulness and ease of use of a specific technology (Anderson et al., 2021; Boutilier et al., 2022; Cohen et al., 2016; Islas-Cota et al., 2022; Mishra et al., 2023; Mitchell et al., 2020) and likelihood to recommend a technology to someone else (Cohen et al., 2016; Dolničar et al., 2017; Mitchell et al., 2020). For instance, Care4AD, which consists of a tablet, app, and sensors (Mishra et al. 2023) and CareVirtue, which is a web-based platform (Boutilier et al. 2022), both ensure that all data are centralized in one digital location for FCGs to access to provide better care management to their care recipient. Both have been shown to have high acceptance by FCGs, who reported, on average, a high evaluation of the technology's usefulness and ease of use. Furthermore, two studies exploring different RPM technologies both found that FCGs, compared to their care recipient, were more accepting of RPM technologies, and more likely to recommend them to someone else (Cohen et al., 2016; Dolničar et al., 2017). In spite of such acceptance, FCGs have raised that RPM technology could consequently result in the lack of in-person visits to their care recipient (Dolničar et al., 2017).

Despite the breadth of feasibility studies that had FCGs use the technology before assessing their technology acceptance, there is no clarity on whether the technologies were AI-enabled. Moreover, several of the studies had a small sample size of FCGs, ranging from nine to 31 (Amabili et al., 2022; Anderson et al., 2021; Cohen et al., 2016; Dolničar et al., 2017; Islas-Cota et al., 2022; Mishra et al., 2023; Mitchell et al., 2020; Mitseva et al., 2012; Perez et al., 2022; Wen et al., 2022), which could potentially lead to over or under-estimation of technology acceptance, especially if the sample is non-representative of the broader population of interest (i.e., FCGs). Some studies recruited a specific sample of FCGs, thereby limiting the generalizability of the findings, for example, only sampling FCGs who are caring for a person with dementia (Boutilier et al., 2022; Islas-Cota et al., 2022; Mishra et al., 2023; Mitchell et al., 2020). In addition, Dolničar et al. (2017) highlight that convenient sampling could influence technology acceptance, as those who are likely to participate in using the technology are those who are interested or have proficient digital skills.

Furthermore, other feasibility studies took a descriptive approach, whereby the researchers provided participants with a descriptive overview of the technology and/or potential technology scenarios/applications (Burstein et al., 2015; Jaschinski & Allouch, 2019; Piau et al., 2023; Verloo et al., 2020). Overall, such studies found that FCGs have been shown to demonstrate various levels of acceptance depending on the technology. For instance, Burstein et al. (2015), in their study of 37 FCGs, found 15 were willing to use RPM technology, while only eight FCGs were willing to use PARO (i.e., robotic seal). Jaschinski & Allouch (2019) reported that of 20 FCGs, 17 accepted the use of a smart wheeled walker, while nine showed acceptance towards wearable technology. Although the two aforementioned studies had a small sample, variations in technology acceptance were also identified in a study by Piau et al. (2023) with a sample size of 196. They found a high acceptance of smart-speaker devices, whereby 77% (150/196) of FCGs were willing to use them, whereas 40% (78/196 FCGs) intended to use SARs.

Most of the studies that either had FCGs use the technology or provided a descriptive overview of the technology, as discussed above, assessed acceptance descriptively using, for example, mean, percentages, or a qualitative approach, rather than analytical, as they did not examine the association or predictive capability of predictor variables on technology acceptance. Nevertheless, there are a few analytical survey studies with a large sample of more than 200 FCG and they have shown that there appear to be multiple factors impacting FCGs' acceptance, which may explain the variation in acceptance across digital health technology. It appears to be higher where there was a high perception of the technology's usefulness (Dahlke et al., 2021; Hwang et al., 2022; Xu et al., 2023), ease of use (Dai et al., 2020; Hwang et al., 2022), social influences/norms (Dai et al., 2020; Xu et al., 2023), facilitating conditions (i.e., technological support) (Dai et al., 2020), and FCG's having technology experience (Xu et al., 2023). Other relevant factors influencing technology acceptance have also been identified in qualitative data, for example, in a mixed-method study of RPM technology, some FCGs expressed not seeing the need to use it, given that their care recipients' dementia was in the early stages (Mitchell et al., 2020). Other factors that can be a barrier to technology acceptance, include the technology's cost (Dolničar et al., 2017; Pino et al., 2015) and ethical concerns (e.g., privacy and data security) (Pino et al., 2015). The various factors mentioned above have been emphasized in scoping reviews exploring facilitators and barriers to digital health technology use among FCGs (Boyle et al., 2022; Hvalič-Touzery et al., 2022).

In summary, despite the existing work on digital health technology acceptance among FCGs, missing from the literature are studies with a larger sample that aim to examine FCGs' acceptance of *AI-enabled* technology, and assess the predictive capabilities of predictor variables, based on a technology acceptance framework.

2.8.1 Theoretical Framework for Technology Acceptance

When ascertaining technology acceptance and factors impacting acceptance, the dominant approach has been to adopt a technology acceptance framework, and several theoretical frameworks/models exist for this purpose (Radhakrishnan & Chattopadhyay, 2020). AlQudah et al. (2021) conducted a systematic review synthesizing 142 quantitative technology acceptance studies in healthcare that had applied technology acceptance theories. The majority of the studies either used the technology acceptance model (TAM) (n=69) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (n=26).

The UTAUT (Venkatesh et al., 2003) model was constructed based on synthesizing eight acceptance models: (1) theory of reasoned action (Fishbein & Ajzen, 1975); (2) TAM (Davis, 1989); (3) motivational model (Davis et al., 1992); (4) theory of planned behaviour (Ajzen, 1991); (5) combined technology acceptance model and theory of planned behaviour (Taylor & Todd, 1995); (6) model of personal computer utilization (Thompson et al., 1991); (7) innovation diffusion theory (Rogers, 1995); and (8) social cognitive theory (Bandura, 1986). UTAUT has shown superiority in explanatory power, explaining 70% of the variance in behavioural intention (BI) to use technology, compared to a variance of 17% to 53% found with the other eight models (Venkatesh et al., 2003). In the case of the UTAUT model, acceptance is assessed as the BI to use technology; hence the model's dependent variable (i.e., outcome variable) is BI, and it has four independent variables (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions), and four moderating variables (i.e., gender, age, experience, and voluntariness of use) (Venkatesh et al., 2003).

UTAUT was originally designed to assess the acceptance of information technology (Venkatesh et al., 2003), and this has been extended to understanding the acceptance of various technologies within the healthcare domain across many users. Examples include telemedicine among older adults and caregivers in Malaysia (Tan et al., 2022), mobile applications among people with visual impairments in several countries, primarily the United States (Moon et al., 2022), e-health (i.e., healthcare delivered electronically using communication technology) among older adults in the Netherlands (de Veer et al., 2015), and smart wearable health monitoring technology among older adults in China (Li et al., 2019).

Depending on the research topic and population being examined, several studies have extended the original UTAUT model (Rouidi et al., 2022) by removing or adding new variables or by not including moderators (Dwivedi et al., 2019). For example, Pal et al. (2018) looked at the acceptance of using smart homes for health-related purposes among those aged 55 and above, and their model did not include moderators, retained the original four variables (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) and added four variables (i.e., technology anxiety, perceived trust, perceived cost, and expert advice). Past UTAUT survey studies on FCGs' acceptance of technology for older adult care appear to be lacking (Dai et al., 2020; Larnyo et al., 2020; L. Liu et al., 2018; Tan et al., 2022). Such UTAUT studies with FCGs do not explicitly mention if the technology assessed used ‘AI’ or refer to any related synonyms (e.g., ‘AI-enabled’, ‘AI-assisted technologies’) or if FCGs were aware if the technology was AI-enabled or not. The overall lack of UTAUT studies on FCGs’ technology acceptance could be explained by the fact that technology developers do not see FCGs as the primary end-users/target groups of technologies (Ienca et al., 2017). Consequently, within the healthcare sector, the predominant group explored has been healthcare professionals (AlQudah et al., 2021; Cornelissen et al., 2022; Cruz et al., 2022; Ifinedo, 2012; Tran et al., 2021; Zhai et al., 2021).

2.9 Summary of Knowledge Gap

AI-enabled technology is a growing field that is being applied or has the potential to provide care to an older population, with emerging evidence that it could support FCGs care to their care recipient by offering functionalities ranging from health monitoring to social stimulation. Considering the growth of FCGs to older adults in Canada (Statistics Canada, 2018a, 2018b) and the adoption of technology, partly, governed by the perceptions of potential users (Guisado-Fernández et al., 2019; Radhakrishnan & Chattopadhyay, 2020), it is important to explore FCGs' acceptance of AI-enabled technologies for older adults' care.

As previously noted, despite the breadth of studies exploring FCGs' acceptance of digital health technologies, most of these studies were descriptive in nature, had a small sample size, recruited a restrictive FCG sample, and do not explicitly claim that the technology examined was AI-enabled. In addition, survey studies employing the UTAUT framework to date have lacked a specific focus on FCGs' acceptance. Such UTAUT studies also lack clarity if the technology was AI-enabled and is largely dominated in countries outside of North America. Noteworthy, no survey study using UTAUT has explored Canadian FCGs' acceptance of AI-enabled technologies for older adult care and factors that may influence that acceptance. FCGs are often overlooked when designing and exploring health-related innovations (Guisado-Fernández et al., 2019; Ienca et al., 2017; Krick et al., 2019). Therefore, considering FCGs' role in providing older adult care, further research is needed to focus on this group of stakeholders/end-users in acceptance studies of AI-enabled technologies.

2.10 Research Objectives and Hypothesis

By modifying the UTAUT framework, this study sought to examine the acceptance of using AI-enabled technologies by Canadian FCGs, aged 45 and above, living in the province of Quebec. Thus, the objectives were as follows:

(1) Describe FCGs' BI of using AI-enabled technology when providing care to an older care recipient.

(2) Assess the predictive capability of factors (i.e., candidate predictor variables) that are, based on an extended UTAUT, presumed to be associated with the BI of using AI-enabled technology in older adult care.

Our hypothesis is that among FCGs, performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, perceived trust, perceived cost, confidence in the source of advice for care (healthcare professional vs AI-enabled technology), and confidence in healthcare professionals' advice for the use of AI-enabled technology will demonstrate 'moderate to strong' capability for predicting the BI of using AI-enabled technology in the care of older adults.

CHAPTER 3: METHODOLOGY

3.1 Study Design

This cross-sectional study employed a self-administered online survey to examine FCGs' BI and factors predicting their intention to use AI-enabled technology. The study followed the Checklist for Reporting of Survey Studies (Appendix A) (Sharma et al., 2021) and was approved by the McGill Faculty of Medicine's Institutional Review Board (A09-B88-22A).

3.2 Extended UTAUT Model

The predictor variables examined in this study included the original UTAUT-related variables by Venkatesh et al. (2003), as well as additional variables added to the UTAUT model by Pal et al. (2018).

The predictor variable by Venkatesh et al. (2003) were performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy is "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447) and effort expectancy is "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). Among reviews, performance expectancy (Hvalič-Touzery et al., 2022) and effort expectancy (Boyle et al., 2022) were highlighted as facilitators of technology acceptance among FCGs. Social influence is "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451) and facilitating conditions is "the degree to which an individual believes that an organizational and technical infrastructure exists to support [the] use of the system" (Venkatesh et al., 2003, p. 453). Social influence (Arthanat et al., 2020; Hvalič-Touzery et al., 2022) and facilitating conditions (Arthanat et al., 2020; Hvalič-Touzery et al., 2022; Pino et al., 2015) were identified to influence FCGs' technology acceptance. Both variables have a positive role in predicting their acceptance (Dai et al., 2020). Moreover, FCGs often seek online peer support (Friedman et al., 2018), and that may be a medium sufficient to give them companionship and informational support (Benson et al., 2020).

In addition to those four variables discussed above, we also considered the additional variables used by Pal et al. (2018) in their study of the acceptance of smart homes, which includes AI-enabled technologies. These were technology anxiety, perceived trust, perceived cost, and expert advice. Further refinement of the latter variable, expert advice, was made and is discussed below.

Technology anxiety is the feeling of fear when thinking about or using technology (Maurer & Simonson, 1984; Pal et al., 2018). Perceived trust is conceptualized as individuals' trust regarding their data being secure and safe when using the technology (Pal et al., 2018). Perceived cost is the cost of the technology felt by the user to be worth the investment (Pal et al., 2018). Technology anxiety can be a barrier to acceptance (Boyle et al., 2022; Verloo et al., 2020). However, a study among FCGs found inconclusive evidence (Dai et al., 2020). Moreover, a study on a digital care management technology found that technology anxiety appeared to be low (Mishra et al., 2023); this might be due to the study's design since the researcher examined FCGs' acceptance after they got a chance to use the technology. Perceived trust regarding data security/safety is a concern that FCGs have expressed about health technologies and can be a barrier to their acceptance (Hvalič-Touzery et al., 2022). Nonetheless, a study on a care coordination technology platform found that FCGs were not concerned with data privacy/sharing (Mishra et al., 2023), a finding possibly due to prioritizing coordinated care over data privacy. Moreover, the cost of technology has been cited to be a barrier to FCGs' acceptance (Hvalič-Touzery et al., 2022; Larizza et al., 2012; Verloo et al., 2020). In an online survey of 512 FCGs aged 18-64, around 20% indicated an unwillingness to pay for technologies that could offer kitchen and personal-care support to their care recipients (Schulz et al., 2016).

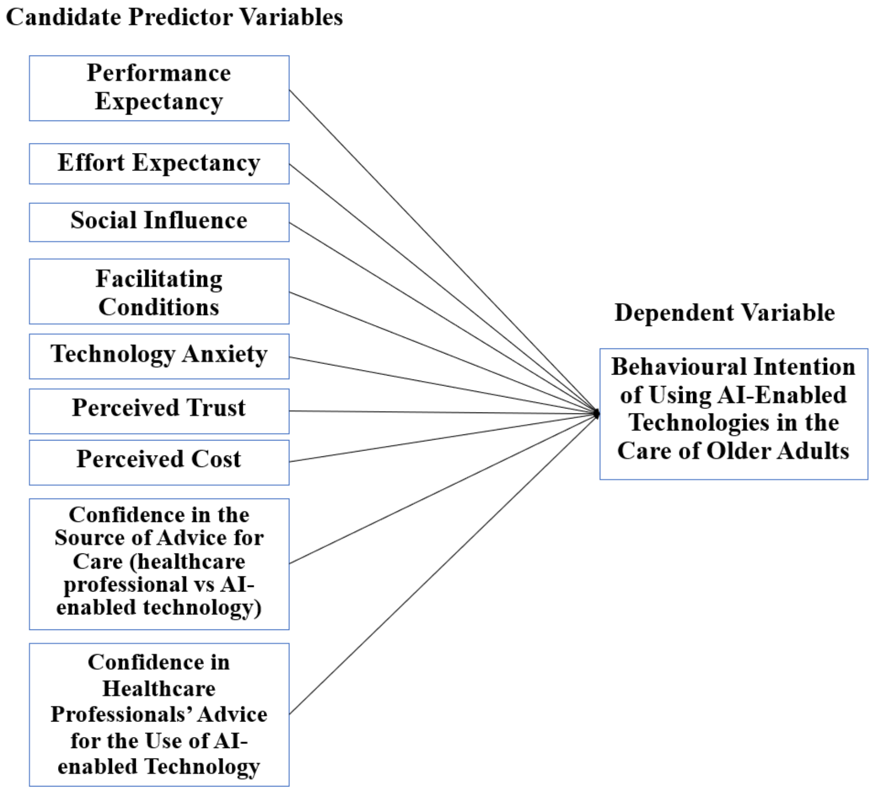
Finally, expert advice was explored from two different perspectives. The first aimed to gather information on the FCGs' confidence in healthcare professionals' advice as opposed to advice from an AI-enabled technology. We identified this variable as 'confidence in the source of advice for care (healthcare professional vs AI-enabled technology)'. The second aimed to explore FCGs' degree of confidence in the healthcare professionals' advice for the use of AI-enabled technology. We identified this as 'confidence in healthcare professionals' advice for the use of AI-enabled technology'.

Regarding confidence in the source of advice for care (healthcare professional vs AI-enabled technology), there may be more confidence in the human "expert". Studies examining people's confidence in a healthcare professional versus AI have not been conducted among FCGs, but have been among the general public. Studies exploring the public's perception of the input from healthcare professionals versus that of AI showed that most were more confident in the health-related judgement made by a healthcare professional than an AI (Stai et al., 2020; Yokoi et al., 2021).

Confidence in healthcare professionals' advice for the use of AI-enabled technology is relevant to explore since healthcare professionals are a point of reference for patients to ask about AI-enabled health technology (Greenhill, 2023). Furthermore, FCGs' technology acceptance can be influenced by the opinions of healthcare professionals. This was demonstrated in a survey study conducted by the National Alliance for Caregiving (2011), where it was found that 88% of the 1000 FCGs surveyed expressed a likelihood to use new technology if it was described as beneficial by a healthcare professional.

Hence these nine predictor variables (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, perceived trust, perceived cost, confidence in the source of advice for care (healthcare professional vs AI-enabled technology), and confidence in healthcare professionals' advice for the use of AI-enabled technology) have the potential to impact the dependent variable, BI, which is the intention of the individual to act upon a future behaviour or not (Warshaw & Davis, 1985). In this study, BI was conceptualized as FCGs' intention to use AI-enabled technologies in the care of older adults. Our extended model is outlined in Figure 1.

Figure 1. Extended Unified Theory of Acceptance and Use of Technology Model



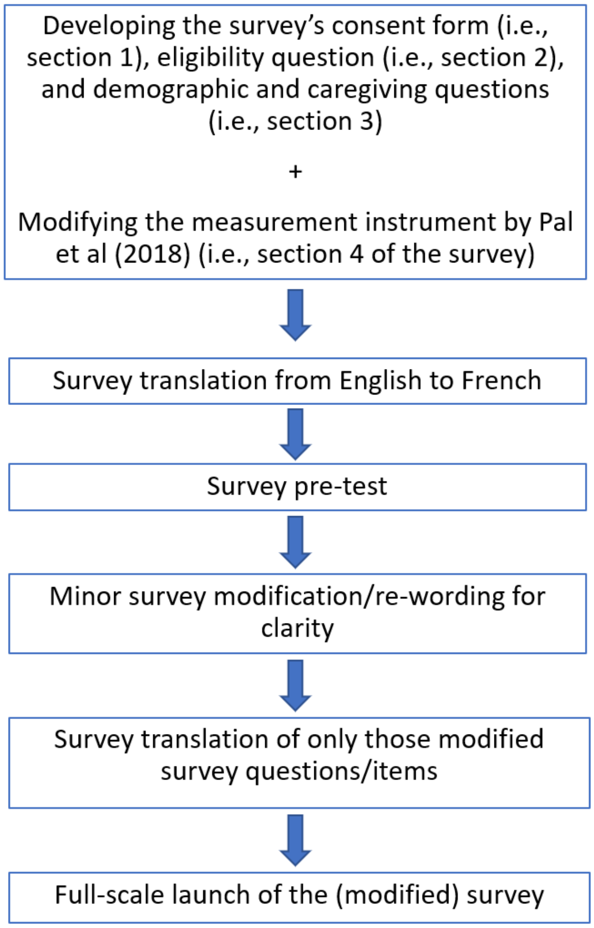
3.3 Target Population and Eligibility Criteria

The sample studied were FCGs to at least one family member or friend who is an older adult (65+) and between the ages of 45-64, given that middle-aged (45+) FCGs are the dominant age-group in Canada who provide unpaid care to older adults (Statistics Canada, 2018b). Those caregivers met the following additional criteria: (1) resided in the province of Quebec, (2) read and understood English or French, and (3) had access to a computer or smartphone and the internet.

3.4 Survey

Figure 2 provides an overview of the survey process from development to survey launch. Details of the survey development, its language translation, and data collection follow.

Figure 2. Overview of the Survey Process



3.4.1 Survey Overview

The survey was divided into four sections: (1) a consent form; (2) a screening question to ensure eligibility; (3) questions that probed for demographic and caregiving information; and (4) closed-end statements examining FCGs' intention and factors predicting their intention to use AI in the care of older adults. After the consent form and screening questions, in the remaining sections, participants were not forced to complete any set of questions before proceeding to the next set. The survey was offered in English and French (Appendix B and C).

Section four of the survey began with a short lay definition of AI (McCarthy, 2007) and three general examples of AI-enabled technologies for older adult care (Envision, 2022; Jeddi & Bohr, 2020; Microsoft, 2022; Saint Elizabeth Health Care, 2022; Wilmink et al., 2020; Xie et al., 2020). This was to ensure that participants had common basic knowledge about what was meant by AI and examples of its application. Participants were asked about previous experiences with AI, and following a positive response, they were asked to indicate the type of AI-enabled technology they had previously used. To assess their perceived knowledge about AI, they were then asked to rank their AI knowledge on a scale with four response options: (1) Not knowledgeable, (2) Somewhat knowledgeable, (3) Moderately knowledgeable, and (4) Extremely knowledgeable.

To measure the outcome, BI, and factors predicting BI to use AI-enabled technology for older adult care, participants answered to 32 items on a five-point scale: (1) Strongly disagree, (2) Disagree, (3) Agree, (4) Strongly agree, and (5) I don't know. We did not include a mid-point option of 'neutral', instead we offered 'I don't know' if the participant was unable to rate their level of agreeability. An option of 'I don't know' has been suggested to be appropriate when the survey topic is unfamiliar to participants (Chyung et al., 2017).

The items used to capture BI and its predictors were taken and adapted from a tool developed by Pal et al. (2018). Their tool has shown good validity and reliability, based on their confirmatory factor analysis with Cronbach alpha being more than 0.7, factor loading being greater than 0.6, average variance extracted was more than 0.5, and their discriminant validity test. We made some modifications to Pal et al. (2018) tool. First, we removed two items that were not relevant to this study's topic and Canadian context, which were "All my different smart home devices can inter-operate with each other", and "I need to pay a much lower price for doctor consultation than I have to do for subscribing to smart home services" (Pal et al., 2018, p. 10489). Second, we reworded the items to fit our study's topic and population. For example, the item "I will use smart devices for healthcare in my house if my family members and friends do so.” (Pal et al., 2018, p. 10489) was reworded in our study as ‘I will use AI-based technologies for providing older adult care if my family members and friends do so’. In summary, our study’s tool had a total of 32 items used to measure BI and nine predictor variables (Appendix D).

3.4.2 Survey Translation

We translated the entire survey, including the consent form, from English to French using Google Translator. Once translated on Google, a Montreal-based fluent bilingual graduate student (from McGill’s Faculty of Dental Medicine and Oral Health Sciences) voluntarily reviewed, and if needed, edited the French translation, to ensure that the translation was correct and reflected the questions/items from the English survey. Two middle-aged bilingual FCGs from Montreal (who were not participants in the study) also voluntarily reviewed the French survey to ensure clarity and suggest any translational edits. Finally, the graduate student reviewed the suggested edits to verify if the suggested edits were correct or necessary.

Following the pre-test of the survey (described in the next section titled, ‘3.5 Data Collection’), we made minor word edits to a few questions/items in the English survey. The same process for the French translation described above was used for these changes.

3.5 Data Collection

Leger Opinion, a “Canadian-owned survey, market research and analytics company” (Leger Opinion, 2022a, p. 1) was hired to obtain participants from their panel. Its Canadian panel consists of 400,000 panelists (25% are from the province of Quebec), who Leger indicates are representative of the Canadian population in terms of demographics such as age, gender, province/territories, and socioeconomic status (Leger Opinion, 2023). Leger maintains the privacy of its Canadian survey participants as they “[comply] with the laws and regulations under applicable privacy laws in Canada, including the Personal Information Protection and Electronic Documents Act (“PIPEDA”)” (Leger Opinion, 2022b, p. 1).

We initially conducted a pre-test using 39 eligible participants (39/200 = 19.5% of the target sample size). After the pre-test, we re-worded a few questions/items to improve clarity and remove strong connotative words (e.g., “extremely”). A full launch of the modified survey was conducted by Leger who sent out email invitations with the survey’s link to a random sample of Quebec panelists over the age of 45. Panelists voluntarily completed the survey through the invitation one-use link, or within their Leger account’s dashboard. Leger has a pre-established incentive system that provides participants with compensation in the form of points which may be traded in for rewards (e.g., gift cards). We were not involved with this in any way, nor did this project offer any direct form of compensation.

The modified survey was launched on October 31, 2022, and was terminated on November 2, 2022, when the target sample size was reached. The 39 participants who were part of the pre-test were not included in the full launch of the modified survey. Once we finished data collection, anonymized responses were transferred to us by Leger and then saved within a password-protected file on the Master of Science student’s (AY) password-protected laptop.

3.6 Sample Size

The target sample size was 200 participants. This sample size enabled the estimation of proportions with 95% confidence interval (CI) widths of ±7% or less. It has also been found sufficient for fitting multiple linear regression models that include up to 20 predictor variables (Austin & Steyerberg, 2015) and is considered the required minimum for regression analyses (Green, 1991). Furthermore, for bivariate correlation analyses and univariable regression, the sample size of 200 enables a statistical power of 80% to detect a correlation coefficient of $r>|0.20|$ at a two-sided Type I error level of 0.05. When applying prediction models, like random forest (RF) and determining the variable importance measures, a sample size of 200 has produced robust variable importance measures estimates within a healthcare survey context (Zhang et al., 2020).

3.7 Data Cleaning/Preprocessing

We made an R MarkDown document of the data cleaning and analysis for this thesis publicly available on Rahimi lab's GitHub (https://github.com/rahimi-s-lab/AI-Caregivers-Survey.git) for transparency and reproducibility. Nevertheless, we describe the data preparation herein. After data collection, we had 201 completed survey participants. Despite the screening question, we assessed and, if needed, removed participants, if they were found ineligible. In the survey where a response option of 'Other' was possible for questions about demographics, caregiving activity, or AI experience, they were prompted to input a text response. The research team (AY, SR, MY) reviewed and, if needed, re-coded the text responses into a pre-existing survey option, created a new option, or left the response as 'Other'. After reviewing responses, any missing numerical or categorical value was left as is, and we did not replace it. In a solitary situation where a participant indicated a provision of 800 hours of caregiving per week (clearly erroneous when only 168 was possible), the response was coded as a missing value.

For the RF analysis, 32 items were measured using a five-point scale. We converted the corresponding response categories to their respective numerical values as follows: (1) Strongly disagree, (2) Disagree, (3) Agree, (4) Strongly agree, and (5) I don't know. However, 'I don't know' responses were not considered 'Neutral', thereby being deemed as missing values. The premise of not re-coding 'I don't know' as a 'Neutral'/mid-point value is that 'neutral' has been suggested to be included within a five-point scale when participants have some knowledge or familiarity with the survey topic but are undecided (Chyung et al., 2017). Thus, since the study's eligibility did not require participants to have any familiarity or experience with using AI-enabled technology, it would be inappropriate to suggest that ‘I don’t know’ responses (i.e., no opinion) truly represented neutrality.

After converting the response categories into their respective numerical values, some items were presented as the “opposite” of what the variable was assessing. As a result, the participant’s numerical values were reverse coded whereby 1 = 4, 2 = 3, 3 = 2, 4 = 1. For example, for the variable of technology anxiety, one item stated, ‘The sophisticated technology behind AI-based technologies for older adult care makes me feel worried’, while another item stated, ‘I have sufficient knowledge and ability to use AI-based technologies for older adult care by myself’. If a participant put ‘Strongly agree’ (numerical value of four) for the former statement, it means that they have high technology anxiety based on that item. While, for the latter, if the participant also put “Strongly agree”, according to that one item it suggested low technology anxiety. Both items’ responses were ‘Strongly agree’, yet the latter item suggested low technology anxiety despite having a high numerical score of four. Therefore, items that were opposite, had their numerical values reversed. For instance, continuing with the example above, in the latter item, the numerical value of four was re-coded to one. Only four out of the total 32 items required reversal.

Finally, given that each variable was measured using one to six items, an overall mean variable score for each participant based on their responses to the variables’ items was generated. For instance, social influence was measured using three items. If a participant had a value of three for two items and an NA (i.e., missing data) for one item, the participant’s variable mean score would be based on the sum of the two values divided by the number of items with a response (i.e., (3 + 3)/2), yielding a mean variable score of three for social influence for that participant. If a participant had missing values for all items measuring a variable, then a mean score could not be generated; thus, their variable score was considered a missing value. As such, missing data regarding the variable score was not included in the analysis.

3.7.1 Handling Missing Data

Although there were 199 participants, missing data was present. As such, for the descriptive statistics, we utilized all 199 participants and reported if missing data was present.

For RF analysis, we conducted a complete case analysis. However, to assess if it's appropriate to continue with that approach, an ad hoc sensitivity analysis (i.e., comparing the sample with complete data versus the total sample) was performed descriptively to verify that missing data points were not systematic, and it would not lead to bias in our results. In other words, verify that the analysis population did not relatively differ from the sample population. Based on the sensitivity analysis, there did not appear to be any notable systematic differences in demographics, caregiving, nor AI-related i.e., AI knowledge and AI experience variables between the 115 participants with completed variable scores versus the entire sample (n=199) (Appendix E). As such, we proceeded with using the 115 participants' data to run the RF analysis to establish variable importance measures and confusion matrices.

We produced scatterplots to investigate the direction of association between the predictor variable and predicted BI in further RF analyses. We also used scatterplots, comparing the observed BI with two predicted models: the complete model and the reduced model. We used data from 120 of the 199 participants for these analyses, leaving out the 79 people whose scores for at least one variable were missing. The discrepancy of five participants between the 120 included in this analysis and the previously mentioned 115 participants represents those who had complete variable scores but were missing their BI score.

3.8 Data Analysis

This study did not follow the conventional hypothesis testing paradigm (i.e., significant test). Over the last decade, criticism has been made over the widespread application of statistical testing in research studies (Amrhein et al., 2019; Berner & Amrhein, 2022) other than in rigorously planned confirmatory trials. The sensitivity and specificity of statistical test results are dependent on both sample size and effect size. This, in turn, provides challenges when solely relying on the dichotomic outcome of such a test (i.e., accepting or rejecting a pre-specified null hypothesis). The absence of a statistically significant test result, for example, cannot be interpreted as "evidence in favour of the null hypothesis" (Leppink et al., 2017, p. 116). This is the case in research studies with limited sample sizes, small underlying effect sizes, and/or relatively high variance of the outcome measure. A research study should generate knowledge about the potential strength of an association (or effect), in other words, " 'is it strong enough to matter?' and to formulate our expectations about the direction and size of that relationship" (Berner & Amrhein, 2022, p. 784). Accounting for those critiques of the conventional testing paradigm discussed above, our study chooses to establish the relative importance/predictive capabilities of predictor variables on the dependent variable by following a modern machine learning lens, as proposed by Leo Breiman in his research article, "Statistical Modeling: The Two Cultures" (Breiman, 2001b).

3.8.1 Random Forest

The data analysis was performed on the statistical software package R and the graphical user interface RStudio (version 4.2.2) (R Core Team, 2022).

Accordingly, variable importance is the capability of a variable to reduce classification or estimation error when predicting the outcome of interest using a machine learning method. Therefore, to implement such a variable importance assessment approach, RFs (Breiman, 2001b) using the R package ‘randomForest’ (Liaw & Wiener, 2022) were used. RF is an ensemble machine-learning approach (Breiman, 2001a; Liaw & Wiener, 2002; Lingjun et al., 2018). It aims to optimize the best prediction or classification rule that minimizes the prediction error within the implied regression or classification trees. Each tree is aggregated (i.e., ensembled) to produce a forest (i.e., combines multiple decision trees to make a prediction) (Breiman, 2001a; Liaw & Wiener, 2002; Lingjun et al., 2018).

RF analysis, rather than conventional logistic regression analysis, was selected given that RFs do not require strong assumptions underlying the data, such as linearity and independence of predictor variables (Lingjun et al., 2018) and require minimal data preprocessing (Zhu, 2020). In a benchmark experiment by Couronné et al. (2018) of several different scientific datasets (n=243), the application of RF (using default hyperparameters) was shown to perform better than logistic regression. Further reasons to utilize RF analysis is because it is “robust to outliers and noise” (Breiman, 2001a, p. 10), and reduces overfitting, as a result of aggregating the predictions generated by several decision trees (Breiman, 2001a). Furthermore, since the RF is based on decision trees, possible predictor variable interactions are taken explicitly into consideration (Lingjun et al., 2018). Therefore, it is easy to determine and interpret the variable importance of the predictor variables on the model (Lingjun et al., 2018). The use of the RF algorithm has been successfully applied to health survey data, for example, to understand factors predicting patients’ healthcare satisfaction (Simsekler et al., 2021; Zhang et al., 2020).

RFs are flexible as they can manage regression and classification tasks (Zhu, 2020). Within our study, RFs method was used for regression tasks. All RF models were run with 1000 regression trees, and we used the default hyperparameter setting as implemented in the R package ‘randomForest’ (Liaw & Wiener, 2022). The RF generates each tree using bootstrapped samples. In other words, using the original dataset, the RF randomly selects observations, with replacement, to create multiple random samples (i.e., bootstrapped samples). Each bootstrapped sample is built using two-thirds of the dataset, while the remaining third is “out-of-bag” data. This latter data encompasses observations that were not included in each bootstrapped sample used to train the trees within the random forest. The out-of-bag data is used to evaluate the predictive performance of the respective tree, fitted within a single bootstrap iteration, through its prediction or classification error (Breiman, 2001a; Liaw & Wiener, 2002; Lingjun et al., 2018). In terms of the hyperparameter, *mtry*, it represents the “number of variables randomly sampled as candidates at each split” with the default being p/3, the number of variables (p) divided by three (Liaw & Wiener, 2022, p. 18). The *replace* hyperparameter dictates whether or not sampling replacement occurs, the default is set to TRUE, which means that sampling replacement will occur (Liaw & Wiener, 2022). The bootstrapped sample size is set by the hyperparameter *sampsize* and the default size is the number of samples within the original dataset (Liaw & Wiener, 2022; Probst et al., 2019). The RF trees’ terminal nodes (i.e., bottom/last node) can have a minimum number of observations, which is established by the *nodesize* hyperparameter, and the default is five observations (Liaw & Wiener, 2022). Also, the *maxnodes* hyperparameter is the “maximum number of terminal nodes trees in the forest can have” (Liaw & Wiener, 2022, p. 18). The default is NULL; therefore, depending on the *nodesize*, the tree will generate until it reaches a maximum (Liaw & Wiener, 2022). As noted by Probst et al. (2019), “the distinction between hyperparameters and algorithm variants is blurred” (p.2); therefore, for further details of the RF algorithm, please see the R package ‘randomForest’ (Liaw & Wiener, 2022), which was used for our data analysis.

Within RFs, variable importance measures can be computed, which rank the relative importance of the predictor variables within the established prediction model. For this purpose, the out-of-bag data is used, and one model variable at a time is essentially removed (permuted) to compute the change in the prediction error for that variable (Breiman, 2001; Liaw & Wiener, 2002). We used the Mean Squared Error (MSE) metric which is commonly used for evaluating the performance of regression models. This metric provides an overall estimation of the model's accuracy as it measures the difference between the predicted values of our machine-learning model and the actual values. In this study, the change in predictive model performance is measured as the percent increase in MSE (%IncMSE) that allows us to understand the variables' relative importance. Thus, a larger MSE percentage suggests that a variable has a higher importance in predicting the outcome. To provide the variable importance measures with a 95% CI, we generated 1000 bootstrapped RFs which generated a bagged estimate, which is the mean of all %IncMSE generated from the bootstrapped RFs. Using the RF regression, we generated scatter plots to explore the direction of the association between each predictor variable and the predicted BI. An approximate regression coefficient (denoted as β, which represents the regression slope) was computed and reported where a linear association was apparent.

Further analysis was conducted to examine the observed and predicted BI, whereby two prediction models were plotted: (1) a full model (with all variables) and (2) a reduced model where one variable at a time was removed. The analysis provided a conversion of the estimated variable importance measures (i.e., relative increase of MSE) on the actual scale (i.e., one to four). Stated otherwise, changes on the four-point scale provided a more intuitive measure of the change in the prediction of BI once a specific variable was removed from the prediction model.

For this study, if the predicted BI score changed by one unit on the four-point scale from the full to reduced model, we considered the variable (that was removed from the prediction model) to have ‘moderate to strong’ predictive capability, as that change implied a change in the level of BI (e.g., change from ‘strongly agree’ to ‘agree’). In contrast, a change of less than one, for example, if a predicted BI score changed from 3.8 (full model) to 3.75 (reduced model), suggested that the specific variable (removed) was essentially inconsequential for the prediction of an individual’s BI. To describe the distribution of changes in predicted BI scores between the full and the reduced model across all participants, we provided the interquartile range (IQR).

To further help illustrate the changes in participants' predicted BI score from the full versus the reduced model, confusion matrices were generated. The confusion matrices were not used for the performance evaluation of the RF model, since our study used regression, not classification, trees. Instead, the purpose of the confusion matrices, in our study, was to help visualize the number of participants whose predicted BI shifted from agreement to disagreement or vice versa when comparing the full to reduced models. As such, the predicted BI score was dichotomized, whereby any score less than 2.5 signified disagreement and above 2.5 represented agreement.

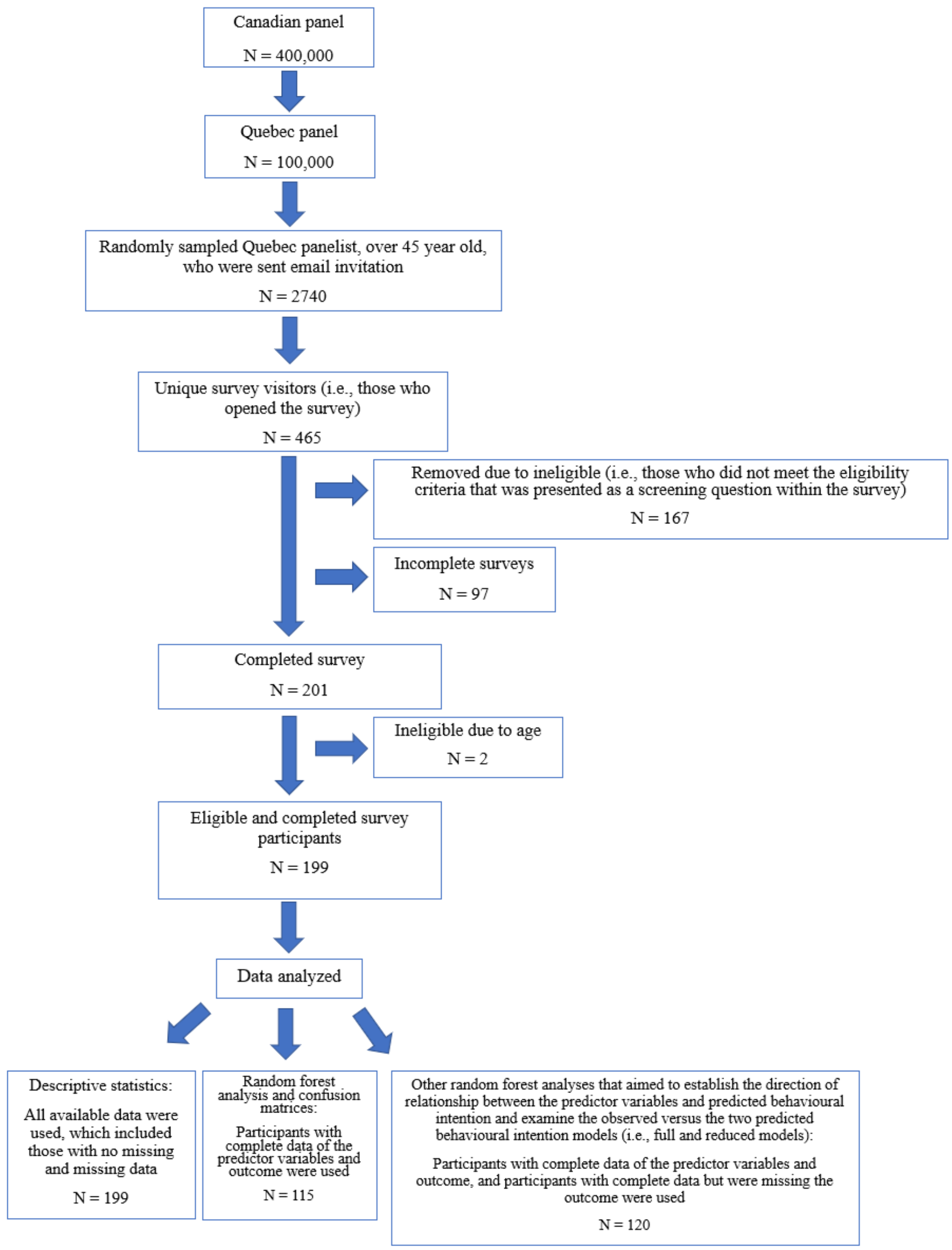
CHAPTER 4: RESULTS

4.1 Flow of Participants

Figure 3 outlines the flow of participants. Of the 400,000 Leger Canadian panelists, 100,000 were from Quebec. A random sample of 2740 Quebec panelists aged 45 and above was sent an email invitation by Leger. We defined unique visitors as 465 people who opened the survey in response to the invitation; 197 of those were removed due to ineligibility, and 97 did not complete the survey, leaving 201 who completed the survey. The response rate (i.e., the number of individuals who opened the survey divided by the number of email invitations

(Fakhfakh et al., 2023)) was 17% (465/2740). The completion rate (i.e., the number of individuals who completed the survey divided by the number of people who opened the survey (Rahimi et al., 2018)) was 43% (201/465). During data cleaning, two participants were identified to be ineligible due to age, consequently, 199 participants remained for descriptive analyses. However, the RF analysis to determine the variable importance measures and confusion matrices used 115 participants. While further analyses that used the fitted values from the RF to (1) examine the direction of the association and (2) examine the observed versus the two predicted models (i.e., full and reduced models) used 120 participants. Details of those sub-data were discussed in section ‘3.7.1 Handling Missing Data’.

Figure 3. Participant Flowchart



4.2 Descriptive Overview

4.2.1 Participants' Characteristics

The demographics of eligible pre-test (n=39) participants (Appendix F) were similar to that of the sample population (n=199).

Table 1 outlines the sociodemographic, caregiving, and other characteristics of the 199 participants. The French version of the survey was accessed by 173 (87%) participants. The mean age of participants was 56.7 years; 128 (64%) identified as a woman; majority showed high educational background, 82 (41 %) had completed CEGEP (i.e., junior college) and 48 (24%) university undergraduate studies; 88 (44%) were employed full time; and the mean years lived in Canada was 55.

Of the 199 participants, 140 (70%) participants were adult children of older care recipients, and the remaining 59 (30%) were spouses, siblings, friends, grandchildren, neighbours, or had another relationship with the older care recipients. As well, out of the 199 participants, 167 (84%) reported caring for a single older adult, while the remaining 32 (16%) were those who reported caring for multiple (i.e., more than one) older adults. In addition, of the 199, 83 (42%) lived independently in their own homes but the remainder lived in situations that provided varying degrees of on-going support. The mean time spent as FCGs was 7.7 years (6.9) and the mean number of care hours per week was 16 (19.5). Predominant caregiving tasks included household activities (n= 142, 71%), provision of psychosocial care (n=140, 70%), assistance with transportation (n=133, 67%) and care coordination (n=127, 64%).

Among FCGs, there was low AI knowledge, with 109 (55%) participants reporting not being knowledgeable about AI. Only 16 (8%) indicated having past AI experience. Among those 16 participants, 11 (6%) had used AI-based wearable devices to provide care to an older adult.

Table 1. Characteristics of Family Caregivers (n=199)

Characteristics	**n=199**
Survey's Language That Participants Accessed n (%)	
French	173 (86.9%)
English	26 (13.1%)
Age (years)	
Mean (SD)	56.7 (5.49)
Median [Min, Max]	57.0 [45.0, 64.0]
Gender n (%)	
Woman	128 (64.3%)

Man	71 (35.7%)
Education n (%)	
CEGEP (junior college) [a]	82 (41.2%)
University Undergraduate	48 (24.1%)
High school	44 (22.1%)
University Post-graduate (e.g., Masters, Ph.D.)	22 (11.1%)
Other	2 (1.0%)
Elementary	1 (0.5%)
Employment n (%)	
Full-time	88 (44.2%)
Retired	65 (32.7%)
Part-time	23 (11.6%)
Unemployed	15 (7.5%)
Other	6 (3.0%)
Full-time caregiver	2 (1.0%)
Years Lived in Canada	
Mean (SD)	55.3 (9.07)
Median [Min, Max]	57.0 [7.00, 64.0]
Relationship to Care Recipient [b] n (%)	
Child	140 (70.4%)
Spouse	20 (10.1%)
Sibling	14 (7.0%)
Friend	12 (6.0%)
Other	12 (6.0%)
Grandchild	2 (1.0%)
Neighbour	1 (0.5%)
Living Arrangement of the Care Recipient [b] n (%)	
Living independently in one's own home	83 (41.7%)
Living with the family caregiver	68 (34.2%)
Living in long-term care/nursing home/residential home	45 (22.6%)
Living in private seniors' homes [c] or equivalent	8 (4.0%)
Number of Older Adults the Family Caregiver is Caring for n (%)	
1	167 (83.9%)
2	29 (14.6%)
3	0 (0%)
4 or more	2 (1.0%)
Missing	1 (0.5%)
Number of Years of Being a Family Caregiver	
Mean (SD)	7.7 (6.94)
Median [Min, Max]	6.00 [0, 56.0]

Estimated Number of Hours of Care Per Week Provided by the Family Caregiver	
Mean (SD)	16.1 (19.5)
Median [Min, Max]	10.0 [0, 168]
Missing	1 (0.5%)
Tasks Family Caregivers Perform [b] n (%)	
Household tasks (e.g., home maintenance, grocery shopping, laundry)	142 (71.4%)
Psychosocial care (e.g., emotional support, companionship)	140 (70.4%)
Transportation (e.g., driving the older adult to appointments)	133 (66.8%)
Care coordinator (e.g., communicate with healthcare providers, translator, schedule appointments)	127 (63.8%)
Substitute decision-maker (e.g., making health, legal and financial decisions on behalf of the older care recipient who is unable to)	87 (43.7%)
Daily living activities (e.g., dressing, feeding, toileting, transferring)	70 (35.2%)
Medical/nursing care (e.g., operating medical equipment like a catheter, providing wound care, assisting with medications/injections)	40 (20.1%)
Other	3 (1.5%)
Family Caregivers' Past AI Experience n (%)	
No	183 (92.0%)
Yes	16 (8.0%)
AI Technology Family Caregivers Have Used Before [d] n (%)	
AI-based wearable devices	11 (5.5%)
AI-based assistive technology	4 (2.0%)
AI-based chatbots/virtual assistants	2 (1.0%)
Family Caregivers' AI Knowledge n (%)	
Not knowledgeable	109 (54.8%)
Somewhat knowledgeable	46 (23.1%)
Moderately knowledgeable	37 (18.6%)
Extremely knowledgeable	6 (3.0%)
Missing	1 (0.5%)

[a] General and Professional Educational College, the junior college education system in Quebec, Canada.

[b] These questions allowed for multiple responses, so the percentages are generated based on more than 199 responses.

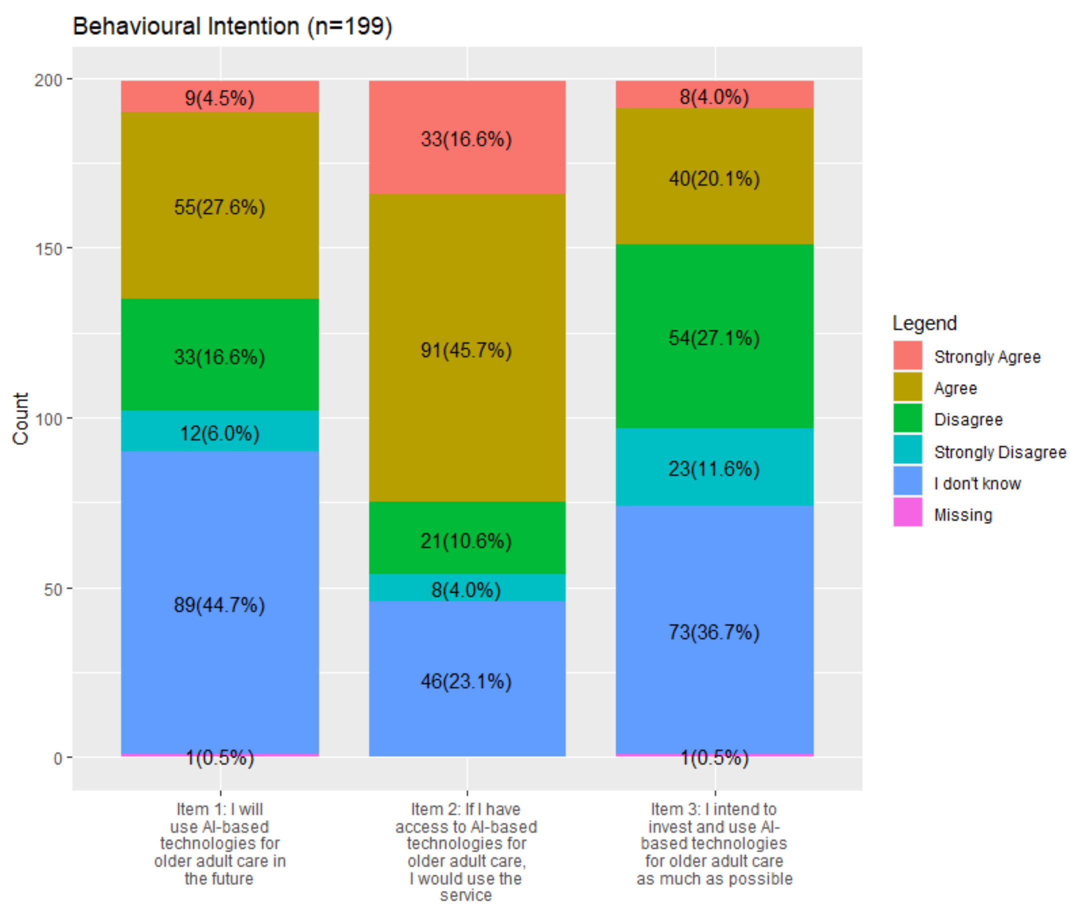
[c] Private seniors' homes in Quebec, Canada are considered private residences/homes primarily for semi-autonomous older adults.

[d] The count and percentage are generated based on a total of 16 participants, as they selected "yes" to having past AI experience.

4.2.2 Behavioural Intention

Figure 4 highlights the distribution of responses on the three items measuring BI. For the first item, 'I will use AI-based technologies for older adult care in the future', 89 (44.7%) participants responded with 'I don't know'. For the second statement, 'If I have access to AI-based technologies for older adult care, I would use the service', 91 (45.7%) participants agreed and 46 (23.1%) responded with 'I don't know'. Finally, 73 (36.7%) participants answered, 'I don't know' to the third item: 'I intend to invest and use AI-based technologies for older adult care as much as possible'.

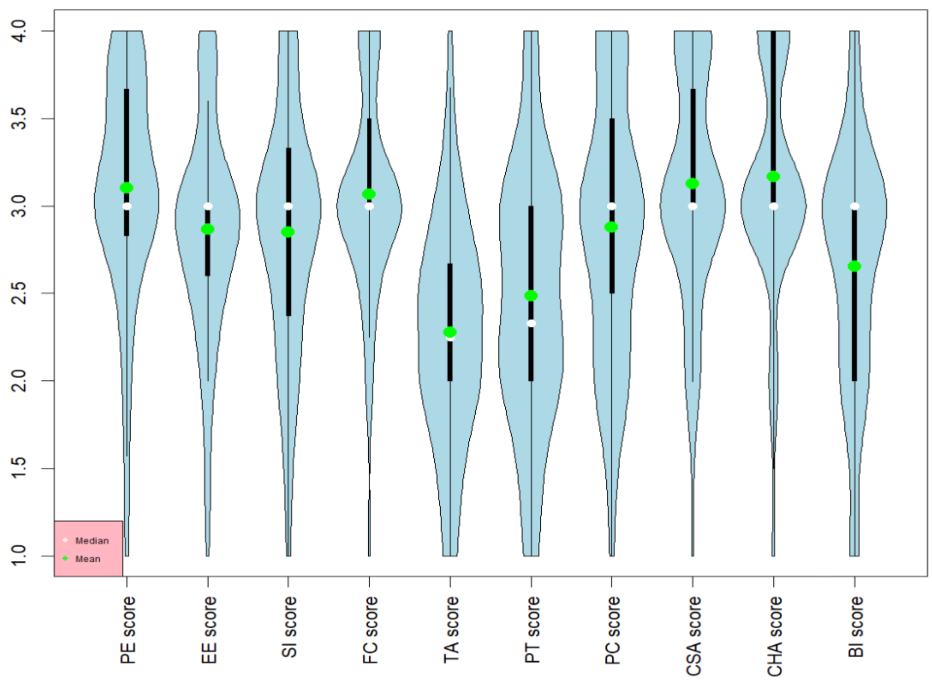
Figure 4. Response Distribution to Behavioural Intention Items



4.2.3 UTAUT-related Variables Scores

Figure 5 illustrates the distribution of UTAUT-related variable scores (possible range one to four) using violin plots. The green and white circles represent the mean and median, respectively. The thick black line represents the interquartile range (IQR). The mean scores ranged from 2.28 to 3.17. All medians were at 3, except technology anxiety and perceived trust, which had a median of 2.25 and 2.33, respectively. Details of the missing data (i.e., count and frequency) within each variable are found in the notes under Figure 5.

Figure 5. Violin Plot of the UTAUT-Related Variables' Score



Note. PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; TA = Technology Anxiety; PT = Perceived Trust; PC = Perceived Cost; CSA = Confidence in the Source of Advice for Care (healthcare professional vs AI-enabled technology); CHA = Confidence in Healthcare Professionals' Advice for the Use of AI-enabled Technology; BI = Behavioural Intention.

Note. There were missing scores, of the 199 participants, 22 (11.1%) from PE, 19 (9.5%) from EE, 25 (12.6%) from SI, 39 (19.6%) from FC, 12 (6.0%) from TA, 17 (8.5%) from PT, 45

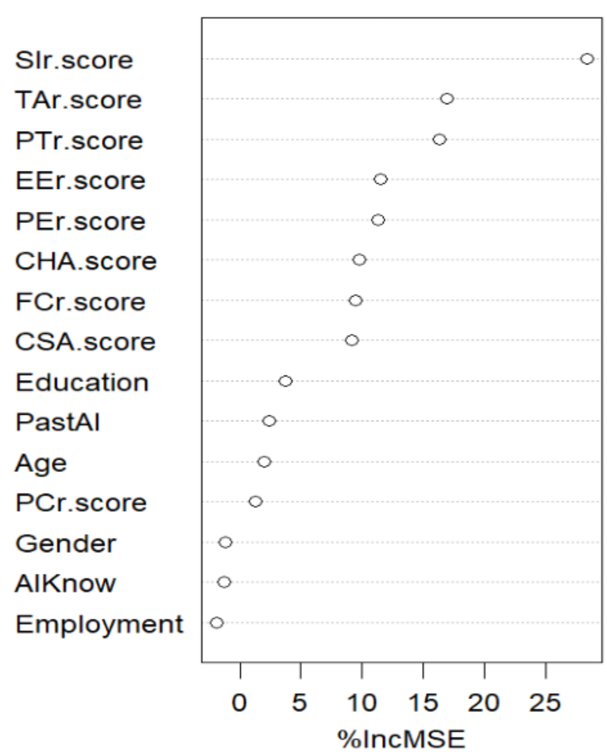
(22.6%) from PC, 21 (10.6%) from CSA, 31 (15.6%) from CHA, and 37 (18.6%) were missing from BI.

4.3 Random Forest Analysis

4.3.1 Variable Importance Measures of the UTAUT-Related Variables, Demographic, and AI-Related Variables

A RF was used to explore the relative importance of the nine UTAUT-related variables, demographics (i.e., age, gender, education, employment), AI knowledge and experience on BI. Figure 6 illustrates that all demographics and AI-related variables yielded less than a 5% IncMSE once removed from the prediction model, which was relatively lower when compared to the UTAUT-related variables' relative increase in MSE, except for the variable of perceived cost ('PCr.score'). Given their negligible predictive capability, we did not include demographics or AI-related variables (i.e., AI knowledge and AI experience) in the subsequent RF analysis.

Figure 6. Variable Importance Measures



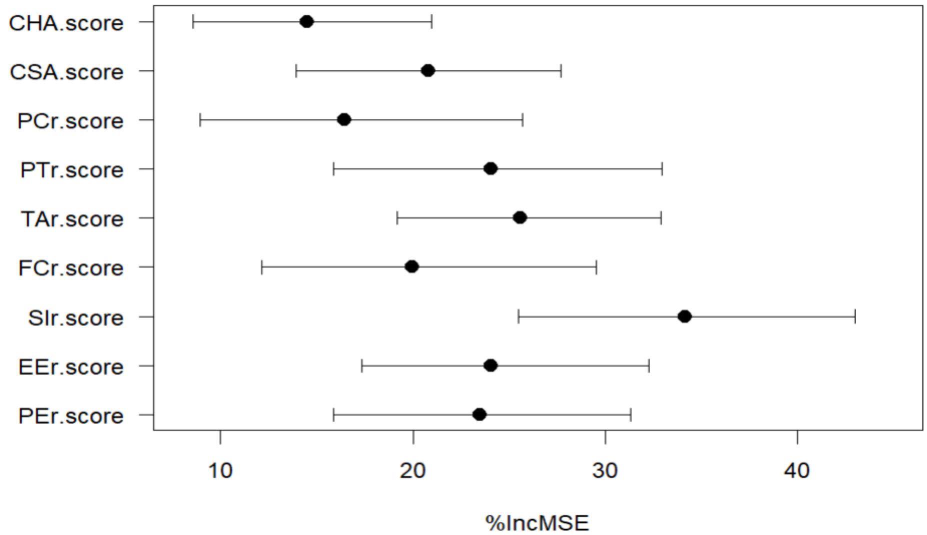
Note. PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; TA = Technology Anxiety; PT = Perceived Trust; PC = Perceived Cost; CSA = Confidence in the Source of Advice for Care (healthcare professional vs AI-enabled technology); CHA = Confidence in Healthcare Professionals' Advice for the Use of AI-enabled Technology; BI = Behavioural Intention; Past AI = Past experience using AI-enabled technology; AIKnow = AI knowledge.

4.3.2 Bagged Variable Importance Measures of the UTAUT-Related Variables

The RF model that included the nine predictor variables for BI explained a substantial portion of the variance, with values ranging between 56% to 83% in the bootstrapped-related samples. Figure 7 visualizes the bagged (i.e., mean) estimate of the predictor variables' importance measures as measured by %IncMSE, which is presented as a black dot. Meanwhile, the black line illustrates the 95% bootstrap CI.

The predictor variables' individual relative importance measures from highest to lowest, with 95% CIs estimated as follows: social influence (34% IncMSE; [25, 43]), technology anxiety (26% IncMSE; [19, 33]), perceived trust (24 % IncMSE; [16, 33]), effort expectancy (24% IncMSE; [17, 32]), performance expectancy (23% IncMSE; [16, 31], confidence in the source of advice for care (healthcare professional vs AI-enabled technology) (21% IncMSE; [14, 28]), facilitating condition (20% IncMSE; [12,30]), perceived cost (16% IncMSE; [9, 26]), confidence in healthcare professionals' advice for the use of AI-enabled technology (15% IncMSE; [9, 21]).

Figure 7. Predictor Variable Bagged (Mean) Variable Importance Measures

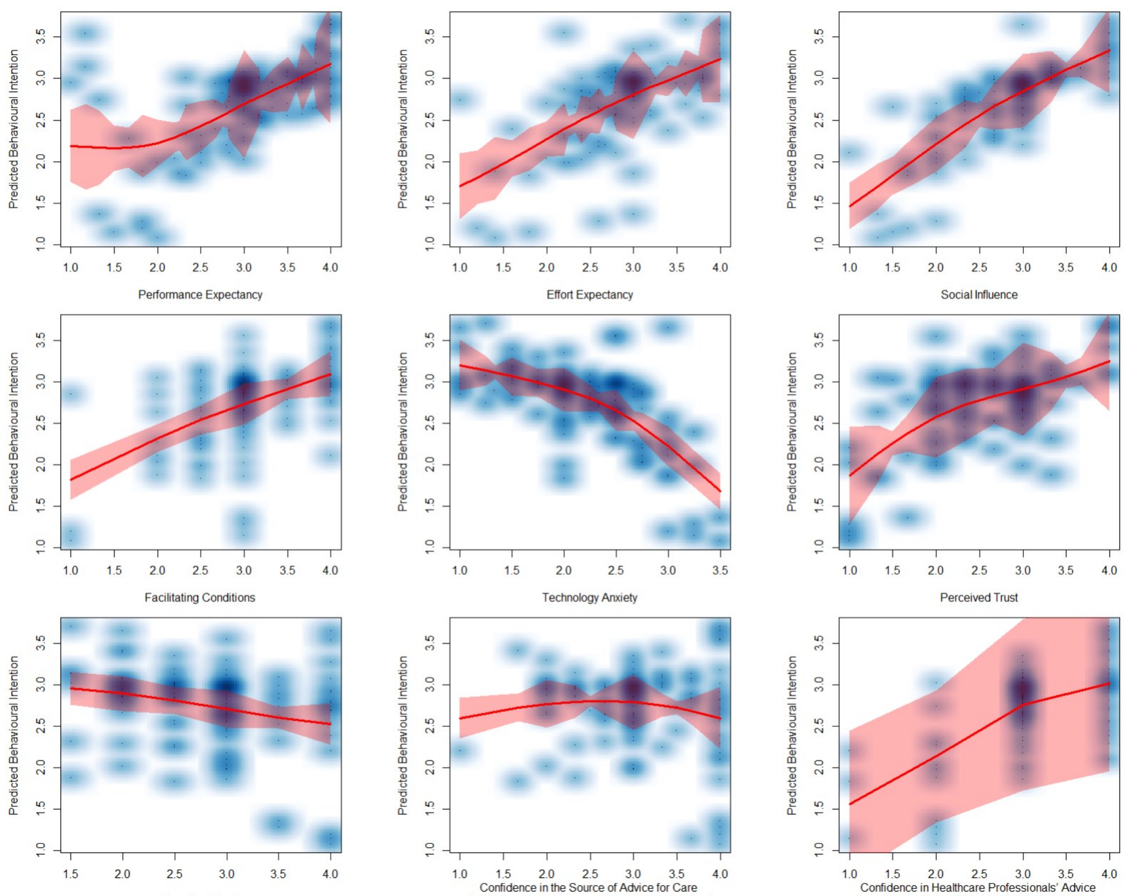


Note. PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; TA = Technology Anxiety; PT = Perceived Trust; PC = Perceived Cost; CSA = Confidence in the Source of Advice for Care (healthcare professional vs AI-enabled technology); CHA = Confidence in Healthcare Professionals' Advice for the Use of AI-enabled Technology; BI = Behavioural Intention.

4.3.3 Direction of Association

Based on the RF model, figure 8 illustrates the direction of the association between the predicted BI and each predictor variable. Data density is represented in blue, with darker areas illustrating more data points. The red line represents fitted smooth splines to visualize the central tendency (direction) of the association and the red area surrounding the smooth spline fitting line represents the uncertainty (95% confidence band). The regression coefficient (β) for a linear association was calculated as the approximate slope (i.e., the difference in the mean predicted score across the range of predicted scores, divided by the respective difference in the predictor variable) and yielded the following values: Performance expectancy ($\beta \approx +0.43$), effort expectancy ($\beta \approx +0.50$), social influence ($\beta \approx +0.58$), facilitating conditions ($\beta \approx +0.37$), perceived trust (β ≈ +0.43), and confidence in healthcare professionals' advice for the use of AI-enabled technology (β ≈ +0.42), showed a positive association on the predicted BI to use AI in older adult care. A negative association was found between the predicted BI and technology anxiety (β ≈ -0.64), and perceived cost (β ≈ -0.12). Lastly, confidence in the source of advice for care (healthcare professional vs AI-enabled technology) suggests a quadratic rather than a linear association; hence, a slope was not estimated.

Figure 8. Scatterplots with Smooth Splines (red) to Illustrate the Direction of the Association Between Predicted Behavioural Intention and Predictor Variables



4.3.4 Quantifying the Change in Behavioural Intention Score on the Item Scale

Figures 9, 10 and 11 illustrate how well the predicted BI, based on two distinct RF models, estimates the actual observed BI. Model one is the full model that includes all predictor variables (represented as green dots). The second model is the reduced model which excluded one predictor variable at a time (represented as red dots). The bolded headings on top of each panel graph display which predictor variable was removed from the second model (i.e., reduce model). The blue lines help visualize the difference in scores between the two prediction models. Figures 9, 10, and 11 each illustrate three things:

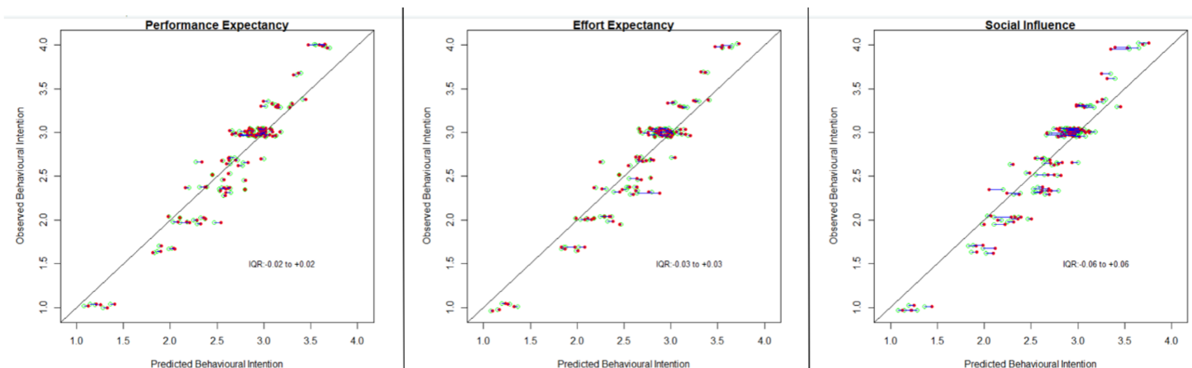
Firstly, it shows the agreement between the observed BI score and predicted BI score, with the black diagonal line representing perfect agreement. Overall, both models fit the data considerably well, correctly separating lower, medium, and high scores. Several observations are close to the black diagonal line which represents the line of perfect agreement. The variance of data points around this perfect fit line is considerably small so that the predicted values resemble a linear pattern. Nevertheless, the model appears to slightly underestimate lower BI scores and overestimate higher BI scores.

Secondly, it shows that most participants' differences in BI scores between the two predicted models fell within the IQR. The IQR slightly varied depending on the variable that was removed. Most participants predicted BI scores from the full to reduce model did not change much as all the IQRs in the figures were within the range of -0.06 to +0.06.

Thirdly, the confusion matrices were generated and presented in a two-by-two table at the bottom of each plot within figures 9,10, and 11. They help visualize how many individuals' initial predicted BI status changed (i.e., agree to disagree or disagree to agree), after removing one predictor variable at a time. For example, in figure 9 under the performance expectancy plot, the finding of the confusion matrix showcased that after removing the predictor variable, performance expectancy, from the full model, one individual's predicted BI score shifted from agree to disagree. While two individuals predicted BI scores shifted from disagreement to agreement.

Overall, the confusion matrices showed that depending on which predictor variable was removed from the full model, out of the 115 participants (the sample used in this analysis was discussed in the section '3.7.1 Handling Missing Data') very few of the participants' predicted BI status changed. In general, depending on the predictor variable that was removed, between 0.9-6% of participants (i.e., 1 to 7 participants) level of BI changed from agreement (BI score >2.5) to disagreement (BI score <2.5). Meanwhile, depending on the removed predictor variable, overall, 0-3% of participants (i.e., 0 to 4 participants) predicted BI shifted from disagreement to agreement from the full to reduced model.

Figure 9. Scatterplots of the Observed Versus Predicted Behavioural Intention (plotting the full model versus the reduced models when performance expectancy, effort expectancy or social influence is removed) and Confusion Matrices



Confusion Matrix (n=115)

Full Model	Reduce Model	
	Disagree	Agree
Disagree	14	2
Agree	1	98

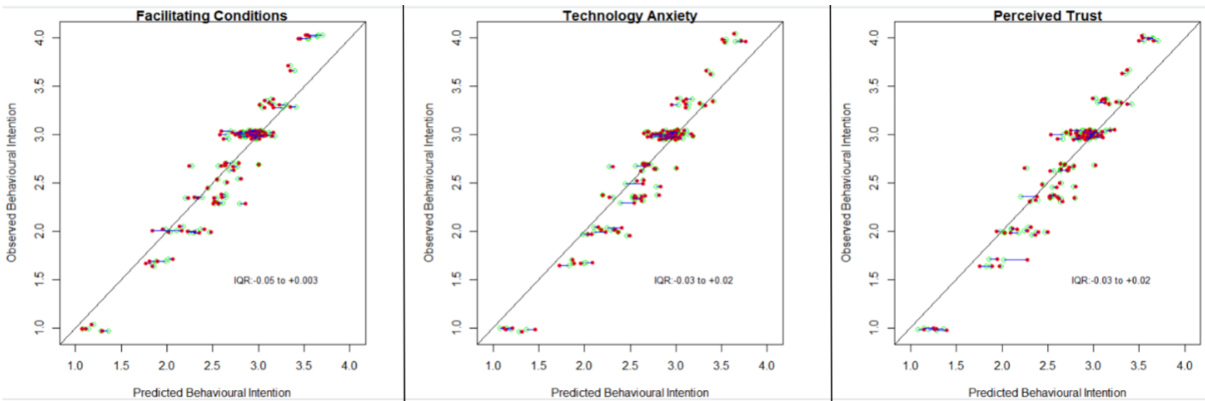
Confusion Matrix (n=115)

Full Model	Reduce Model	
	Disagree	Agree
Disagree	16	0
Agree	2	97

Confusion Matrix (n=115)

Full Model	Reduce Model	
	Disagree	Agree
Disagree	12	4
Agree	4	95

Figure 10. Scatterplots of the Observed Versus Predicted Behavioural Intention (plotting the full model vs. reduced model when facilitating conditions, technology anxiety, or perceive trust is removed) and Confusion Matrices



Confusion Matrix (n=115)

Full Model	Reduce Model: Disagree	Reduce Model: Agree
Disagree	16	0
Agree	7	92

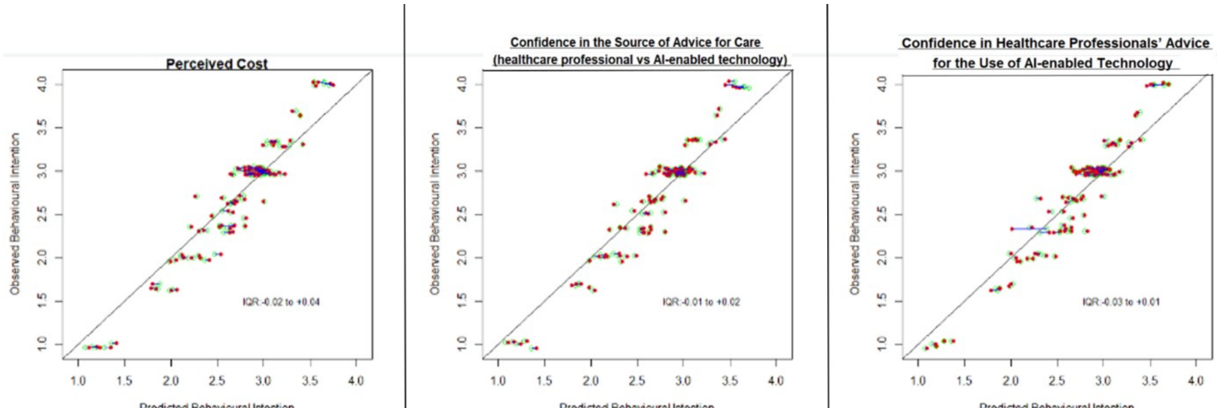
Confusion Matrix (n=115)

Full Model	Reduce Model: Disagree	Reduce Model: Agree
Disagree	15	1
Agree	4	95

Confusion Matrix (n=115)

Full Model	Reduce Model: Disagree	Reduce Model: Agree
Disagree	15	1
Agree	3	96

Figure 11. Scatterplots of the Observed Versus Predicted Behavioural Intention (plotting the full model versus the reduced models when perceived cost, confidence in the source of advice for care (healthcare professional vs AI-enabled technology), or confidence in healthcare professionals' advice for the use of AI-enabled technology is removed) and Confusion Matrices



Confusion Matrix (n=115)

Full Model	Reduce Model: Disagree	Reduce Model: Agree
Disagree	16	0
Agree	3	96

Confusion Matrix (n=115)

Full Model	Reduce Model: Disagree	Reduce Model: Agree
Disagree	15	1
Agree	3	96

Confusion Matrix (n=115)

Full Model	Reduce Model: Disagree	Reduce Model: Agree
Disagree	15	1
Agree	2	97

CHAPTER 5: DISCUSSION

This study examined FCGs' acceptance of AI-enabled technology for older adult care according to the following objectives: (1) describe FCGs' BI of using AI-enabled technologies in the care of older adults and (2) determine the predictive capability of nine candidate predictor variables on FCGs' BI. The three key findings are: 1) FCGs mean BI was high, 2) social influence had the highest relative importance, and 3) all nine candidate predictor variables had a complementary explanatory value on the model's predictive accuracy. A discussion of the findings and implications is elaborated below.

5.1 Principal Findings

5.1.1 Family Caregivers' Behavioural Intention

As noted by Fakhfakh et al. (2023), "there is no definitive threshold for a clinically significant intention score in the literature" (p.5). The mean BI score among our sample of FCGs was high (2.7 out of 4), suggesting overall acceptance of AI-enabled technology for older adult care. Consistent with our study, a high mean BI score was also identified in past studies exploring FCG's intentions to use digital care coordination/management technologies (Boutilier et al., 2022; Wen et al., 2022).

However, when examining the five-point scale responses to the three BI items separately, it appears that FCGs exhibited varying acceptance of different situations. In terms of using AI-enabled technology *in the future,* close to half of FCGs expressed uncertainty. Similarly, when probed about their BI to use AI-enabled technology *as much as possible*, over a third of FCGs were unsure, and another third showed low acceptance (i.e., disagreed with using AI-enabled technology as much as possible). Our findings differ from a previous study that explored FCGs' acceptance of a variety of technologies for older adult care (Burstein et al., 2015). When Burstein et al. (2015) asked, "I could imagine using this technology in the future", overall, FCGs reported strongly agreeing to their BI to use the technologies *in the future* (p. 51). A possible explanation for this difference in findings may lie in our sample's self-reported lack of AI experience and knowledge. Moreover, despite our sample having a high level of schooling, they might not have had a background in a science or AI-related program (e.g., Engineering, Computer Science, Data Analytics). This emphasizes the importance of fostering AI literacy by integrating and strengthening AI curricula within the educational systems (Laupichler et al., 2022).

Finally, in our study, close to two-thirds of FCGs agreed to use AI-enabled technology if they had *access to the technology*. Accessibility can be impacted by factors like one's awareness of the technology (Botelho, 2021). FCGs have been reported to demonstrate a lack of awareness of currently available technologies (e.g., fall detectors and safety devices for the kitchen stove) and where to purchase them (Burstein et al., 2015). This was also evident in our study, as almost all of the FCGs reported not having any previous experience with using AI-enabled technologies. This emphasizes the need to improve informational awareness about AI-enabled technologies to FCGs to improve technology acceptance. Other factors shaping technology access can include the availability of technology, technical training on how to use it (Botelho, 2021), and the ability of the technology to be adaptive to the user to meet their needs or impairments (Botelho, 2021; Xiong et al., 2022).

5.1.2 Predictor Variables' Relative Importance

Social influence had a 34% IncMSE, meaning that it had the highest relative importance in predicting BI, compared to the other predictor variables. This result suggests that FCGs' intention to use AI-enabled technology is largely shaped by the norms/expectations within their social group. Our findings were consistent with a study that found social influence to be the most important variable in predicting FCGs' BI to use digital health technology devices and services, such as technology for fall detection and medication reminders (Hwang et al., 2022). However, another study found that although social influence contributed to FCGs' BI to use wearable devices, compared to other variables, it played a less prominent role (Dai et al., 2020).

A potential reason for our study's high importance could be explained by culture. Our study was conducted in Quebec and French Canadians have been found to value social harmony (Crafa et al., 2019). Another possible explanation is our sample's lack of AI knowledge and experience. Under such circumstances, FCGs might defer to what others in their social group would do or how they would react, to compensate for their lack of knowledge and experience. Interestingly, confidence in healthcare professionals' advice for the use of AI-enabled technology had the lowest relative importance. The heightened importance of FCGs' social networks and the low importance of confidence in healthcare professionals' advice for the use of AI-enabled technology, in our study may reflect the effects of the COVID-19 pandemic. The pandemic disrupted formal care services and support (e.g., homecare services) and the ability of FCGs to communicate and obtain information from healthcare professionals (Irani et al., 2021). This may have resulted in FCGs relying more on their immediate social networks and online sources, thus being greatly influenced by them.

5.1.3 All Nine Candidate Predictor Variables had a Complementary Explanatory Value on the Model's Predictive Accuracy

The RF analysis showed substantial goodness of fit, with the average percentage of the outcome variance explained ranging from 56% to 83% in bootstrapped-related samples. Although we hypothesized that performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, perceived trust, perceived cost, confidence in the source of advice for care (healthcare professional vs AI-enabled technology), and confidence in healthcare professionals' advice for the use of AI-enabled technology would demonstrate 'moderate to strong' capability for predicting the BI, the results (as seen in figures 9 to 11) imply that none of the nine candidate predictor variables, independently, showed 'moderate to strong' predictive capability in changing FCGs' BI. Instead, all nine candidate predictor variables have a complementary explanatory value for the model's predictive accuracy, as shown by the high proportion of variance explained by the model.

Our findings align with a previous study that examined FCG's acceptance of wearable technology and identified the joint contributions of the variable's performance expectancy, effort expectancy, social influence, facilitating conditions, and technology anxiety on the variance explained in FCG's BI (Dai et al., 2020). Furthermore, UTAUT studies among other user groups have also shown similar results regarding the complementary values of the predictor variables (Fan et al., 2020; Napitupulu et al., 2021). For instance, in a study by Pal et al. (2018), the model's predictive accuracy in explaining BI of older adults to use smart home technology was attributed to the variables, performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, perceived trust, and perceived cost. Moreover, while expert advice has been found to be a predictor of BI (Napitupulu et al., 2021), it has yet to be explored when examining it from the perspective of 'confidence in the source of advice for care (healthcare professional vs AI-enabled technology)' and 'confidence in healthcare professionals' advice for the use of AI-enabled technology'. Our findings suggest that these variables contribute to predicting FCGs BI to use AI-enabled technologies, which highlights the influence that healthcare professionals have in shaping FCGs' decision-making. This provides further evidence for the importance of doctors building a trusting relationship with FCGs (Mitnick et al., 2010). Our study provides support for the value of the nine predictor variables in technology acceptance, specifically within the context of understanding FCGs' acceptance of AI-enabled technology in Canada.

5.2 Implications

The results suggest the complementary role of performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, perceived trust, perceived cost, confidence in the source of advice for care (healthcare professional vs AI-enabled technology), and confidence in healthcare professionals' advice for the use of AI-enabled technology on the BI to use AI-enabled technology for older adult care among FCGs. To encourage current and future uptake of AI-enabled technology for older adult care, stakeholders in the industry, government, and healthcare sector, should enhance facilitators and mitigate the barriers among those nine variables that shape FCGs' acceptance of AI-enabled technology for older adult care.

5.2.1 Performance Expectancy

The study showed that performance expectancy had a positive association with the predicted BI. This means that the higher the expectation of AI-enabled technology's ability to help provide care to older adults, the higher the FCGs' intention to use it. This positive relationship has been reported in past UTAUT studies examining other types of technologies (e.g., telehealth, digital health information systems, smart homes) among various users (Bai & Guo, 2022; Napitupulu et al., 2021; Pal et al., 2018).

Our mean scores for the expectation of AI's ability/performance were quite high (3.1 out of 4). Such optimistic expectations of AI are in agreement with those of the general Canadian population, with almost 60% of it believing it is likely for AI (including robotics) will be used for healthcare and medical diagnostics within the next decade (Canadian Medical Association, 2019). The World Health Organization (2021) has warned, however, that "the appeal of technological solutions and the promise of technology can lead to overestimation of the benefits and dismissal of the challenges" (p.31). The discrepancy between one's expectation of the technology’s benefits versus the reality could lead to users’ disappointment – thereby, negatively impacting technology implementation (Thordardottir et al., 2019).

With consideration of such concerns and our sample’s low experience with, and knowledge about AI, it is important to promote realistic expectations of AI-enabled technology’s ability for care. Acceptance-facilitating interventions, often in the form of a video, should be offered to communicate about a technology’s applications, effectiveness, data security, and other relevant implications (Ebert et al., 2015; Hein et al., 2022). Acceptance-facilitating interventions, have been shown to help improve acceptance and performance expectancy of physicians and medical students about health apps for chronic pain patients (Hein et al., 2022). Moreover, such video interventions can be easily included on websites or training programs (Hein et al., 2022).

5.2.2 Effort Expectancy

Our study showed that effort expectancy has a positive association with the predicted BI; hence the higher the FCGs' expectation of AI-enabled technology's ease of use, the higher their intention to use it. This is consistent with other research, for example, technology acceptance of the use of telehealth during COVID-19 among the general public in Indonesia (Napitupulu et al., 2021) and acceptance of information systems among Nova Scotia healthcare professionals (Ifinedo, 2012). The observed high expectancy (2.9 out of 4) in our research may have been influenced by the orientation presentation on technology applications we made at the beginning of our survey. One example we provided was of AI-enabled assistive technology, specifically smartphone applications to help people with vision impairments (Envision, 2022; Microsoft, 2022). This might have inadvertently introduced a positive halo effect, whereby FCGs perceive that similar to using a smartphone, AI-enabled technologies would be easy to use. Nonetheless, to promote AI-enabled technology’s ease of use, developers should focus on the learnability of the technology (Alzahrani et al., 2021), as well as the design of the technology. For instance, care robots with anthropomorphic (i.e., human-like) characteristics and those using speech communication, are preferred features among users, as they evoke a sense of familiarity, as such interacting with them becomes intuitive – thus, easier to use (Klüber & Onnasch, 2022). If designed inadequately, technology may exacerbate one's workload (Asan & Choudhury, 2021) and create frustration among FCGs (Xiong et al., 2022). As such, stakeholders should incorporate users by engaging in a participatory design approach (Rubeis, 2020; World Health Organization, 2022), whereby technology developers collaborate with FCGs and their older care recipients.

5.2.3 Social Influence

Our study showed that the mean score of social influence within our sample was relatively high (2.9 out of 4), and the variable showed a positive association with the predicted BI. This implies that the greater the FCG's belief that other people in their social group (i.e., relatives/family, friends, media, and government) will support their use of AI-enabled technology, the more likely they will have the intention to use it. The positive relationship is also identified in Canadian survey studies examining the acceptance of information systems among healthcare professionals in Nova Scotia (Ifinedo, 2012) and the acceptance of electronic decision-aid among older adults across Canada (Fakhfakh et al., 2023). It is common for FCGs to seek support from family and peers, especially when there is inadequate support from the healthcare system (Xiong et al., 2022). They are also likely to seek the opinions of other family members to help inform their decision-making about the recipient's care (Su et al., 2020).

The media plays a pervasive role in providing information about AI, thereby, influencing people's views and understanding of AI (Nguyen & Hekman, 2022). This has been demonstrated in a Canada-wide survey among people over 18, which found that rather than school or work being a dominant place to hear/learn about AI, the majority of participants reported hearing about AI through online/media sources (Government of Canada, 2021b). This places an important focus on the training of media personnel such that they not only have good conceptual AI knowledge but also an ability to critically and effectively communicate the implications of AI (Nguyen & Hekman, 2022). Another source of influence on FCGs may come from the government which can shape narratives and the public's opinion about AI. National AI policies in Canada emphasize collaboration for research and development; however, there appears to be insufficient attention to AI ethics and trustworthiness (Guenduez & Mettler, 2023).

5.2.4 Facilitating Conditions

The study showed that facilitating conditions showed a positive association with the predicted BI. This means the higher the expectancy about the technological support/guidance available, the more likely FCGs will intend to use it. Past studies on technology acceptance have also supported the findings that facilitating conditions have a positive relationship with the BI on the use of decision-aid among Canadian older adults (Fakhfakh et al., 2023) and AI-enabled technology among radiation oncologists in China (Zhai et al., 2021).

Facilitating conditions had a mean score of 3.1 out of 4 among FCGs. One explanation for this high score may be an artifact of our study methodology: all our participants had to have access to the internet and technology (i.e., computer and/or smartphone) in order to participate. As such they were likely more aware of facilitating conditions. This impacts our study's generalizability, considering that some Canadians, for example, with a lower income have poorer access to basic technological resources (Andrey et al., 2021).

Among FCGs to older adults, few have reported taking basic caregiving-related training (Burgdorf et al., 2019). If one considers adding technology-based training, one must be mindful of the other responsibilities of the caregiver, such as work and child-rearing (National Academies of Sciences, Engineering, and Medicine, 2016). To accommodate FCGs' complex busy schedules, technology companies should consider training programs that offer flexibility, such as evening or online self-paced programs, along with support services that are available and convenient.

5.2.5 Perceived Trust

The study showed that perceived trust showed a positive association with the predicted BI. This means the higher the perceived trust that the AI-enabled technology will keep the older care recipient's information secure, the more likely FCGs will intend to use it. This relationship has been reported in other studies exploring BI on the use of smart homes among older adults residing across four different Asian countries (Pal et al., 2018) and the acceptance of an intelligent diagnostic support system among India's healthcare professionals (Prakash & Das, 2021).

Our study examined trust in AI-related data security and privacy. Canadians desire control over their health data, and this also implies data access and ownership (Canadian Medical Association, 2019). The mean perceived trust score of 2.5 out of 4 suggests that more is needed to improve upon FCGs' trust that AI-enabled technology will ensure the security of the care recipient's health data and information. There is a current lack of formal legal AI regulation (Law Commission of Ontario & Research Chair on Accountable Artificial Intelligence in a Global Context, 2021), which poses a potential challenge in promoting trust toward AI among users.

Trust can encompass other dimensions such as the AI's robustness, transparency, and accountability (European Commission, 2019). Key stakeholders like AI developers should continuously share/update information regarding the AI-enabled technology (e.g., AI's operating protocol, data usage) (World Health Organization, 2021). Moreover, transparency can be fostered through the inclusivity of the public in the design of the technology and AI codes being open-sourced (i.e., publicly available) (World Health Organization, 2021). Furthermore, the government can play a vital role as a regulator to ensure AI is deployed safely, whereby potential harm is reduced (Guenduez & Mettler, 2023). As such, in addition to improving data security, other aspects like transparency among AI developers is crucial to foster trust. Moreover, further research should apply different conceptualizations of trust to then assess its predictive capabilities on BI.

5.2.6 Technology Anxiety

The study showed that technology anxiety has a negative association with the predicted BI. The greater the anxiety FCGs have towards using AI-enabled technology, the less likely they intend to use AI-enabled technology for caregiving. These findings are also reflected in previous studies as technology anxiety had a negative relationship with BI in using mobile health among older adults in Bangladesh (Hoque & Sorwar, 2017) and intentions in using wearable health technology among older adults in China (Talukder et al., 2020). Our observed low mean score for technology anxiety of 2.3 out of 4 may be an artifact of the study design since the study was internet based and therefore participants had to already have a degree of familiarity and comfort with basic technology.

Technology anxiety can stem from a lack of exposure/practice, fear of making mistakes when using the technology (Mitra et al., 2022), or lack of confidence (Di Giacomo et al., 2020). These may be decreased with technology training (A. Chu & Mastel-Smith, 2010). Acceptance-facilitating interventions that use video to showcase the technology have also been shown to improve anxiety about an internet-based intervention for patients with depression (Ebert et al., 2015).

Given that technology anxiety is found to be an inhibitor to BI, AI-enabled technology companies might consider providing multimedia demonstrations and training to FCGs to minimize their anxiety. Furthermore, users' anxiety about the technology might be reduced if co-design approaches were employed by engaging the lay population and allowing people to voice their concerns and better learn about the technology's potential (Aneja & Latonero, 2021).

5.2.7 Perceived Cost

The study showed our sample has a high perceived cost mean score (2.9 out of 4) and the variable has a negative association with the predicted BI, indicating that the higher FCGs assume AI-enabled technology will be a financial burden for purchase and maintenance, the less likely they intend to use AI-enabled technology for caregiving. This is consistent with past studies demonstrating that perceived cost had a negative relationship with BI in using smartphones among older adults from Asian countries (Pal et al., 2018) and China's university students' BI in using digital health information systems (Bai & Guo, 2022). Although our study did not focus on one specific AI-enabled technology and FCGs' lack of AI experience, the high perceived cost and negative association with BI suggest the need to reduce or mitigate this factor.

There is a wide range of AI-enabled technologies; the price can range from, for example, free smartphone AI-enabled applications (Microsoft, 2022) to purchasable AI robots, for example, PARO, a robotic seal, costs around $10,000 (Sense Medical Limited, 2023). Ensuring that AI-enabled technology is affordable might be addressed through governmental interventions. The model for this could be approached similarly to current Canadian provincial government programs that offer financial support to help offset the costs of assistive products (e.g., wheelchairs) (Government of Ontario, 2022) and home alterations (Gouvernement du Québec, 2022). Private insurance has been suggested as another means to cover the costs of AI-enabled technology (Gudala et al., 2022). In some cases pricing transparency for AI-enabled technology is murky as "many apps are freemium or monetize user data in exchange for being free" (Greenhill, 2023, p. 415).

5.2.8 Confidence in the Source of Advice for Care (healthcare professional vs AI-enabled technology)

In our study, confidence in the source of advice for care (healthcare professional vs AI-enabled technology) had a mean score of 3.1 out of 4. This means that within our sample of FCGs, they have more confidence in the physician to provide care to older adults compared to AI-enabled technology providing care. Similarly, another study found that if a diagnosis and therapeutic advice is different between an AI and a physician, patients prefer the advice from the physician (Yang et al., 2019). Moreover, the variable demonstrated a slight quadratic (concave) association with the predicted BI: for lower scores of confidence in the source of advice for care (healthcare professional vs AI-enabled technology) (1 to 2.5), predicted BI showed a positive association; whereas, for higher scores (2.5 to 4.0), predicted values of BI decreased with increasing levels of confidence in the source of advice for care (healthcare professional vs AI-enabled technology). There was evidence that the impact of AI was tempting for FCGs as seen by the slight increase in BI in between the extremes of the curve. However, BI to use AI-enabled technology was paradoxically lower for situations when FCGs had less and more confidence towards physicians compared to AI. As such, it is likely that our participants were ambivalent about the issues being asked about this variable. This might be analogous to the situation in which a family physician caring for a patient for 30 years has presumably garnered high confidence from their patient. However, the appearance of an unusual set of symptoms might prompt the patient, despite the high confidence, to request a consultation from a particular specialist.

5.2.9 Confidence in Healthcare Professionals' Advice for the Use of AI-enabled Technology

Confidence in healthcare professionals' advice for the use of AI-enabled technology had a high mean score of 3.2 out of 4. Moreover, it showed a positive association with the predicted BI, this implies that if FCGs are confident in the advice of a physician's suggestion to use AI-enabled technology for older adult care, they are more likely to demonstrate their intention to use the technology. It has been asserted, in fact, that healthcare professionals can play important roles in providing recommendations about AI-enabled technology (Greenhill, 2023).

Doctors currently may show hesitancy with this due to low knowledge and consequent fear over malpractice liability (Greenhill, 2023). Technology recommendation guidelines for healthcare professionals (Hein et al., 2022) are needed to help guide them in recommending the most appropriate AI-enabled technologies if asked. Physicians who may want to conduct their own assessment of technology, often lack the time and resources to perform such a task (Greenhill, 2023). Furthermore, the World Health Organization (2021) has recommended that healthcare professionals should receive education and training on AI-enabled technology to better understand the functionality and ethical and legal challenges it could pose (World Health Organization, 2021).

The Canadian Medical Association (2015) developed a guideline to help physicians recommend the use of mobile health applications to their patients but it is unclear if they encompass AI-enabled mobile health applications, or whether it touches upon other forms of AI-enabled technology for care. The recommendations on mobile health applications within the guidelines can be extrapolated to be applied to AI-enabled technology (Greenhill, 2023). For instance, the guidelines seem to suggest that technology recognized by a healthcare organization should be the ones that physicians could recommend (Canadian Medical Association, 2015). The same recommendation could be generalized to AI-enabled technology (Greenhill, 2023). To improve FCGs' trust in the healthcare professionals' advice to use AI-enabled technology, AI developers/companies and healthcare organizations should partner to develop guidelines for recommending AI-enabled technology and promoting continuous AI education among current and emerging healthcare professionals.

5.3 Limitations

This study is the first to use an extended UTAUT and apply RF to explore middle-aged Quebec FCGs' behaviour intention and factors predicting their intentions to use AI in the care of older adults. Despite such a contribution to the literature, we are aware of certain limitations. First, due to the time limitation imposed on a Master's degree, a confirmatory factor analysis was not performed; however, we assured methodological rigour through the adaptation and modification of the pre-existing and reliable UTAUT measurement tool by Pal et al. (2018). Second, we did not engage in a forward-backward translation approach (Koller et al., 2012) potentially impacting the rigour of the French survey. However, the comprehensibility and clarity of the translation were ensured by having a bilingual graduate student and two bilingual FCGs review the survey and conducting a pilot test. Third, despite conducting a pilot test, some survey items might have lacked sufficient specificity. For example, the statement 'Doctors are more responsible and intelligent than the AI-based technologies for older adult care', may not be specific enough. In that example, it is unclear which doctor participants should think about (i.e., a family doctor, a specialist, or all doctors lumped together). Fourth, the study's eligibility criteria, recruitment method, and hosting an online survey generated a unique sample of FCGs who were highly educated, inherently are digitally literate, and have access to the internet and technology (i.e., computer and/or smartphone). Hence our findings may not be generalizable to other FCG populations who have lower educational attainment, are digitally illiterate or don't have access to basic technological infrastructure and devices. Finally, in Quebec, French Canadians are linguistically and culturally different than the English-speakers (Crafa et al., 2019). Therefore, given our uneven linguistic distribution, with the majority of participants accessing the French survey, cultural differences may have influenced approaches to caregiving and thus, their technology acceptance.

5.4 Future Directions

First, this study applied RF using the default hyperparameters. Despite the rigour of the default RF package, we recognize that future studies could improve the predictive accuracy by testing and identifying the optimal hyper-parameters. Second, in this study's sample, based on the low %IncMSE, there does not appear to be strong evidence to indicate the role (i.e., direct or indirect) of demographics (i.e., age, gender, education, employment), AI knowledge, and AI experience on BI. However, this should be taken with caution, as it is dependent on the representation of individuals in the sample, where imbalanced data may play a driving role in determining the %IncMSE. For instance, among the 115 participants (who had complete data), 101 (88%) had no past AI experience, while the remaining 14 (12%) did. Hence, perhaps a larger study with a better distribution of demographic variables of FCGs could further explore the role of demographics, AI knowledge, and AI experience on BI when applying a RF. Third, future studies could examine specific AI-enabled technologies and assess if there are differences in intentions and factors predicting them based on the type of technology in question. Finally, our cross-section study provides insight into FCGs' *intention*; however, as AI-enabled technology becomes increasingly available, especially within the consumer market, research is needed to examine the factors predicting the sustained use of AI-enabled technology.

CHAPTER 6: CONCLUSION

Older adults with complex healthcare needs may require various degrees of care and monitoring, much of which is done by FCGs. The emergence of AI-enabled technologies could offer support for such activities, but several factors shape FCGs' acceptance of using AI-enabled technology for older adult care. The study sought to examine FCGs' BI to use AI-enabled technology for older adult care and assess the predictive capability of the predictor variables. The results show that there was variable interest in using AI in the future; that if used, there was a degree of uncertainty as to how often it would be used; but the intention to use AI would likely increase if the technology is accessible. The results suggest that social influence had the highest relative importance in predicting BI. None of the predictor variables, independently, appear to show ‘moderate to strong’ predictive capability in predicting the BI that we had hypothesized. Rather, the RF analyses highlighted that performance expectancy, effort expectancy, social influence, facilitating conditions, technology anxiety, perceived trust, perceived cost, confidence in the source of advice for care (healthcare professional vs AI-enabled technology), and confidence in healthcare professionals’ advice for the use of AI-enabled technology all play a complementary role in influencing FCGs’ acceptance of AI-enabled technology. A collaborative approach between AI-enabled companies/developers, healthcare teams, and government/policymakers should be encouraged to develop acceptance-facilitating interventions (i.e., informational video of the technology), create guidelines and training for care providers, and engaged in user-centred approaches that will enhance the facilitators and mitigate the barriers of those factors explored in our study to help FCGs consider the use of AI-enabled technology for older adult care.

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APPENDICES

Appendix A. Checklist for Reporting Of Survey Studies (CROSS) (Sharma et al., 2021)

Section/topic	**Item**	**Item description**	**Reported on page #**
Title and abstract			
Title and abstract	1a	State the word "survey" along with a commonly used term in title or abstract to introduce the study's design.	5
	1b	Provide an informative summary in the abstract, covering background, objectives, methods, findings/results, interpretation/discussion, and conclusions.	5-9
Introduction			
Background	2	Provide a background about the rationale of study, what has been previously done, and why this survey is needed.	13-42
Purpose/aim	3	Identify specific purposes, aims, goals, or objectives of the study.	43
Methods			
Study design	4	Specify the study design in the methods section with a commonly used term (e.g., cross-sectional or longitudinal).	43
Data collection methods	5a	Describe the questionnaire (e.g., number of sections, number of questions, number and names of instruments used).	47-50
	5b	Describe all questionnaire instruments that were used in the survey to measure particular concepts. Report target population, reported validity and reliability information, scoring/classification procedure, and reference links (if any).	49-50, Appendix D

	5c	Provide information on pretesting of the questionnaire, if performed (in the article or in an online supplement). Report the method of pretesting, number of times questionnaire was pre-tested, number and demographics of participants used for pretesting, and the level of similarity of demographics between pre-testing participants and sample population.	51, 61, Appendix F
	5d	Questionnaire if possible, should be fully provided (in the article, or as appendices or as an online supplement).	Appendix B and C
Sample characteristics	6a	Describe the study population (i.e., background, locations, eligibility criteria for participant inclusion in survey, exclusion criteria).	47
	6b	Describe the sampling techniques used (e.g., single stage or multistage sampling, simple random sampling, stratified sampling, cluster sampling, convenience sampling). Specify the locations of sample participants whenever clustered sampling was applied.	50
	6c	Provide information on sample size, along with details of sample size calculation.	51-52
	6d	Describe how representative the sample is of the study population (or target population if possible), particularly for population-based surveys.	50
Survey administration	7a	Provide information on modes of questionnaire administration, including the type and number of contacts, the location where the survey was conducted (e.g., outpatient room or by use of online tools, such as SurveyMonkey).	50-51
	7b	Provide information of survey's time frame, such as periods of recruitment, exposure, and follow-up days.	51
	7c	Provide information on the entry process: –>For non-web-based surveys, provide approaches to minimize human error in data entry. –>For web-based surveys, provide approaches to prevent "multiple participation" of participants.	51
Study preparation	8	Describe any preparation process before conducting the survey (e.g., interviewers' training process, advertising the survey).	NA
Ethical	9a	Provide information on ethical approval for the survey if obtained, including informed consent, institutional review board	43

considerations		[IRB] approval, Helsinki declaration, and good clinical practice [GCP] declaration (as appropriate).	
	9b	Provide information about survey anonymity and confidentiality and describe what mechanisms were used to protect unauthorized access.	51
Statistical analysis	10a	Describe statistical methods and analytical approach. Report the statistical software that was used for data analysis.	55-59
	10b	Report any modification of variables used in the analysis, along with reference (if available).	NA
	10c	Report details about how missing data was handled. Include rate of missing items, missing data mechanism (i.e., missing completely at random [MCAR], missing at random [MAR] or missing not at random [MNAR]) and methods used to deal with missing data (e.g., multiple imputation).	54
	10d	State how non-response error was addressed.	54
	10e	For longitudinal surveys, state how loss to follow-up was addressed.	NA
	10f	Indicate whether any methods such as weighting of items or propensity scores have been used to adjust for non-representativeness of the sample.	NA
	10g	Describe any sensitivity analysis conducted.	54, Appendix E
Results			
Respondent characteristics	11a	Report numbers of individuals at each stage of the study. Consider using a flow diagram, if possible.	59-61
	11b	Provide reasons for non-participation at each stage, if possible.	59-61
	11c	Report response rate, present the definition of response rate or the formula used to calculate response rate.	59-60
	11d	Provide information to define how unique visitors are determined. Report number of unique visitors along with relevant proportions (e.g., view proportion, participation proportion, completion proportion).	59
Descriptive	12	Provide characteristics of study participants, as well as	61-65

results		information on potential confounders and assessed outcomes.	
Main findings	13a	Give unadjusted estimates and, if applicable, confounder-adjusted estimates along with 95% confidence intervals and p-values.	NA
	13b	For multivariable analysis, provide information on the model building process, model fit statistics, and model assumptions (as appropriate).	67-73
	13c	Provide details about any sensitivity analysis performed. If there are considerable amount of missing data, report sensitivity analyses comparing the results of complete cases with that of the imputed dataset (if possible).	54, Appendix E
Discussion			
Limitations	14	Discuss the limitations of the study, considering sources of potential biases and imprecisions, such as non-representativeness of sample, study design, important uncontrolled confounders.	87-88
Interpretations	15	Give a cautious overall interpretation of results, based on potential biases and imprecisions and suggest areas for future research.	74-88
Generalizability	16	Discuss the external validity of the results.	74-88
Other sections			
Role of funding source	17	State whether any funding organization has had any roles in the survey's design, implementation, and analysis.	11
Conflict of interest	18	Declare any potential conflict of interest.	11
Acknowledgements	19	Provide names of organizations/persons that are acknowledged along with their contribution to the research.	10-11

NA = Not Applicable

Note. Checklist developed by: Sharma, A., Minh Duc, N. T., Luu Lam Thang, T., Nam, N. H., Ng, S. J., Abbas, K. S., Huy, N. T., Marušić, A., Paul, C. L., Kwok, J., Karbwang, J., de Waure, C., Drummond, F. J., Kizawa, Y., Taal, E., Vermeulen, J., Lee, G. H. M., Gyedu, A., To, K. G., … Karamouzian, M. (2021). A Consensus-Based Checklist for Reporting of Survey Studies (CROSS). Journal of General Internal Medicine, 36(10), 3179–3187. https://doi.org/10.1007/s11606-021-06737-1

Appendix B. English Survey

Screening

Are you a 45-64-year-old family caregiver* from Quebec (province), who provides care to an older (65+) family or friend?

*Family caregiver: A person who provides unpaid short or long-term care to a family member or friend with a physical, cognitive, and/or psychological impairment. The care can include, but not be limited to, medical/nursing care, psychosocial support, transportation, and home maintenance.

Select one

- Yes
- No

☐ I wish to withdraw

Continue »

Demographic and Caregiving Questions

How old are you (Respond with the number of years)?

Please enter a whole number

☐ I wish to withdraw

Continue »

What is your gender?

Select one

- Woman
- Man
- Transgender
- Non-binary
- Other, please specify

☐ I wish to withdraw

Continue »

What is the highest level of education that you completed?

Select one

- Elementary
- High school
- College / CEGEP
- Undergraduate
- Post-graduate (e.g., Masters, Ph.D.)
- Other, please specify

☐ I wish to withdraw

Continue »

What is your current employment status?

Select one

- Full-time
- Part-time
- Unemployed
- Retired
- Other, please specify

I wish to withdraw

Continue »

Approximately, how many years have you lived in Canada?

Please enter a whole number

I wish to withdraw

Continue »

Thinking about the person for whom you are the caregiver, what is your relationship with that person? (Multiple options are acceptable if you are a caregiver to more than one older adult)

Select all that apply

- Child
- Grandchild
- Spouse
- Sibling
- Friend
- Other, please specify

I wish to withdraw

Continue »

What is the living situation of the older care recipient(s)? (Multiple options are acceptable if you are a caregiver to more than one older adult)

Select all that apply

- Living with the family caregiver
- Living independently in one's own home
- Living in long-term care/nursing home/residential home
- Other, please specify

I wish to withdraw

Continue »

This study defines a family caregiver as a person who provides unpaid short or long-term care to a family member or friend with a physical, cognitive, and/or psychological impairment. The care can include, but not be limited to, medical/nursing care, psychosocial support, transportation, and home maintenance.

According to that definition, how many older adult(s) are you a family caregiver for?

Select one

- 1
- 2
- 3
- 4 or more

☐ I wish to withdraw

Continue »

Approximately how many years have you been a family caregiver to an older adult(s)?

Please enter a whole number

☐ I wish to withdraw

Continue »

What do you estimate regarding the number of hours of care you provide as a caregiver per week?

Please enter a whole number

☐ I wish to withdraw

Continue »

What are the main tasks you perform as a caregiver? (Multiple options are acceptable)

Select all that apply

- ☐ Medical/nursing care (e.g., operating medical equipment like a catheter, providing wound care, assisting with medications/injections)
- ☐ Care coordinator (e.g., communicate with healthcare providers, translator, schedule appointments)
- ☐ Psychosocial care (e.g., emotional support, companionship)
- ☐ Daily living activities (e.g., dressing, feeding, toileting, transferring)
- ☐ Household tasks (e.g., home maintenance, grocery shopping, laundry)
- ☐ Transportation (e.g., driving the older adult to appointments)
- ☐ Substitute decision-maker (e.g., making health, legal and financial decisions on behalf of the older care recipient who is unable to)
- ☐ Other, please specify

☐ I wish to withdraw

Continue »

Family Caregivers' Intentions and Factors Predicting the Intentions to Using AI

Please read the following before proceeding:

Definition of Artificial Intelligence (AI):
AI can be defined as the "science and engineering of making intelligent machines", with the intent of developing technology that mimics the intelligence of humans.

Examples of AI-based technologies:

1. Wearable device (similar to a Fitbit/smartwatch worn on a person's wrist) combined with AI algorithms can monitor an older adult's behaviours and activities (e.g., eating, sleeping) as well as health data (e.g., heart rate). This can warn the caregiver of any irregularities.

2. AI-based assistive technology to support older adults with disabilities, for example, many smartphone applications are using AI (e.g., Seeing AI by Microsoft, Envision AI by Envision) to assist people with visual impairments. These AI-based apps can verbally read and describe whatever the smartphone camera is pointing at (e.g., documents, people, product barcodes).

3. AI chatbots/virtual assistants can engage in a text or speech-based conversation with a user through text messaging or voice-activated devices, like Alexa. AI chatbots can provide, for example, immediate information to questions and personalized emotional/self-health support.

☐ I wish to withdraw

Continue »

AI Experience: Have you used AI to provide care to an older adult before?

Select one

○ Yes
○ No

☐ I wish to withdraw

Continue »

Which of the following AI-based technologies have you used before?

Select all that apply

☐ AI-based wearable devices
☐ AI-based assistive technology
☐ AI-based chatbots/virtual assistants
☐ Other, please specify

☐ I wish to withdraw

Continue »

AI Knowledge: Prior to this survey, how would you rank your current knowledge about AI?

Select one

Not knowledgeable	Somewhat knowledgeable	Moderately knowledgeable	Extremely knowledgeable
○	○	○	○

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
Using AI-based technologies could allow me to monitor the care recipient's health	○	○	○	○	○
I believe that using AI-based technologies for older adult care could be helpful in my daily caregiving life	○	○	○	○	○
Using AI-based technologies for older adult care could make me feel safe about the older care recipient overall	○	○	○	○	○
AI-based technologies could enhance the capability to access medical care services for older adults when needed	○	○	○	○	○
AI-based technologies could definitely help in the independent assisted living of an older adult	○	○	○	○	○
Overall, I think AI-based technologies for older adult care could be useful	○	○	○	○	○

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
It is easy and clear for me to use AI-based technologies for older adult care	○	○	○	○	○
Using various features and services provided by AI-based technologies could be simple and easy to learn	○	○	○	○	○
In general, I can/will be able to operate AI-based technologies for older adult care by myself	○	○	○	○	○
It is not difficult for me to use AI-based technologies for providing older adult care	○	○	○	○	○
Overall, I think that using AI-based technologies for older adult care will be convenient for me	○	○	○	○	○

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
I will use AI-based technologies for providing older adult care if my family members and friends do so	○	○	○	○	○
I will use AI-based technologies for providing older adult care if the media/government encourages us to use them	○	○	○	○	○
People who are important to me will support my use of AI-based technologies for providing older adult care	○	○	○	○	○

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
I believe proper guidance will be available when using AI-based technologies for older adult care	◯	◯	◯	◯	◯
I believe proper service is available if I face difficulty in using the AI-based technologies for older adult care	◯	◯	◯	◯	◯

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
I have sufficient knowledge and ability to use AI-based technologies for older adult care by myself	◯	◯	◯	◯	◯
The sophisticated technology behind AI-based technologies for older adult care makes me feel worried	◯	◯	◯	◯	◯
I am very enthusiastic to learn about AI-based technologies for older adult care	◯	◯	◯	◯	◯
I hesitate to use AI-based technologies for older adult care for the fear of making mistakes	◯	◯	◯	◯	◯

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
I fear using AI-based technologies due to the loss of older care recipient's personal data and privacy	◯	◯	◯	◯	◯
The AI-based technologies could offer a secure medium through which sensitive personal information can be sent confidentially	◯	◯	◯	◯	◯
I find it risky to disclose older care recipient's personal details and health information to the AI-based technologies providers	◯	◯	◯	◯	◯

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
The cost of investing into the various AI-based technologies for older adult care are too expensive	○	○	○	○	○
Purchasing and maintaining an AI-based technology for older adult care will be a burden for me	○	○	○	○	○

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
I trust the care recipient's doctor's judgement more than the care-related suggestions given by AI-based technologies	○	○	○	○	○
The experience that the healthcare professionals have likely makes them more accurate and trustworthy than AI-based technologies for older adult care	○	○	○	○	○
I trust the care recipient's doctor's judgement regarding the use of AI-based technologies for older adult care purposes	○	○	○	○	○
Doctors are more responsible and intelligent than the AI-based technologies for older adult care	○	○	○	○	○

☐ I wish to withdraw

Continue »

Instructions: You are presented with statements that you need to rate on a scale from Strongly Disagree to Strongly Agree, with a 5th option of 'I don't know'.

Select one in each row

	Strongly Disagree	Disagree	Agree	Strongly Agree	I don't know
I will use AI-based technologies for older adult care in the future	○	○	○	○	○
If I have access to AI-based technologies for older adult care, I would use the service	○	○	○	○	○
I intend to invest and use AI-based technologies for older adult care as much as possible	○	○	○	○	○

☐ I wish to withdraw

Continue »

Appendix C. French Survey

Dépistage

Êtes-vous un aidant familial* âgé de 45 à 64 ans provenant du Québec (la province), qui fournit des soins à une famille ou à un ami âgé (65 ans et plus)?

* Aidant familial : Personne qui fournit des soins non rémunérés à court ou à long terme à un membre de la famille ou à un ami ayant une déficience physique, cognitive et/ou psychologique. Les soins peuvent inclure, mais ne se limitent pas à, les soins médicaux/infirmiers, le soutien psychosocial, le transport et l'entretien du domicile.

Sélectionnez-en un

- Oui
- Non

Je souhaite me retirer

Continuer »

Questions sur les facteurs démographiques et les soins fournis

Quel âge aves-vous (indiquez votre âge à l'aide de chiffres uniquement)?

Veuillez entrer un nombre entier

Je souhaite me retirer

Continuer »

Quel est votre sexe?

Sélectionnez-en un

- Femme
- Homme
- Transgenre
- Non binaire
- Autre, veuillez préciser

Je souhaite me retirer

Continuer »

Quel est le niveau de scolarité le plus élevé que vous avez complété?

Sélectionnez-en un

- Primaire
- Secondaire
- Collège / CEGEP
- Université (Premier cycle)
- Études supérieures (par exemple, maîtrise, doctorat)
- Autre, veuillez préciser

Je souhaite me retirer

Continuer »

Quel est actuellement votre situation d'emploi?

Sélectionnez-en un

- Travail à temps-plein
- Travail à temps-partiel
- Sans emploi
- Retraité(e)
- Autre, veuillez préciser

Je souhaite me retirer

Continuer »

Pendant environ combien d'années avez-vous vécu au Canada?

Veuillez entrer un nombre entier

Je souhaite me retirer

Continuer »

En pensant à la personne pour laquelle vous êtes le proche aidant, quelle est votre relation avec cette personne ? (Plusieurs options sont permises si vous êtes un proche aidant de plus d'une personne âgée)

Sélectionnez tout ce qui s'y rapporte

- Enfant
- Petit-enfant
- Conjoint(e)
- Frère ou sœur
- Ami(e)
- Autre, veuillez préciser

Je souhaite me retirer

Continuer »

Quelle est la situation de vie du/des bénéficiaire(s) de soins âgés? (Plusieurs options sont permises si vous êtes un proche aidant de plus d'une personne âgée)

Sélectionnez tout ce qui s'y rapporte

- Cohabite avec l'aidant familial
- Vit de façon autonome dans son propre logement
- Habite un établissement de soins de longue durée/maison de soins/foyer résidentiel
- Autre, veuillez préciser

Je souhaite me retirer

Continuer »

Cette étude définit un proche aidant comme étant une personne qui fournit des soins non rémunérés à court ou à long terme à un membre de la famille ou à un ami ayant une déficience physique, cognitive et/ou psychologique. Les soins peuvent inclure, mais ne se limitent pas aux soins médicaux/infirmiers, le soutien psychosocial, le transport et l'entretien du domicile.

Selon cette définition, pour combien d'adulte(s) âgé(s) êtes-vous un aidant familial?

Sélectionnez-en un

- 1
- 2
- 3
- 4 ou plus

☐ Je souhaite me retirer

Continuer »

Depuis environ combien d'années êtes-vous un proche aidant d'une ou de plusieurs personne(s) âgée(s)?

Veuillez entrer un nombre entier

☐ Je souhaite me retirer

Continuer »

Quelle est votre estimation du nombre d'heures de soins que vous fournissez par semaine en tant que proche aidant ?

Veuillez entrer un nombre entier

☐ Je souhaite me retirer

Continuer »

Quelles sont les tâches principales que vous effectuez en tant que proche aidant? (Plusieurs options sont permises)

Sélectionnez tout ce qui s'y rapporte

- ☐ Soins médicaux/infirmiers (par exemple, operer du matériel médical comme un cathéter, soigner les plaies, aider avec les médicaments/les injections)
- ☐ Coordonnateur des soins (par exemple, communiquer avec les fournisseurs de soins de santé, interpréter, planifier des rendez-vous)
- ☐ Soins psychosociaux (par exemple, soutien émotionnel, tenir compagnie)
- ☐ Activités de la vie quotidienne (par exemple, s'habiller, se nourrir, faire sa toilette, se déplacer)
- ☐ Tâches ménagères (par exemple, entretien de la maison, achat d'épicerie, faire la lessive)
- ☐ Transport (par exemple, conduire la personne âgée à ses rendez-vous)
- ☐ Décideur substitut (par exemple, prendre des décisions en matière de santé, juridiques et financières au nom du bénéficiaire de soins âgé qui est incapable de le faire par lui-même)
- ☐ Autre, veuillez préciser

☐ Je souhaite me retirer

Continuer »

Les intentions des proche aidants familiaux et les facteurs prédisant les intentions d'utiliser l'IA

Veuillez lire ce qui suit avant de continuer :

Définition de l'intelligence artificielle (IA) :

L'IA peut être définie comme la « science et l'ingénierie de la fabrication de machines intelligentes » dans le but de développer une technologie qui imite l'intelligence des humains.

Exemples de technologies basées sur l'IA :

1. Un appareil portable (semblable à une Fitbit/montre intelligente portée au poignet d'une personne) jumelé à des algorithmes d'IA peut surveiller les comportements et les activités d'une personne âgée (par exemple, manger, dormir) ainsi que recueillir des données sur la santé (par exemple, rythme cardiaque). Cela peut aviser le soignant de toutes irrégularités.

2. La technologie d'assistance basée sur l'IA peut aider les personnes âgées handicapées, par exemple, de nombreuses applications pour smartphones utilisent l'IA (p. ex., Seeing AI de Microsoft, Envision AI d'Envision) pour aider les personnes ayant une déficience visuelle. Ces applications basées sur l'IA peuvent lire et décrire verbalement tout ce que la caméra du téléphone intelligent saisie (par exemple, des documents, des personnes, des codes-barres de produits).

3. Les chatbots/assistants virtuels d'IA peuvent démarrer une conversation textuelle ou vocale avec un utilisateur via la messagerie texte ou des appareils à commande vocale, comme l'Alexa. Les chatbots d'IA peuvent fournir, par exemple, des informations immédiates reliées aux questions posées et un soutien émotionnel/santé personnalisé.

☐ Je souhaite me retirer

Continuer »

Expérience IA : Avez-vous déjà utilisé l'IA pour fournir des soins à une personne âgée?

Sélectionnez-en un

○ Oui
○ Non

☐ Je souhaite me retirer

Continuer »

Parmi les technologies suivantes basées sur l'IA, lesquelles avez-vous déjà utilisées?

Sélectionnez tout ce qui s'y rapporte

☐ Appareils portables basés sur l'IA
☐ Technologie d'assistance basée sur l'IA
☐ Chatbots/assistants virtuels basés sur l'IA
☐ Autre, veuillez préciser

☐ Je souhaite me retirer

Continuer »

Connaissance de l'IA : Avant la prise de ce sondage, comment classeriez-vous vos connaissances actuelles sur l'IA ?

Sélectionnez-en un

Pas bien informé	Assez bien informé	Modérément bien informé	Extrêmement bien informé
○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
L'utilisation de technologies basées sur l'IA pourrait me permettre de surveiller la santé du bénéficiaire des soins	○	○	○	○	○
Je pense que l'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées pourrait être utile dans ma vie quotidienne en tant que personne proche aidante	○	○	○	○	○
L'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées pourrait me permettre de me sentir en sécurité vis-à-vis l'ensemble de soins du bénéficiaire âgé	○	○	○	○	○
Les technologies basées sur l'IA pourraient améliorer la capacité d'accéder aux services de soins médicaux pour les personnes âgées en cas de besoin	○	○	○	○	○
Les technologies basées sur l'IA pourraient certainement aider à la vie assistée et semi-autonome d'une personne âgée	○	○	○	○	○
Globalement, je pense que les technologies basées sur l'IA pour les soins aux personnes âgées pourraient être utiles	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
Il est facile et clair pour moi d'utiliser les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
L'utilisation de diverses fonctionnalités et services fournis par les technologies basées sur l'IA pourrait être simple et facile à apprendre	○	○	○	○	○
En général, je peux/serai capable d'utiliser par moi-même les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
Il n'est pas difficile pour moi d'utiliser des technologies basées sur l'IA pour fournir des soins aux personnes âgées	○	○	○	○	○
Globalement, je pense que l'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées sera pratique pour moi	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
J'utiliserai des technologies basées sur l'IA pour fournir des soins aux personnes âgées si les membres de ma famille et mes amis le font	○	○	○	○	○
J'utiliserai des technologies basées sur l'IA pour fournir des soins aux personnes âgées si les médias/le gouvernement nous encouragent à les utiliser	○	○	○	○	○
Les personnes qui sont importantes pour moi soutiendront mon utilisation des technologies basées sur l'IA pour fournir des soins aux personnes âgées	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
Je pense que des conseils adéquats seront disponibles lors de l'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
Je pense qu'un service adéquat est disponible si je rencontre des difficultés à utiliser les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
J'ai suffisamment de connaissances et de capacités pour utiliser par moi-même les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
La technologie sophistiquée derrière les technologies basées sur l'IA pour les soins aux personnes âgées m'inquiète	○	○	○	○	○
Je suis très enthousiaste à l'idée d'en savoir plus sur les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
J'hésite à utiliser les technologies basées sur l'IA pour les soins aux personnes âgées par peur de commettre des erreurs	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
Je crains d'utiliser des technologies basées sur l'IA en raison de la perte des données personnelles et de la vie privée des bénéficiaires de soins âgés	○	○	○	○	○
Les technologies basées sur l'IA pourraient offrir un moyen sécurisé par lequel des informations personnelles et sensibles peuvent être envoyées de manière confidentielle	○	○	○	○	○
Il me paraît risqué de divulguer les données personnelles et les informations sur la santé d'un bénéficiaire de soins âgé aux fournisseurs de technologies basées sur l'IA	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
Le coût d'investissement dans les diverses technologies basées sur l'IA pour les soins aux personnes âgées est trop élevé	○	○	○	○	○
L'achat et l'entretien d'une technologie basée sur l'IA pour les soins aux personnes âgées seront un fardeau pour moi	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
Je fais plus confiance au jugement du médecin du bénéficiaire des soins qu'aux suggestions de soins données par les technologies basées sur l'IA	○	○	○	○	○
Grâce à leur expérience, les professionnels de la santé sont probablement plus précis et plus fiables que les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
Je fais confiance au jugement du médecin du bénéficiaire de soins concernant l'utilisation des technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
Les médecins sont plus responsables et intelligents que les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Instructions: Évaluez les énoncés suivants sur une échelle allant de « Fortement en désaccord » à « Tout à fait d'accord » avec une 5ème option de « Je ne sais pas »

Sélectionnez-en un dans chaque ligne

	Fortement en désaccord	En désaccord	En accord	Tout à fait d'accord	Je ne sais pas
À l'avenir, j'utiliserai des technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○
Si j'ai accès aux technologies basées sur l'IA pour les soins aux personnes âgées, j'utiliserais ce service	○	○	○	○	○
J'ai l'intention d'investir et d'utiliser autant que possible les technologies basées sur l'IA pour les soins aux personnes âgées	○	○	○	○	○

☐ Je souhaite me retirer

Continuer »

Appendix D. UTAUT-realted variabless and measurement items – English and French version

PERFORMANCE EXPECTANCY		
PE1	Using AI-based technologies could allow me to monitor the care recipient's health	L'utilisation de technologies basées sur l'IA pourrait me permettre de surveiller la santé du bénéficiaire des soins
PE2	I believe that using AI-based technologies for older adult care could be helpful in my daily caregiving life	Je pense que l'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées pourrait être utile dans ma vie quotidienne en tant que personne proche aidante
PE3	Using AI-based technologies for older adult care could make me feel safe about the older care recipient overall	L'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées pourrait me permettre de me sentir en sécurité vis-à-vis l'ensemble de soins du bénéficiaire âgé
PE4	AI-based technologies could enhance the capability to access medical care services for older adults when needed	Les technologies basées sur l'IA pourraient améliorer la capacité d'accéder aux services de soins médicaux pour les personnes âgées en cas de besoin
PE5	AI-based technologies could definitely help in the independent assisted living of an older adult	Les technologies basées sur l'IA pourraient certainement aider à la vie assistée et semi-autonome d'une personne âgée
PE6	Overall, I think AI-based technologies for older adult care could be useful	Globalement, je pense que les technologies basées sur l'IA pour les soins aux personnes âgées pourraient être utiles
EFFORT EXPECTANCY		
EE1	It is easy and clear for me to use AI-based technologies for older adult care	Il est facile et clair pour moi d'utiliser les technologies basées sur l'IA pour les soins aux personnes âgées
EE2	Using various features and services provided by AI-based technologies could be simple and easy to learn	L'utilisation de diverses fonctionnalités et services fournis par les technologies basées sur l'IA pourrait être simple et facile à apprendre
EE3	In general, I can/will be able to operate AI-based technologies for older adult care by myself	En général, je peux/serai capable d'utiliser par moi-même les technologies basées sur l'IA pour les soins aux personnes âgées
EE4	It is not difficult for me to use AI-based technologies for providing older adult care	Il n'est pas difficile pour moi d'utiliser des technologies basées sur l'IA pour fournir des soins aux personnes âgées
EE5	Overall, I think that using AI-based technologies for older adult care will be convenient for me	Globalement, je pense que l'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées sera pratique pour moi
SOCIAL INFLUENCE		
SI1	I will use AI-based technologies for providing older adult care if my family members and friends do so	J'utiliserai des technologies basées sur l'IA pour fournir des soins aux personnes âgées si les membres de ma famille et mes amis le font
SI2	I will use AI-based technologies for providing older adult care if the	J'utiliserai des technologies basées sur l'IA pour fournir des soins aux personnes âgées si les

	media/government encourages us to use them	médias/le gouvernement nous encouragent à les utiliser
SI3	People who are important to me will support my use of AI-based technologies for providing older adult care	Les personnes qui sont importantes pour moi soutiendront mon utilisation des technologies basées sur l'IA pour fournir des soins aux personnes âgées
FACILITATING CONDITIONS		
FC1	I believe proper guidance will be available when using AI-based technologies for older adult care	Je pense que des conseils adéquats seront disponibles lors de l'utilisation de technologies basées sur l'IA pour les soins aux personnes âgées
FC2	I believe proper service is available if I face difficulty in using the AI-based technologies for older adult care	Je pense qu'un service adéquat est disponible si je rencontre des difficultés à utiliser les technologies basées sur l'IA pour les soins aux personnes âgées
TECHNOLOGY ANXIETY		
TA1	I have sufficient knowledge and ability to use AI-based technologies for older adult care by myself	J'ai suffisamment de connaissances et de capacités pour utiliser par moi-même les technologies basées sur l'IA pour les soins aux personnes âgées
TA2	The sophisticated technology behind AI-based technologies for older adult care makes me feel worried	La technologie sophistiquée derrière les technologies basées sur l'IA pour les soins aux personnes âgées m'inquiète
TA3	I am very enthusiastic to learn about AI-based technologies for older adult care	Je suis très enthousiaste à l'idée d'en savoir plus sur les technologies basées sur l'IA pour les soins aux personnes âgées
TA4	I hesitate to use AI-based technologies for older adult care for the fear of making mistakes	J'hésite à utiliser les technologies basées sur l'IA pour les soins aux personnes âgées par peur de commettre des erreurs
PERCEIVED TRUST		
PT1	I fear using AI-based technologies due to the loss of older care recipient’s personal data and privacy	Je crains d'utiliser des technologies basées sur l'IA en raison de la perte des données personnelles et de la vie privée des bénéficiaires de soins âgés
PT2	The AI-based technologies could offer a secure medium through which sensitive personal information can be sent confidentially	Les technologies basées sur l'IA pourraient offrir un moyen sécurisé par lequel des informations personnelles et sensibles peuvent être envoyées de manière confidentielle
PT3	I find it risky to disclose older care recipient’s personal details and health information to the AI-based technologies providers	Il me paraît risqué de divulguer les données personnelles et les informations sur la santé d'un bénéficiaire de soins âgé aux fournisseurs de technologies basées sur l'IA
PERCEIVED COST		

PC1	The cost of investing into the various AI-based technologies for older adult care are too expensive	Le coût d'investissement dans les diverses technologies basées sur l'IA pour les soins aux personnes âgées est trop élevé
PC2	Purchasing and maintaining an AI-based technology for older adult care will be a burden for me	L'achat et l'entretien d'une technologie basée sur l'IA pour les soins aux personnes âgées seront un fardeau pour moi
CONFIDENCE IN THE SOURCE OF ADVICE FOR CARE (HEALTHCARE PROFESSIONAL VS AI-ENABLED TECHNOLOGY)		
EA1	I trust the care recipient's doctor's judgement more than the care-related suggestions given by AI-based technologies	Je fais plus confiance au jugement du médecin du bénéficiaire des soins qu'aux suggestions de soins données par les technologies basées sur l'IA
EA2	The experience that the healthcare professionals have likely makes them more accurate and trustworthy than AI-based technologies for older adult care	Grâce à leur expérience, les professionnels de la santé sont probablement plus précis et plus fiables que les technologies basées sur l'IA pour les soins aux personnes âgées
EA3	Doctors are more responsible and intelligent than the AI-based technologies for older adult care	Les médecins sont plus responsables et intelligents que les technologies basées sur l'IA pour les soins aux personnes âgées
CONFIDENCE IN HEALTHCARE PROFESSIONALS' ADVICE FOR THE USE OF AI-ENABLED TECHNOLOGY		
EA2.1	I trust the care recipient's doctor's judgement regarding the use of AI-based technologies for older adult care purposes	Je fais confiance au jugement du médecin du bénéficiaire de soins concernant l'utilisation des technologies basées sur l'IA pour les soins aux personnes âgées
BEHAVIOURAL INTENTIONS		
BI1	I will use AI-based technologies for older adult care in the future	À l'avenir, J'utiliserai des technologies basées sur l'IA pour les soins aux personnes âgées
BI2	If I have access to AI-based technologies for older adult care, I would use the service	Si j'ai accès aux technologies basées sur l'IA pour les soins aux personnes âgées, j'utiliserais ce service
BI3	I intend to invest and use AI-based technologies for older adult care as much as possible	J'ai l'intention d'investir et d'utiliser autant que possible les technologies basées sur l'IA pour les soins aux personnes âgées

Note: The English version of the items was adapted from "Internet-of-Things and Smart Homes for Elderly Healthcare: An End User Perspective," by D. Pal et al., 2018, *IEEE Access, 6*, 10487 (https://doi.org/10.1109/ACCESS.2018.2808472). © 2018 IEEE. Adapted with permission.

Appendix E. Comparing the demographic, caregiving, and AI-related characteristics between the entire sample (n=199) versus the sample with full/completed UTAUT-related variable scores (n=115)

Characteristics	**Entire Sample (n=199)**	**Sample with No Missing UTAUT-related variable Scores (n=115)**
Survey's Language That Participants Accessed n (%)		
French	173 (86.9%)	100 (87.0%)
English	26 (13.1%)	15 (13.0%)
Age (years)		
Mean (SD)	56.7 (5.49)	55.5 (5.77)
Median [Min, Max]	57.0 [45.0, 64.0]	56.0 [45.0, 64.0]
Gender n (%)		
Woman	128 (64.3%)	68 (59.1%)
Man	71 (35.7%)	47 (40.9%)
Education n (%)		
Elementary	1 (0.5%)	0 (0%)
High school	44 (22.1%)	22 (19.1%)
CEGEP (junior college) [a]	82 (41.2%)	48 (41.7%)
University Undergraduate	48 (24.1%)	30 (26.1%)
University Post-graduate (e.g., Masters, Ph.D.)	22 (11.1%)	14 (12.2%)
Other	2 (1.0%)	1 (0.9%)
Employment n (%)		
Full-time	88 (44.2%)	56 (48.7%)
Part-time	23 (11.6%)	13 (11.3%)
Unemployed	15 (7.5%)	6 (5.2%)
Retired	65 (32.7%)	37 (32.2%)
Full-time caregiver	2 (1.0%)	2 (1.7%)
Other	6 (3.0%)	1 (0.9%)
Years Lived in Canada		
Mean (SD)	55.3 (9.07)	54.4 (8.70)
Median [Min, Max]	57.0 [7.00, 64.0]	56.0 [15.0, 64.0]
Relationship to Care Recipient [b] n (%)		
Child	140 (70.4%)	83 (72.2%)
Grandchild	2 (1.0%)	1 (0.9%)
Spouse	20 (10.1%)	10 (8.7%)
Sibling	14 (7.0%)	8 (7.0%)
Friend	12 (6.0%)	9 (7.8%)
Neighbour	1 (0.5%)	1 (0.9%)
Other	12 (6.0%)	5 (4.3%)
Living Arrangement of the Care Recipient [b] n (%)		

Living with the family caregiver	68 (34.2%)	41 (35.7%)
Living independently in one's own home	83 (41.7%)	45 (39.1%)
Living in long-term care/nursing home/residential home	45 (22.6%)	28 (24.3%)
Living in private seniors' homes [c] or equivalent	8 (4.0%)	5 (4.3%)
Number of Older Adults the Family Caregiver is Caring For n (%)		
1	167 (83.9%)	98 (85.2%)
2	29 (14.6%)	15 (13.0%)
3	0 (0%)	0 (0%)
4 or more	2 (1.0%)	2 (1.7%)
Missing	1 (0.5%)	0 (0%)
Number of Years of Being a Family Caregiver		
Mean (SD)	7.7 (6.94)	7.7 (7.44)
Median [Min, Max]	6.00 [0, 56.0]	6.00 [0, 56.0]
Estimated Number of Hours of Care Per Week Provided by the Family Caregiver		
Mean (SD)	16.1 (19.5)	17.1 (20.2)
Median [Min, Max]	10.0 [0, 168]	10.0 [0, 168]
Missing	1 (0.5%)	1 (0.9%)
Tasks Family Caregivers Perform [b] n (%)		
Medical/nursing care (e.g., operating medical equipment like a catheter, providing wound care, assisting with medications/injections)	40 (20.1%)	25 (21.7%)
Care coordinator (e.g., communicate with healthcare providers, translator, schedule appointments)	127 (63.8%)	73 (63.5%)
Psychosocial care (e.g., emotional support, companionship)	140 (70.4%)	83 (72.2%)
Daily living activities (e.g., dressing, feeding, toileting, transferring)	70 (35.2%)	41 (35.7%)
Household tasks (e.g., home maintenance, grocery shopping, laundry)	142 (71.4%)	79 (68.7%)
Transportation (e.g., driving the older adult to appointments)	133 (66.8%)	75 (65.2%)
Substitute decision-maker (e.g., making health, legal and financial decisions on behalf of the older care recipient who is unable to)	87 (43.7%)	51 (44.3%)
Other	3 (1.5%)	3 (2.6%)
Family Caregivers Past AI Experience		
Yes	16 (8.0%)	14 (12.2%)
No	183 (92.0%)	101 (87.8%)
AI Technology Family Caregivers Have Used Before [d] n (%)		
AI-based wearable devices	11 (5.5%)	10 (8.7%)
AI-based assistive technology	4 (2.0%)	4 (3.5%)
AI-based chatbots/virtual assistants	2 (1.0%)	1 (0.9%)

Family Caregivers’ AI Knowledge n (%)		
Not knowledgeable	109 (54.8%)	59 (51.3%)
Somewhat knowledgeable	46 (23.1%)	29 (25.2%)
Moderately knowledgeable	37 (18.6%)	22 (19.1%)
Extremely knowledgeable	6 (3.0%)	5 (4.3%)
Missing	1 (0.5%)	0 (0%)

[a] General and Professional Educational College, the junior college education system in Quebec, Canada.

[b] These questions allowed for multiple responses, so the percentages are generated based on more than 199 or 115 participants, respectively.

[c] Private seniors' homes in Quebec, Canada is considered a private residence/home primarily for semi-autonomous older adults.

[d] The count and percentage are generated based on a total of 16 or 14 participants, respectively, as they selected “yes” to having past AI experience.

Appendix F. Demographic, caregiving, and AI-related characteristics of the pre-test participants (n=39)

Characteristics	**n = 39**
Survey's Language That Participants Accessed n (%)	
French	35 (89.7%)
English	4 (10.3%)
Age (years)	
Mean (SD)	54.5 (5.73)
Median [Min, Max]	54.0 [45.0, 62.0]
Gender n (%)	
Woman	24 (61.5%)
Man	15 (38.5%)
Education n (%)	
University Undergraduate	13 (33.3%)
CEGEP (junior college) [a]	12 (30.8%)
University Post-graduate (e.g., Masters, Ph.D.)	8 (20.5%)
High school	6 (15.4%)
Elementary	0 (0%)
Employment n (%)	

Full-time	24 (61.5%)
Retired	9 (23.1%)
Part-time	6 (15.4%)
Unemployed	0 (0%)
Years Lived in Canada	
Mean (SD)	52.9 (8.19)
Median [Min, Max]	54.0 [20.0, 62.0]
Relationship to Care Recipient [b] n (%)	
Child	34 (87.2%)
Spouse	4 (10.3%)
Grandchild	2 (5.1%)
Sibling	2 (5.1%)
Other	2 (5.1%)
Friend	0 (0%)
Number of Older Adults the Family Caregiver is Caring for n (%)	
Living with the family caregiver	16 (41.0%)
Living independently in one's own home	14 (35.9%)
Living in long-term care/nursing home/residential home	9 (23.1%)
Other, please specify	2 (5.1%)
Number of Years of Being a Family Caregiver	
1	30 (76.9%)
2	8 (20.5%)
3	0 (0%)
4 or more	1 (2.6%)
Number of Years of Being a Family Caregiver	
Mean (SD)	7.6 (5.51)
Median [Min, Max]	5.00 [1.00, 23.0]
Estimated Number of Hours of Care Per Week Provided by the Family Caregiver	
Mean (SD)	18.7 (22.3)
Median [Min, Max]	12.0 [1.00, 100]
Tasks Family Caregivers Perform [b] n (%)	
Household tasks (e.g., home maintenance, grocery shopping, laundry)	32 (82.1%)
Transportation (e.g., driving the older adult to appointments)	29 (74.4%)
Psychosocial care (e.g., emotional support, companionship)	25 (64.1%)
Care coordinator (e.g., communicate with healthcare providers, translator, schedule appointments)	24 (61.5%)
Daily living activities (e.g., dressing, feeding, toileting, transferring)	21 (53.8%)
Substitute decision-maker (e.g., making health, legal and financial decisions on behalf of the older care recipient who is unable to)	17 (43.6%)
Medical/nursing care (e.g., operating medical equipment like a catheter, providing wound care, assisting with medications/injections)	8 (20.5%)
Family Caregivers' Past AI Experience n (%)	
No	34 (87.2%)

Yes	5 (12.8%)
AI Technology Family Caregivers Have Used Before [c] n (%)	
AI-based wearable devices	2 (5.1%)
AI-based assistive technology	2 (5.1%)
AI-based chatbots/virtual assistants	1 (2.6%)
Family Caregivers' AI Knowledge n (%)	
Not knowledgeable	24 (61.5%)
Somewhat knowledgeable	7 (17.9%)
Moderately knowledgeable	7 (17.9%)
Extremely knowledgeable	1 (2.6%)

[a] General and Professional Educational College, the junior college education system in Quebec, Canada.

[b] These questions allowed for multiple responses, so the percentages are generated based on more than 39 participants.

[c] The count and percentage are generated based on a total of 5 participants, as they selected "yes" to having past AI experience.