A New Health Care System Enabled by Machine Intelligence: Elderly People's Trust or Losing Self Control

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Abstract
An autonomous homecare system can ensure independence for elderly people and increase cooperation, social interaction, and adaptation. Widespread diffusion and inclusion of information and communication technology (ICT) in modern equipment has advanced the concept of machine autonomy. This study seeks to understand the effect of trust required for

elderly people to accept autonomous homecare systems instead of human support. It attempts to reveal how trust and personal characteristics can increase intent to adopt an autonomous system. In this regard, different trust models and literature on human psychology to adopt ICT driven system are explored and analyzed to develop a parsimonious trust disposition model for autonomous system. The study was conducted among elderly and disabled people in retirement homes and rehabilitation centers of different major cities of Ontario, Canada through random sampling by employing both experiment and survey. In the first phase, a structured and designed experiment was conducted in three retirement homes which included 159 elderly people and in two rehabilitation centers which included 20 disabled people. Then a survey-based empirical study was conducted among the same people with the structured questionnaire to answer the questions based on their perceptions of both receiving service from human beings and viewing the video about an autonomous system governed by ambient intelligence. This study reveals that elderly people can be motivated to develop trust in this less-familiar system if they both believe they can operate it and find a sense of belongingness and feelings of social interactivity from this seemingly living machine system. The findings of this study provide clear direction for academics and practitioners. This research indicates that elderly people must have control on using any system in the absence of human support while maintaining a more solitary life in a retirement home. However, the system must be easy to learn and operate. It should also be designed in such a way that can create and impart social feelings.

Keywords: autonomous homecare system, adoption behavior, trust, behavioral intention, elderly people, human behavior, ambient intelligence

1. Introduction

Increased application of information and communication technology (ICT) has led to more intelligently designed products for human use. The traditional view of discrete use of machines has been replaced by the interdependent operation of different products dominated by ICT (Rijsdijk & Hultink, 2003; Angeli et al., 2016; Zhu & Porter, 2002). For example, taking photographs through a digital camera can be then emailed through a smartphone, and a scanner can transfer memory to a desktop computer. These interactive and intertwined functions of different products operating through ICT reflect the future performance of machines that we call intelligent or smart products, or, more specifically, autonomous systems (Rijsdijk & Hultink, 2003; Such, 2017; Summary Report, 2015).

Widespread diffusion and inclusion of ICT in modern equipment since the final decades of the twentieth century has advanced the concept of machine autonomy (Adamuthe & Thampi, 2019; Phillips & Linstone, 2016). Autonomy in a product line represents the evolution from the manual stage to the second generation… (Broadbent, Stafford, & MacDonald, 2009; Frost, 2010; Kachouie, Sedighadeli, Khosla, & Chu, 2014). Within this service-oriented movement, an automated system does not have independent operating capability and self-judgment, rather it is preset, predesigned, and predetermined, and performs with limited choice of self-judgment (Acampora, Cook, Behkami & Daim, 2012; Rashidi, & Vasilakos, 2013). In fact, these machines reflect human experience. The underlying concept of an autonomous system is that it upholds an intelligent and smart product idea where the content changes according to changing context—i.e., like in human beings, interaction and function is dynamic (Frost, 2010). It can accommodate its desired and specified goals locally with its own intelligence and can interact with external events without direct human intervention (Frost, 2010; Marchant & Lindor, 2012; Rijsdijk &

Hultink, 2003). This study conceptualizes an autonomous system as any integrated and interconnected process or product that can act independently, making appropriate contextual decisions within a changing environment and without any human intervention (Garza, 2012; Marchant & Lindor, 2012; Rijsdijk & Hultink, 2003; Rijsdijk, Hultink, & Diamantopoulos, 2007). It is interesting that the idea and pragmatic application of an autonomous system indicates the enhancement of intelligence of any product/machine, reflecting the possibility of less required participation from human beings during the application phase (Marchant & Lindor, 2012; Rijsdijk et al., 2007).

However, the degree of innovation and level of independence of any autonomous system varies significantly, depending on vendor strategy, design criteria, system cost, and, most importantly, consumer requirements, adaptability, and behavioral attitude (Acampora et al., 2013; Rijsdijk et al., 2007). Using as an example of the functions of a washing machine, Baber (1996) defines four levels of machine autonomy: the manual level, where everything is managed by human-directed operation; bounded autonomy, where certain functions are executed from pre-coded commands, although still operated through human interaction; supervised autonomy, where the machine can perform its set functions independently, yet still needs some human presence; and the symbiosis, which indicates completely independent actions and decision making without direct involvement of a human (Rijsdijk & Hultink, 2003; Rijsdijk & Hultink, 2007). Streamlining the functions, patterns of intelligence, and the levels of intelligence as an alternative service provider, any autonomous system is intended to reduce the functions and active involvement of users after product design (Rijsdijk et al., 2007).

Several researchers (Acampora et al., 2013; Heerink, Krose, Evers, & Wielinga, 2010; Nehmer, Karshmer, Becker, & Lamm., 2006) have addressed vulnerable issues in machine autonomy, and recent progress has confirmed that this requirement can be met if we are able to design proper systems that include ambient intelligence. Design and attributes of an autonomous homecare system should ensure the independence of elderly people and increase their self-control, reactivity, self-judgment, social interaction, and adaptation (Broadbent et al, 2009; Kachouie et al., 2014). As a result, if properly designed, autonomous homecare system can ensure revolutionary improvement in healthcare of elderly people, particularly which is now mandatory due to necessity of social isolation for Covid-19. This system can reduce dependency on human support, which is now very limited, and thus, can increase scope to provide adequate health support to elderly people (Rashidi & Mihailidis, 2013). Due to Covid-19, different governments are now continuously imposing social isolation. As a result, availability of healthcare support for retirement homes and rehabilitation centers is becoming very limited (The Guardian, 2020). Recent studies on Covid-19 pandemic revealed that elderly people are not getting adequate health support due to essential obligation of social isolation. Consequently, necessity of the application of autonomous system in retirement homes and rehabilitation centers has increased tremendously (Wang et al., 2020; Zhong et al., 2020). In this context, it is worth to note that all over the world, the number of elderly and disabled people is growing as life expectancy has increased enormously (Acampora et al., 2013). As per the American Community Survey Reports (2018), in 2016, 19.2% population was aged 65 or over in Europe and 16% in North America. By 2030, it is projected that all over the world, the older population will be about 1 billion (12 percent of total world population).

However, while struggling to enhance self-control, independence, and self-esteem, necessary interaction and orientation with non-human assistive caregivers can create substantial compounding resistance from those who are used to a traditional living support system (Heerink et al., 2010; Nehmer et al., 2006; Rijsdijk & Hultink, 2003). This phenomenon may have a subversive effect on the cognitive and psychological status of elderly people (Acampora et al., 2013; Broadbent et al, 2009; Heerink et al., 2010; Nehmer et al., 2006). Therefore, any effective design of an ambient intelligence support system cannot ensure that it will be accepted as a daily routine support to elderly and disabled people if they resist its use as an effective alternative to human support.

Nevertheless, present research on autonomous systems and ambient intelligence support is primarily and substantially engaged in designing the technological aspects of the system (Marchant & Lindor, 2012). Researchers are also attempting to emphasize the needs of disabled and elderly people when designing convenient autonomous systems (Broekens et al., 2009; Frost, 2010; Garza, 2012; Rijsdijk & Hultink, 2007). However, user acceptance is primarily dependent and related to cognitive and affective behavioral attitudes and perceptions about autonomous system in general. Also important is users' trust in interaction-free autonomous systems (Rijsdijk & Hultink, 2003). There is a potential research gap concerning the behavioral aspects of users regarding acceptance of human interaction-free machine intelligence under particular conditions. Yet, it is worthwhile to note that the ultimate application of these systems potentially depends on both convenience and acceptance criteria of users. Consequently, this research seeks to develop a theoretical paradigm of trust levels for elderly people to accept innovative autonomous systems and recommend a practical application based on a comprehensive model of trust associated with behavioral intention. At this point, this research is engaged in addressing, exploring, and conceptualizing the following twofold objectives that have immense potential for contributing to extensive and effective implementation of this system:

1. Development of a comprehensive model of trust related to autonomous systems for elderly and disabled people, integrating security and privacy risks.
2. Identification of behavioral issues, covering both psychological and cognitive parameters related to trust that might inhibit elderly and disabled people's acceptance of autonomous homecare systems.

This research has significant merit and can contribute to the existing knowledge of designing autonomous systems driven by ambient intelligence to advance extensive application of this evolutionary system. The next section assesses existing knowledge on technical aspects and behavioral phenomena. That is followed by a description of the theoretical model employed for investigating the present's study's research objectives. After that, the research methodology is presented, including questionnaire design, sample selection, and data collection. Statistical analysis is then presented, followed by results interpretation and a discussion section. From there, managerial and theoretical interpretation is explained with a discussion of the limitation of the research, along with future research guidelines. The article ends with a conclusion of the research.

2. Literature review

Marketing literature has long understood that product intelligence must consider consumer behavior and requirements. If the system is intelligent enough to make its own decisions, it should manage as many tasks as is convenient, required, and possible to perform independently

(Broadbent et al, 2009; Kachouie et al., 2014). Specifically, it can perform several multidimensional tasks and manage complex sequences of operations that are extremely laborious, dangerous, and time and cost consuming, like cleaning a nuclear system, accompanying older and disabled people, or removing health hazards (Frost, 2010; Such, 2017; Summary Report, 2015). Keeping the pace of ICT proliferation, particularly software, sensors, microchips, and complex algorithms, a new era of human-independent intertwined systems/machines is rapidly expanding (Frost, 2010; Rijsdijk et al., 2007). Due to a change in lifestyle, urbanization, technological habituation, and cost-effectiveness, consumers are increasingly become interested and keen to perform many daily tasks with the assistance of independent products, like AIBO (a robotic dog) or autonomous vacuum cleaners and lawnmowers, that can perform their intended tasks without human intervention (Acampora et al., 2013; Rijsdijk & Hultink, 2003). Highly familiar with modern ICT, consumers are developing new relations with smart and intelligent system interfaces when adopting autonomous products (Rijsdijk & Hultink, 2003). The innovation and application of independent products that replace human effort in the application phase is gradually creating a new window for government policymakers and marketers to regulate and design new products to reach out to customers. On the other hand, technology related to security breaches, potential risks, and untrustworthiness are also penetrating our daily life at an exponential rate, particularly amongst autonomous systems (Rijsdijk et al., 2007). Different researchers working on risks associated with human use of autonomous machines (Rijsdijk & Hultink, 2003; Rijsdijk et al., 2007; Such, 2017) has revealed that security threats and privacy risks, including cybercrime, has made consumer wariness one of the most contentious issues for managing autonomous systems, and this sometimes inhibits the expected proliferation and commercialization of this new pattern of innovation (Frost, 2010; Such, 2017).

Several government departments and private organizations employ different forms of autonomous systems for diverse uses, such as drone systems, spacecraft, orbital express, and exploration of Mars (Estlin et al., 2008; Ogilvie, Allport, Hannah, & Lymer, 2008). Despite many compelling stories of autonomous systems in several areas and forecasting of Google bringing forth an autonomous car within the next couple of years (Summary Report, 2015), researchers have identified enormous obstacles to diffusion of these systems. The unavoidable problem is that although they do not require human intervention, they require human acceptance (Such, 2017). Marketing, technology, and software experts acknowledge several benefits, like cost and process efficiency, management of complexity, reduction of hazard contamination, and, more importantly, relative advantages and convenience in daily life (Frost, 2010; Rijsdijk & Hultink, 2003; Rijsdijk et al., 2007). Smart products can offer better interconnectivity and communicability (Nwana & Azarmi, 1997; Poo & Tang, 2000), enormous sources of resources in place of scarcity of medical service (Hancock et al., 2011; Körber, Baseler, & Bengler, 2018), a higher degree of information processing (Nicoll, 1999), and effortless decision making (Poo & Tang, 2000). Nevertheless, the unexpected challenges in this context may undermine widespread adoption of this smart system (Such, 2017). One obvious concern raised by several researchers (Frost, 2010; Such, 2017) in the exploration of risks associated with autonomous systems is how the introduction of these revolutionary systems might affect traditional and philanthropic values and principles of human beings as consumers. Application and proliferation of these systems could potentially hamper users' perception of control over their lives (Rijsdijk & Hultink, 2003). Researchers of behavioral psychology recognize the essential desire of human beings to maintain and exercise control over personal life-affiliated issues (Burger & Cooper, 1979;

Trimpop, Kerr, & Kirkcaldy, 1997), as many functions of daily life can now be operated and governed by independent systems where they are unable to exert any decision in the application phase (Burger & Cooper, 1979; Clifford & Clifton, 2012; Clifton, Clifton, Pimentel, Watkinson, & Tarassenko, 2012; Rashidi & Mihailidis, 2013). Another psychological inconvenience that consumers might experience is loss of freedom, as sometimes users might perceive that an autonomous system represents commercial interests, and that control primarily reflects vendor interests (Such, 2017). Marketing researchers have long argued that consumer satisfaction is the primary threshold for reinforcement of continued usage; however, researchers reveal that several inhibiting parameters—like security breaches due to faulty design or inappropriate functionality, actual or perceived risks from interconnectivity, lack of privacy due to exposed information, and, most importantly, absence of trust of machine systems—can inhibit development and widespread use of autonomous systems (Frost, 2010; Such, 2017).

Among many human-intensive autonomous systems, health care is a major area where recent development in intelligence design is showing substantial and emergency application (Heerink et al., 2010; Nehmer et al., 2006; Summary Report, 2015). All over the world, particularly in western nations, the number of elderly and disabled people is growing as life expectancy has increased enormously (Acampora et al., 2013). In the next decade, the number of those over seventy years old will represent around 10 percent of the North American population. These elderly people are suffering from different kinds of disabilities, such as changes in gait, diabetes, blood pressure issues, visual acuity changes, hearing impairment, neurological alterations, vestibular compromise, spontaneous fractures and falls, cardiac alteration with syncope, strokes, and mental depression. At the same time, in the western world, specialized healthcare service is becoming extremely costly as the service requirement is surpassing its original availability (Acampora et al., 2013; Heerink et al., 2010). Many social researchers (Acampora et al., 2013; Broadbent et al, 2009; Kachouie et al., 2014) are skeptical that service availability for elderly people will be sufficient to maintain their standard of life. Severe shortage of caregivers and other essential facilities and exponential requirement of service is creating a serious challenge for healthcare service providers, government policy makers, and humanitarian organizations. In this context, the necessity of autonomous social assistive support for elderly people, often called ambient intelligence, has never felt so urgent (Acampora et al., 2013; Nehmer et al., 2006). The elderly need walking aids, intelligent wheelchairs, regular health advisors, nursing, communication facilities, robotic butlers, washroom support, movement support, empathetic relation, and medication reminders, to name a few. Table 1 shows the summarized findings of literature on the application of human-intensive autonomous systems.

Table 1
Summary findings from studies on automation system

Study	Area	Findings
Acampora et al., 2013; Clifton et al., 2012; Kaburlasos & Vrochidou, 2019; Nehmer et al., 2006; Rashidi & Mihailidis, 2013; Wang et al.,	Ambient intelligence in healthcare	Usage of ambient intelligence for elderly people is essential and can open a new healthcare support system

2020		
Broadbent et al, 2009; Broekens et al., 2009; Kachouie et al., 2014; Martinez-Martin et al., 2020	Healthcare robots	As an alternative support system for elderly people, robot can be used to provide assistance for daily routine life
de Visser et al., 2020; Ferguson et al., 2019; Rijsdijk et al., 2007	Autonomous machines design	Design of autonomous system should be done very carefully considering satisfaction of consumers
Hancock et al., 2011; Körber et al., 2018; Lewis et al., 2018; Lu & Sarter, 2019; Satterfield et al., 2017; Schaefer et al., 2016	Ambient intelligence and human trust	Trust is an important issue for the design of autonomous system. Criteria for development of trust should be explored before designing autonomous system.
Erzurumlu & Pachamanova, 2020; Estlin et al., 2008; Garza, 2012; Marchant & Lindor, 2012; Ogilvie et al., 2008	Innovation of autonomous system for engineering application	These studies investigated how autonomous systems can be used to assist different areas of innovation, for instance, satellite, car driving, office assistance etc.
Heerink et al., 2010; Pachidis et al., 2019; Rantanen et al., 2017	Social assistive technology for elderly people	Adoption behavior of elderly people for machines is explored and examined to identify the antecedents.
Belpaeme et al., 2018; Schneider & Kummert, 2020; Wang et al., 2016	Usage of Robot for household tasks	Comparison between human and robot assistive support is done in this paper. It is identified that trust is an important issue for ambient intelligence.

3. Theoretical background and hypotheses development

Considering previous studies (Dwivedi et al., 2016; Gefen et al., 2003; Hancock et al., 2011; Körber et al., 2018; McKnight et al., 2002; Pavlou, 2003; Satterfield et al., 2017; Schaefer et al., 2016; Shareef et al., 2008) and theoretical analysis (Diffusion of Innovation, Rogers, 2003; GAM, Shareef, Kumar, Kumar, & Dwivedi, 2011; IDT model, Moore & Benbasat, 1991; MPCU model, Thompson, Higgins, & Howell, 1991; TAM, Davis, 1989; UTAUT model, Venkatesh, Thong, & Xu, 2012) the following conceptual model in Figure 1 has been proposed. Subsequent justifications of different plausible cause-effect relations in the theoretical model, the grounded framework that will be investigated in this study, have been explained following Figure1.

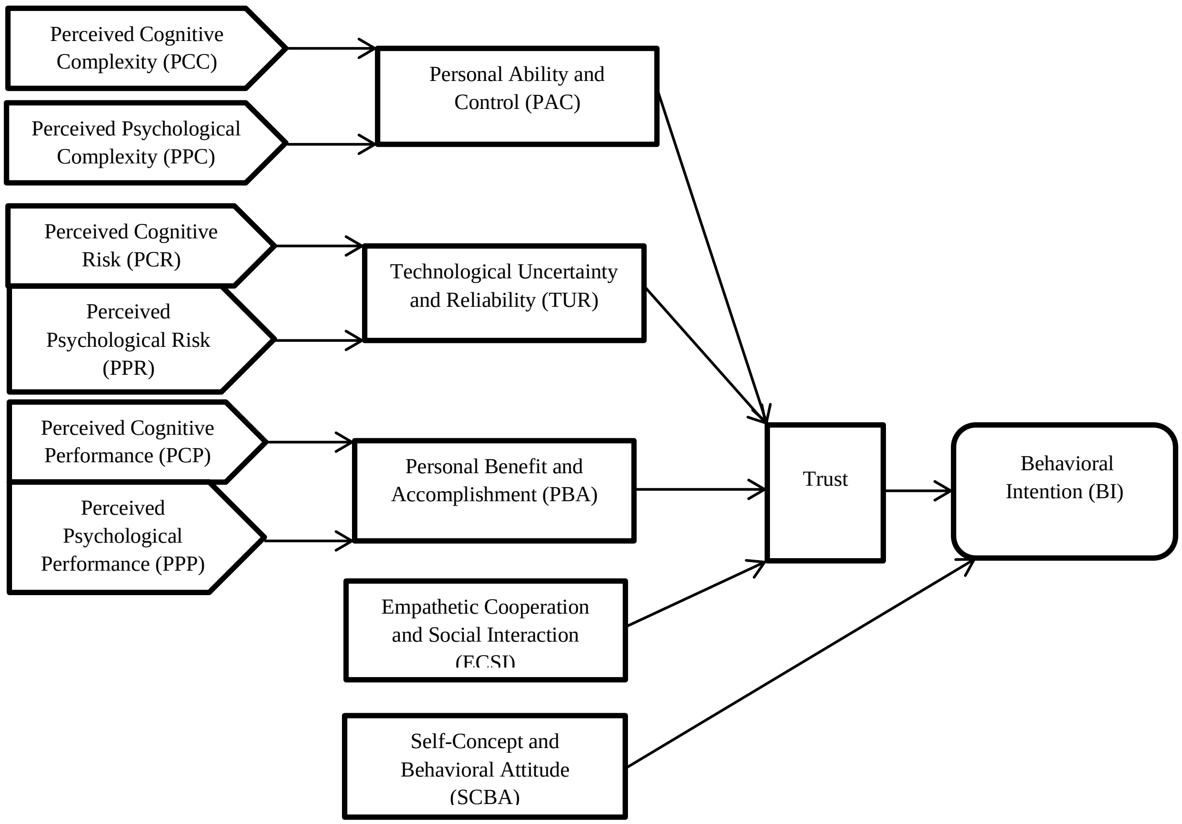

Fig. 1. A proposed trust-disposition model for understanding adoption of an autonomous homecare system

Researchers working on acceptance criteria for intelligent social assistive support (Nehmer et al., 2006; Rijsdijk & Hultink, 2003; Rijsdijk & Hultink, 2007) have identified several driving factors, such as relative advantage, perceived usefulness, and compatibility. On the other hand, complexity and perceived risk of uncontrollable intelligence can lead to resistance to accepting such a system (Rijsdijk & Hultink, 2007; Such, 2017). Heerink et al. (2010) use both a technology acceptance model (TAM) (Davis, 1989) and a unified theory of acceptance and use of technology (UTAUT) model (Venkatesh, Thong, & Xu, 2012), adding some new constructs—trust, social presence, perceived sociability, perceived enjoyment, perceived adaptability, and anxiety—to measure behavioral intentions of elderly people. Researchers of marketing (Pavlou, 2003; Shareef & Kumar, 2012; Shareef, et al., 2013) and virtual technology (Carter & Bélanger, 2005; Dwivedi et al., 2016; Kim, 2016; Molins-Ruano et al., 2016; Shareef et al., 2011) unanimously assert that for consumers to accept anything virtual, they must trust that system.

Looking at consumers' adoption behavior model for mobile health (Dwivedi et al., 2016), which developed its theoretical concept based on a UTAUT2 model (Venkatesh et al., 2012), it is observed that effort expectancy is an important predictor for consumer acceptance of any complicated technology. The notion of easy operation, as perceived by users, is also supported by several behavioral theories like TAM (Davis, 1989), complexity (see MPCU; Thompson, Higgins, & Howell, 1991), and ease of use (IDT) (Moore & Benbasat, 1991). Therefore, this study, employing social learning theory (Bandura, 1986), argues that elderly and disabled people's ability to achieve control and become accustomed to the system's use should consider effort expectancy, with an expanded conceptual paradigm that considers both cognitive and psychological ability. Thus, this study introduces a new construct that incorporates ideas about effort expectancy, perceived ease of use, and complexity, which is termed here as personal ability and control (PAC). This term is defined here as *the level of perception of personal ability and control to be familiar and accustomed with, and to use any autonomous system driven by ambient intelligence*. Based on this argument, this study proposes:

H_1: Personal ability and control (PAC) of users has an impact on developing trust (TT) in an autonomous system.

However, researchers of autonomous systems (Bloss, 2011; Broekens et al., 2009; Clifford & Clifton, 2012; Clifton et al., 2012; Rashidi & Mihailidis, 2013) have analyzed users' behavior and asserted that to use an autonomous system dominated by ambient technology, elderly people's perception about their ability to use and achieve control is not just about their physical abilities. Rather, it is much more complicated, compounded by psychological ability (Bloss, 2011; Broekens et al., 2009). Elderly and disabled people's understanding of their control of and familiarity with these systems entails both analytical perceptions (i.e., perceived cognitive complexity — PCC: A*nalytical and practical realization about personal ability and control to be familiar and accustomed with and use any autonomous system*—and psychological perceptions (i.e., perceived psychological complexity — PPC: *Psychological evaluation of personal ability and control to be familiar*, *accustomed with and use any autonomous system*). Based on this argument, the following hypotheses are proposed,

H_{1a}: Perceived cognitive complexity (PCC) of users has an impact on developing personal ability and control (PAC) of an autonomous system.

H_{1b}: Perceived psychological complexity (PPC) of users has an impact on developing personal ability and control (PAC) of an autonomous system.

Elderly people have a strong perception of risk that inhibits them from considering acceptance and use of autonomous systems (Bloss, 2011; Clifton et al., 2012). Due to long years' experience and familiarity with human-involved and -supported systems for facilitation of any social environment, they feel, assume, and realize uncertainty and unpredictable risk, which can be termed in this study as perceived psychological risk (PPR) *(Psychological evaluation of potential threats to interact with a technology driven instrument having no self-generated emotional attributes*). This perception is derived from a general attitude of human beings about any uncertain and uncontrollable environment, something supported by social and behavioral psychological theory (Gefen, Karahanna, & Straub, 2003). However, experience and social dependence also help analyze several symptoms of the unreliability of autonomous systems (Clifton et al., 2012; Nehmer et al., 2006; Rashidi & Mihailidis, 2013; Such, 2017). Furthermore, elderly and disabled people realize the absence of lively two-way communication with any autonomous system controlled by ambient technology (Bloss, 2011; Clifford & Clifton, 2012; Clifton et al., 2012; Satterfield, Baldwin, de Visser, & Shaw, 2017).

Many studies exploring potential risks from use of an ICT-driven system (Featherman & Pavlou, 2003; Liao et al., 2011; Satterfield et al., 2017; Shareef et al., 2008) argue that consumer trust disposition is the single most important issue (Featherman et al., 2010; Gefen et al., 2003; Shareef et al., 2013). For an autonomous system, whose interconnectivity means many systems are simultaneously open and active, feelings of risk are much higher than with any static system operated manually (Broadbent et al, 2009; Kachouie et al., 2014; Rijsdijk et al., 2007). Considering certain issues related to risk aversion behavior in a trust disposition model of autonomous adoption, this behavior is potentially significant (Hancock et al., 2011; Körber et al., 2018; Nehmer et al., 2006; Such, 2017; Shareef et al., 2019a). This realization of risk is composed of several realistic security threats, noted here as perceived cognitive risk (PCR) *(Analytical and practical realization of potential threats to interact with a technology driven instrument having no self-generated emotional attributes*).

Elderly and disabled people's perception of risk is made up of these two forms of risk, which are termed here as technological uncertainty and reliability (TUR). Borrowing the conceptual idea from scholarly articles dealing with perception of risk on unassisted modern technology and virtual environment (Nehmer et al., 2006; Satterfield et al., 2017; Such, 2017), this construct can be defined *as the level of perception of inability to avail any proper assistance whenever it is required from an autonomous system not requiring human involvement*. Based on the aforementioned arguments, this study proposes the following hypotheses:

H_2: Perception of technological uncertainty and reliability (TUR) has an impact on developing trust (TT) in an autonomous system.

Analyzing users' behavior in the light of transaction cost analysis (Williamson, 1981), it is clearly understandable that perception of an autonomous system's uncertainty, particularly by disabled and elderly people who always have less potentiality in technological advancement (Bloss, 2011; Rashidi & Mihailidis, 2013) and are basically haggard to accept any innovation (see diffusion of innovation theory; Rogers, 2003), is an important inhibiting issue for the acceptance of an ICT-driven living system. Perception of risks can be derived from several facets, such as performance, financial, time, psychological, social, and privacy (Featherman & Pavlou, 2003; Rijsdijk & Hultink, 2007). Sometimes, elderly people may not trust a commercial autonomous system, as they may fear that it can be guided by opportunistic outsiders (Broadbent et al., 2009). Elderly people perceive psychological risk (PPR) and cognitive risk (PCR) which ultimately contribute in the perception of technological uncertainty and reliability (TUR) (Satterfield et al., 2017; Such, 2017). As such, the following two hypotheses are proposed,

H_{2a}: Perceived cognitive risk (PCR) of users has an impact on developing perception of technological uncertainty and reliability (TUR) of an autonomous system.

H_{2b}: Perceived psychological risk (PPR) of users has an impact on developing perception of technological uncertainty and reliability (TUR) of an autonomous system.

Venkatesh et al. (2012), using their refined UTAUT2 model, theorize performance expectancy as a strong predictor for consumer acceptance of any complex system. Shedding light on the theoretical concept of performance expectancy, Dwivedi et al. (2016) reveal that while adopting any virtual ICT-related complicated system like mobile health that has potential importance, consumers often evaluate the system and compare it with alternatives to perceive the absolute and relative advantages they might gain. For this kind of risky item, which has substantial importance in their daily life, consumers typically perceive relative advantage not only from physical benefits that have visible outcomes, but are also tempted to consider its advantages from a psychological perspective (Broekens et al., 2009; Clifford & Clifton, 2012; Such, 2017). Considering an autonomous system for elderly people while developing intrinsic and extrinsic motivations to replace lively human beings with seemingly dead material, it is quite apparent that people will analyze the system to realize its relative benefits, which can be treated as perceived cognitive performance (PCP) (*Analytical and practical realization of getting benefits to perform a task and achieve desired goal through the use of any autonomous system*). However, they also try to find advantages of this system from affective attitudes that can be termed here as perceived psychological performance (PPP) (*Psychological evaluation of getting benefits to perform a task and achieve desired goal through the use of any autonomous system*). Integrating both evaluations, users develop their perceptions of receiving personal benefit and accomplishment (PBA) about the autonomous system t governed by ambient technology. This construct can be defined within a broader concept of receiving cognitive and affective benefits as *the level of achievements users believe they receive while evaluating performance of any unknown system that has potential in their life*.

Marketers and technology experts accept the versatile impact of users' trust disposition behavior on their selection process while evaluating the relative benefits of the system to accomplish desired tasks (Dwivedi et al., 2016; Shareef et al., 2013; Shareef et al., 2018a; Sprott, 2008). *Trust is the overall confidence of users about the credibility and reliability of an autonomous system that, interacting with the artificially intelligent caregivers, will fulfill their value expectation in exchange for a financial, physical, and psychological contribution* (Heerink et al., 2010; Such, 2017). Thus, this study proposes that:

H_3: Personal benefit and accomplishment (PBA) of users has an impact on developing trust (TT) in an autonomous system.

Behavioral psychologists have asserted that humans are likely to accept a new system if they derive benefit from using that system (Dwivedi et al, 2016). Davis (1991), in his TAM model, also asserts this idea based on a theory of planned behavior (Fishbein & Ajzen, 1975) that users' perception of usefulness is a strong predictor for accepting innovation. Pursuing favorable attitudes is substantially connected with a belief of gain or achievement that is certified by this theory. Rogers (2003) reveals the same concept in his diffusion of innovation theory, and introduces a construct called relative advantage. To transform behavioral attitude favorable to adoption of electronic governance, Shareef et al. (2011) also affirm in the theoretical framework of GAM that perception of relative benefits, both cognitively and psychologically, encourages users to adopt innovation in a virtual environment. This argument justifies that personal benefit and accomplishment (PBA) depends on the perception of cognitive performance (PCP) and psychological performance (PPP). Thus, the following two hypotheses are proposed,

H_{3a}: Perceived cognitive performance (PCP) of users has an impact on developing personal benefit and accomplishment (PBA) from an autonomous system.

H_{3b}: Perceived psychological performance (PPP) of users has an impact on developing personal benefit and accomplishment (PBA) from an autonomous system.

Consumers' natural expectation in surplus value (i.e., achievement of higher value than cost) can be analyzed in this bilateral dilemma of constraints in an autonomous structure of patterns of interactions and associated affective behaviors. Following social exchange theory (Homans, 1961; Lawler, 2001), like any financial exchange, elderly people always evaluate acceptance and usage of a autonomous home care system in terms of investment (for instance, physical labour, financial cost, opportunity cost, time spent, social value, psychological annoyance, or hedonic benefit) against benefits achieved empathetically from that exchange (Thibaut & Kelley, 2008). In essence, they look for higher reward or satisfaction from the kinds of investment needed to accomplish that desired task (Kumar & van Dissel, 1998; Malone et al., 1987; Shareef et al., 2019).

Since implementation and acceptance of an autonomous home care system driven by ambient intelligence can hamper self-control and give the appearance of being guided by a dead system pretending to be alive, before conceptualizing a trust formation model it is important to first identify and examine certain extrinsic and intrinsic factors that help generate trust. Researchers from ICT management (Shareef & Kumar, 2012; Wicks, Berman, & Jones, 1999) have identified trust from two perspectives: confidence in the predictability of one's expectations, and confidence in another's goodwill to maintain that promise. From an exchange point of view, trust can be developed when one party has confidence in an exchange partner's reliability and integrity. Mayer, Davis, and Schooman (1995) certify that the study of trust is a complex phenomenon. Multidimensionality and versatile functionality of trust, particularly for elderly people toward innovation, is a very complex issue to theorize for practical implementation.

Scholarly articles dealing with computer-mediated communications (CMC) acknowledge that internal and external environments for communication media significantly affect interpersonal trust building (Gefen et al., 2003; Shareef & Kumar, 2012). Artificial intelligence is now being adopted in various contexts including retailing, organizational decision making, healthcare, operations, and service delivery (Duan et al., 2019; Dwivedi et al., 2019; Grover et al., 2020; Gursoy et al., 2019; Pillai et al., 2020). For autonomous systems operating through artificial intelligence, researchers argue that accepting this autonomous assistive social system is more persuasive if the living interactions can provide an environment of hedonic motivation, affection, and social interaction (Acampora et al., 2013; Gefen et al., 2003; Heerink et al., 2010; Nehmer et al., 2006). Researchers of ICT-driven systems, virtual environments, and autonomous systems (Bloss, 2011; Broekens et al., 2009; Clifford & Clifton, 2012; Clifton et al., 2012; Rashidi & Mihailidis, 2013; Shareef et al., 2019b; Such, 2017) have explicitly revealed and acknowledged that elderly and disabled people who are, to some extent, psychologically and physically detached from functional and active society, have a strong urge to interact affectionately with human caregivers (Hancock et al., 2011; Körber et al., 2018; Schaefer, Chen, Szalma, & Hancock, 2016). This study argues that the desire for psychological affection can be a strong predictor for developing trust in an autonomous system. This is strongly supported by trust literature, which reveals that empathetic behavior and hedonic motivation is a clear reason to impart trust (Gefen et al., 2003; Jarvenpaa & Todd, 1997; McKnight & Chervany, 2002; McKnight, Choudhury, & Kacmar, 2002). Based on trust literature and scholarly articles that define empathy, this study proposes a construct entitled empathetic cooperation and social interaction (ECSI), conceptualized as *the level of scope and availability of sympathetically and* *socially interactive service that develops the perception of esteemed social involvement*. Thus, this study proposes:

H_4: Perception of empathetic cooperation and social interaction (ECSI) has an impact on developing trust (TT) in an autonomous system.

Research on remote virtual environments acknowledges the significant relationship between trust and personality (Dwivedi et al., 2016). Cheskin Research (1999) has identified six foundational dimensions of trustworthiness: seals of approval, brand, navigation, fulfillment, presentation, and technology. Extensive research conducted by Staples and Ratnasingham (1998) categorizes online trust from two perspectives: cognitive (specific performance evaluation) and affective (general psychological evaluation). Honesty, familiarity, predictability, competence, integrity, benevolence, vulnerability, and sincerity are also predetermined issues for determining trust of a system (Burger & Cooper, 1979; Gefen et al., 2003; Jarvenpaa & Todd, 1997; McKnight & Chervany, 2002; Shareef & Kumar, 2012; Shareef et al., 2020). Shareef et al., (2013) envision trust as the combination of behavioral attitude, cognitive perception, perceived security, perceived privacy, and fulfillment. In this aspect, willingness to depend on an artificial living system is also a crucial issue supported by Morgan and Hunt (1994). Gefen et al. (2003) identify the following antecedents of trust: knowledge-based trust, institution-based trust (structural assurance) and institution-based trust (situational normality), calculative-based trust, cognition-based trust (illusion of control), and personality-based trust. However, researchers assert that the building blocks of trust are substantially dependent on a person's personal attitude, trustworthiness, personality, self-image, and influence of social people (Shareef et al., 2019a). Dwivedi et al. (2016) acknowledge that self-concept and social influence both have potential impact on users' willingness to adopt any technological innovation, such as mobile health. A theory of planned behavior also asserts that individual attitudes and subjective norms have a conjoint effect on behavioral intention toward trust (Gefen et al., 2003; Roth, 1995; Shareef et al., 2013). Drawing inference from the aforementioned parameters and epistemological and ontological paradigms of trusting behavior, the following construct, self-concept and behavioral attitude (SCBA) is proposed. This study argues that if elderly and disabled people do not feel compatibility with an autonomous system, they will not develop a behavioral intent to adopt it. This construct can be defined here in light of previous studies about this idea (Hancock et al., 2011; Körber et al., 2018; Satterfield et al., 2017; Schaefer et al., 2016) as *an individual's overall evaluation about the level of compatibility of their own characteristics, influenced by their attitude and social norms, with a system*. Thus, this study proposes that for elderly people to accept an autonomous homecare system:

H_5: Self-concept and behavioral attitude (SCBA) of users has a direct impact on behavioral intention (BI) toward an autonomous system.

Shareef et al. (2008) conducted an empirical study of consumers to identify their trusting behavior and its relation to adoption. The research revealed that perceived site security, perceived operational security, disposition towards trust, and perceived local environmental security were the main factors for forming perceptions of trust. However, overall credibility, reliability, and reputation of sellers is comprised of several dimensions of trust, such as behavioral, social, psychological, and technological aspects (Gefen et al., 2003; Shareef et al., 2019a). After reviewing scholarly studies dealing with trust disposition attitudes (Gefen et al., 2003; Pavlou, 2003; Shareef et al., 2016), it can be articulated rhetorically that autonomous system-related trust is substantially associated with perceptions of security and privacy risks, as well as reputation, reliability, familiarity, sociability, and complexity (Heerink et al., 2010; Such, 2017). Termination of these facets of risks associated with the implementation of autonomous homecare service that can ultimately contribute and enhance elderly people's trusting attitude for acceptance is the most important issue rooted in the interaction of a human-autonomous machine interface (Acampora et al., 2013; Heerink et al., 2010; Nehmer et al., 2006). Within this context, this study, with reference to many scholarly studies (Frost, 2010; Such, 2017; Summary Report, 2015), argues that identification of a comprehensive model of trust is the single-most important factor for elderly people having conventional attitude.

Demonstrating compatibility with the special dynamic characteristics of these systems, some elderly people may have keen interest toward acceptance (Featherman et al., 2010; Acampora et al., 2013; Heerink et al., 2010; Rijsdijk et al., 2007; Such, 2017). Nevertheless, many elderly people may refrain from using this ambient intelligence system due to an absence of trust (Heerink et al., 2010). Considering human behavior in adopting a technology-related system, particularly when the system replaces human interaction for continuous accompaniment, nothing can be more important for elderly people than trusting the system (Hancock et al., 2011; Körber et al., 2018; Satterfield et al., 2017; Schaefer et al., 2016). Shedding light on human psychology, like a cognitive theory of trust (Gefen et al., 2003; Hancock et al., 2011; Körber et al., 2018; McKnight et al., 2002; Schaefer et al., 2016), it can be decisively inferred that trust is the single-most important predictor for human beings accepting an autonomous system. Thus, this study argues that:

H_6: Trust (TT) of users has a direct impact on behavioral intention (BI) toward an autonomous system.

4. Research method

The study was conducted among elderly and disabled people in retirement homes and rehabilitation centers in Ontario, Canada. The number of old and disabled people is growing very quickly in Ontario, and around 29% of this group live in retirement homes (Statscan, 2016). According to a Statscan (2016) survey, the number of people over 65 years is around 25%; the same figure was less than 5% in 1971. The concept of retirement homes and rehabilitation centers is present for long years. Although it is traditionally reliant on human support, the use of limited autonomous systems is growing (Bloss, 2011; Broekens et al., 2009; Rashidi & Mihailidis, 2013). In Canada, some private organizations, as well as government, are considering introducing autonomous systems in retirement homes and rehabilitation centers (Statscan, 2016). Another important issue observed from this survey is that cultural diversity is profound in Canada. Therefore, any empirical study of elderly and disabled people in Canada, particularly Ontario, provides an excellent opportunity to capture variations of cultural diversity. They get the scope to use different levels of autonomous systems as homecare assistive support. Elderly and disabled people of this country can thus provide deep insights not only about significant cultural differences, but also from the potential differences in providing and using autonomous systems.

4.1.Development of scale items

Measuring items for the five second-order independent constructs of Trust (TT), Personal Ability and Control (PAC), Technological Uncertainty and Reliability (TUR), Personal Benefit and Accomplishment (PBA), Empathetic Cooperation and Social Interaction (ECSI), and Self-Concept and behavioral Attitude (SCBA) are mostly adopted from Dwivedi et al.'s (2016) mobile health adoption model, along with other studies (Davis, 1989; Gefen et al., 2003; Rogers, 2003; Shareef et al., 2011). However, these scale items were revised to consider the broader conceptual definitions of the constructs. Measuring items of the six first-order constructs—PCC, PPC, PCR, PPR, PCP, and PPP—are extracted from different studies related to ambient intelligence, trust, security and risk, ICT, and virtual medium (Gefen et al., 2003; Hancock et al., 2011; Körber et al., 2018; McKnight et al., 2002; Satterfield et al., 2017; Schaefer et al., 2016; Shareef et al., 2011). Measuring items for TT and BI were taken from several studies engaged in identifying technology and adoption behavior (Dwivedi et al., 2016; Gefen et al., 2003; Pavlou, 2003; Shareef et al., 2008; Shareef et al., 2011). However, these scale items were revised and reformatted, reflecting the nature of this study of autonomous systems.

To keep the questionnaire consistent with the extended concepts of autonomous systems, and to maintain conceptual clarity, the authors organized a focus group. This was made up of four business professors from Canada having knowledge of autonomous systems, marketing, virtual medium, and human psychology. The authors also conducted an experiment through a pilot study among twenty elderly people in Bangladesh who were living in apartments with their family members. This was done to obtain a thorough view regarding the clarity of the intended meanings of the scale items. The final questionnaire is shown in Appendix A. The scale items of all the first- and second-order independent and dependent variables were measured by a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Previous studies conducting research on healthcare system acknowledged that 5-point Likert scale is adequate and suitable for elderly people (Weber et al., 2014). It is easier for them to fill out while maintaining standard accuracy (Chyung et al., 2017).

4.2.Data collection

This study was conducted by employing the following two methods: i) experiment and, ii) survey. At first, an experiment was designed for elderly people in retirement homes and disabled people in rehabilitation centers to demonstrate different types of simple homecare autonomous systems. This demonstration was done by video about the functions of autonomous systems. Then a survey-based empirical study was conducted with the structured questionnaire among the same members to capture their perceptions of both receiving service from human beings and viewing the video about an autonomous system governed by ambient intelligence. Entire experiment and survey was conducted among the elderly and disabled people living in several big cities in Ontario, Canada. This sample was chosen randomly.

4.3.Experiment

In the first phase, a structured and designed experiment was conducted in three retirement homes and included 159 elderly people in Ottawa, Kingston, and Toronto (all are cities in Ontario), and in two rehabilitation centers and included 20 disabled people in Hamilton and Windsor (cities in Ontario). All three old homes are managed by private organizations. The two rehabilitation centers (located in hospitals) are managed by the provincial government. A 30-minute documentary video was designed and developed with the help of three digital media and three computer and system engineering students in Ottawa. Under the guidance of the researchers, they designed a self-controlled robot and an automatic vacuum cleaner. In the short video, the robot and the vacuum cleaner are shown providing services without human assistance (such as providing medicine, helping in some small routine tasks, accompany evening walks, assisting in limited nursing, and cleaning houses). This video was shown to the aforementioned sample together or individually in their living locations. This experiment was conducted over a three-month period (May to July 2019). Special arrangements were made to obtain permission from private and government organizations to conduct this experiment, plus that of a later survey.

4.4.Survey-based Empirical Study

Among the sample members, a survey-based empirical study was conducted with the structured questionnaire found in Appendix A. It was conducted in August–September 2019. At the beginning, the questionnaire was physically distributed among members of the mentioned sample with clear guidelines. They were asked to answer the questions based on their perceptions of both receiving service from human beings and viewing the video about an autonomous system governed by ambient intelligence. After three weeks, the completed questionnaires were collected. A total number of 112 valid and completed questionnaires were received.

5. Data analysis and results

Respondents had significant variations in terms of demographic factors, particularly for disabled people. Therefore, at the beginning, demographic analysis was performed to assess the sample characteristics for both countries. Some general representative traits are shown in Table 2.

Table 2

Demographic factors

Traits	**Canadian Sample**
Average Age	74.75 years
Gender	41:59 (Male: Female)
Average Length of Time Residing in Retirement Homes/Rehabilitation Centres	8.9 years
Average Education	College Degree
Children	1 child
Smart Phone Usage Experience	84%
Computer Usage Experience	74%

5.1. *Reliability and Validity Assessment*

This study followed the suggested two-step approach of Anderson and Gerbing (1988) and Zhou (2012) to validate the final model. It examined the measurement model first through a confirmatory factor analysis (CFA), and then for a cause-effect relationship through the structural model. Because the constructs and measuring items of this study were extracted from established theory and published literature, and were verified by both focus group and pilot study, exploratory factor analysis (EFA) was not conducted. However, because the constructs and their measuring items were revised, reflecting the cognitive and affective perspectives of attitude, the first-order and second-order constructs and their measuring items were verified through CFA to assess construct validity and examine convergent and discriminant validity.

5.2. CFA and Construct Validity

CFA was performed on the preliminary 23 measuring items of six first-order constructs—PCC, PPC, PCR, PPR, PCP, and PPP—and 28 measuring items of five second-degree constructs—PAC, TUR, PBA, ECSI, and SCBA. CFA was then conducted to examine the two dependent constructs, TT and BI, with nine measuring items. All 11 independent variables and 2 dependent variables with scale items showed an over-identified model and satisfied the requirements of the CFA. They were loaded on the respective constructs over 0.50 except two measuring items from the first-order constructs and four measuring items from the second-order constructs. CFA was conducted while considering the cut-off value to remove any item loaded with a magnitude less than 0.50 (Kline, 2010). It is assumed that any scale item loaded less than 0.50 does not contribute significant variance to form the construct, and so can be removed (Kline, 2010). Items PPC4 and PPR3 from the first-order constructs, and PAC4, PBA2, ECSI5, and SCBA1 from the second-order constructs were removed as they were loaded in the respective construct with a value less than 0.50 (Fornell & Larcker, 1981; Kline, 2010). A correlation matrix of the scale items under each construct was also examined for justification of this removal. It was observed that those insignificant items had high correlations with the existing items. So, those scale items were dropped (see Appendix A). Finally, 21 accepted scale items of the six first-order constructs and 24 scale items of the five second-order constructs (termed here as independent variables), and 9 scale items of the two dependent constructs satisfied the minimum cut-off point requirements suggested by Fornell & Larcker (1981) and Kline (2010). The CFA results confirmed the convergent validity as the measuring items retained for each construct in this CFA, as the constructs had average variances extracted (AVE) higher than 0.50 (Fornell & Larcker, 1981). Discriminant validity among the independent and dependent variables was also verified as the largest shared variance between these factors was lower than the least AVE value for each factor and its measures (Kline, 2010). This finding affirmed good discriminant validity (Gefen et al., 2000; Zhou, 2012). Finally, the study selected 11 independent constructs with 45 measuring items and 2 dependent variables with 9 measuring items (see Appendix A).

In light of the CFA analysis with its loading pattern and the recommendation of literature for model fitness, the result confirmed that the reflective indicators of this study could adequately measure their respective constructs, meaning that construct validity was confirmed (Chau, 1997). This study deployed internal validity suggested by the variance-extracted test (Fornell &

Larcker, 1981). To ensure discriminant validity between two constructs, the explicit assumption is that both variances must be greater than the squared correlations between these two constructs. Examining the results shown in Table 3, we can observe that the lowest AVE value is 0.756 (for first degree construct, PPC), which is higher than the largest squared correlation between any pair of constructs (0.601, between PCP and PBA). Therefore, discriminant validity among all the independent constructs is confirmed.

Table 3

Correlation matrix and AVE of independent constructs

	PCC	PPC	PAC	PCP	PPP	PBA	ECSI	PCR	PPR	TUR	SCBA
PCC	**0.861**										
PPC	0.014	**0.756**									
PAC	0.260	0.114	**0.783**								
PCP	0.007	0.012	0.0007	**0.868**							
PPP	0.003	0.008	0.0005	0.348	**0.893**						
PBA	0.002	0.016	0.00002	0.601	0.339	**0.842**					
ECSI	0.122	0.099	0.283	0.0002	0.0004	0.001	**0.763**				
PCR	0.0002	0.00002	0.007	0.004	0.002	0.009	0.003	**0.760**			
PPR	0.013	0.001	0.006	0.003	0.001	0.009	0.008	0.044	**0.818**		
TUR	0.007	0.050	0.033	0.007	0.016	0.002	0.025	0.008	0.293	**0.877**	
SCBA	0.271	0.00008	0.274	0.003	0.00002	0.001	0.151	0.001	0.032	0.003	**0.826**

Diagonals are the square root of AVE and others are squared correlation

5.3.*Reliability Testing*

Reliability of the constructs is an important aspect to verify and understand acceptance of the constructs. This study evaluated internal reliability by composite reliability score (Fornell & Larcker, 1981). According to the literature (Fornell & Larcker, 1981; Hair, Hult, Ringle, & Sarstedt, 2006), the score of composite reliability should be greater than the benchmark of 0.7. The reliability scores for all the constructs ranged from 0.787 to 0.943. Therefore, all the independent and dependent constructs showed adequate reliability according to composite reliability (Table 3), which is estimated by calculating standardized factor loadings and the indicator's measurement error. The mean of the constructs is also shown in Table 4, examining the trend of the constructs and the respondents' agreement, as per the Likert scale.

Table 4

Composite reliability and mean score

Constructs	Composite Reliability based on Standardized Loading Value	Mean of the Constructs
PCC	**0.919**	**3.599**
PPC	**0.829**	**3.754**

PAC	**0.895**	**4.211**
PCP	**0.923**	**2.815**
PPP	**0.922**	**3.018**
PBA	**0.921**	**2.583**
ECSI	**0.901**	**4.024**
PCR	**0.844**	**3.867**
PPR	**0.846**	**3.437**
TUR	**0.943**	**3.667**
SCBA	**0.803**	**3.953**
TT	**0.849**	**4.189**
BI	**0.787**	**4.250**

5.4.Causal Relationship by Structural Model

A cause-effect relationship of the model was undertaken using structural equation modeling (SEM) through LISREL with maximum likelihood estimation. Actually, SEM enables analysis of interrelated hierarchical constructs (both first degree and second degree) with dependent variables in a single frame by simultaneously modeling relationships among the constructs. Based on the refined and finalized six first-degree constructs and five second-degree constructs with their respective scale items, and two dependent constructs with nine measuring-scale items, a cause-effect relationship was examined and evaluated through the structural model. Fundamentally, the syntax of this structural model was arranged following the relations proposed in the hypotheses. After several iterations, it was found that the model fitness parameters suggested in SEM literature (Chau, 1997; Kline, 2010), such as root mean square error of approximation (RMSEA) (0.110), Chi-Square (85.75), P-value (0.00002), and other fitness indices, such as, goodness of fit index (GFI), adjusted goodness of fit index (AGFI), normed fit index (NFI), incremental fit index (IFI), relative fit index (RFI), and comparative fit index (CFI), did not fit well.

Based on the analysis of the structural model in light of cause-effect relations, two hypotheses with TT and two hypotheses with BI were found to be significant at the 0.05 level. It was found that PAC and ECSI had a potential contribution to develop trust in users' perception, even at the 0.01 level. However, TUR and PBA failed to contribute adequately in the formation of TT to be significant, even at the 0.10 level. Thus, the hypotheses related to these constructs were not accepted. Both TT and SCBA have significant contributions to developing behavioral intention.

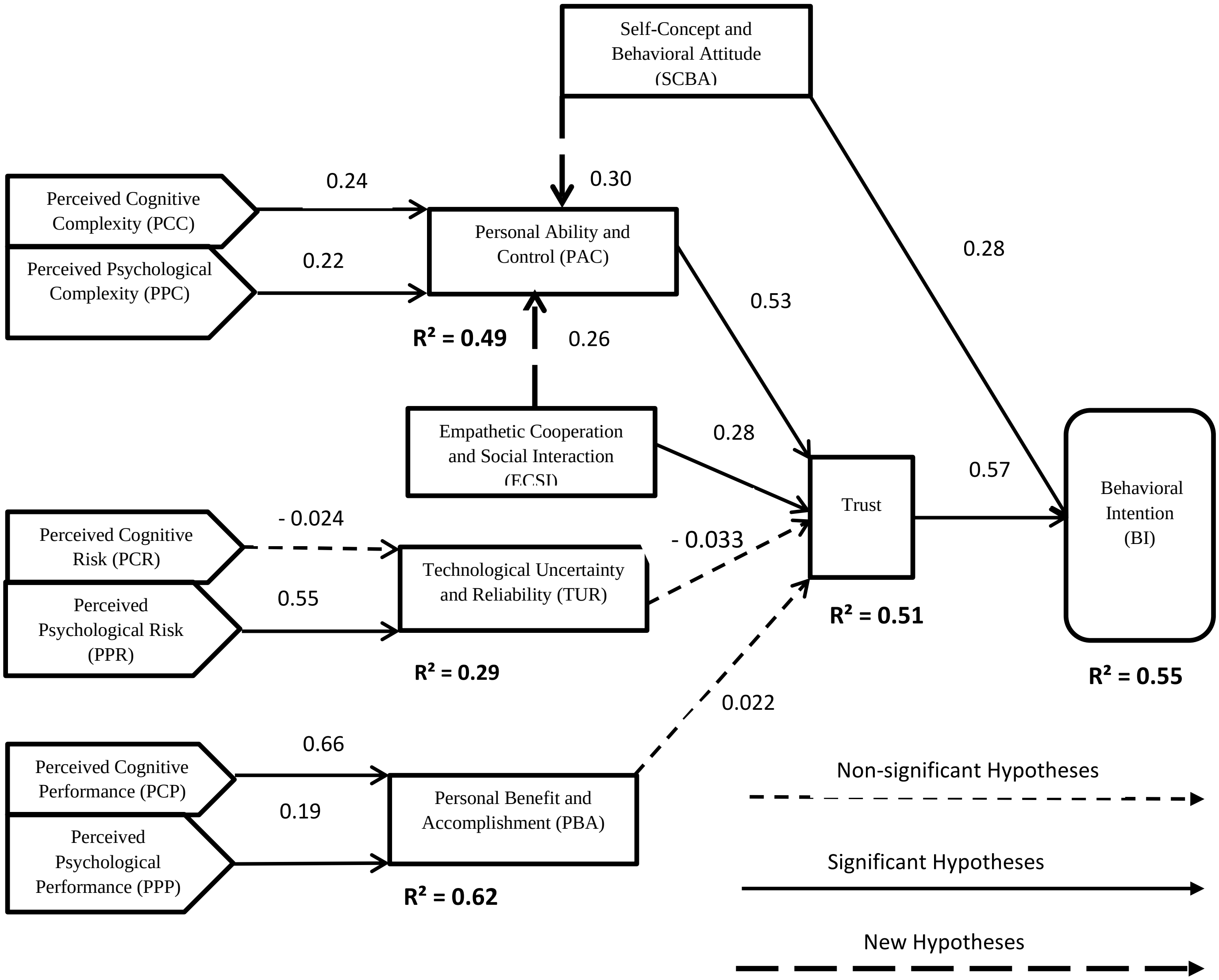

Fig. 2. Autonomous trust model (ATM) for adopting an autonomous homecare system

For better model fitness, two new relations among the independent constructs were suggested where it was indicated SCBA and ECSI have cause-effect relations with PAC. This means that these two variables are expected to contribute to developing the perception of control amongst the elderly about the use of an automation system. Correlation coefficients between the constructs PAC and SCBA (0.525) and between PAC and ECSI (0.532) were checked and theoretical justification was also verified (see Discussion and Result Interpretation). After inclusion of the two new relations, as suggested by the analysis, the model was run again.

At this stage, the structural model showed acceptable fitness with the data as per the literature (Chau, 1997). The "t" values of all the cause-effect relations were verified as per 0.05 significance level. The final accepted model (ATM) with loading values is shown in Figure 2.

The final model fitness indices that inhibit accepted values are shown against the literature in Table 5. RMSEA value is a little bit on the higher side, but any value below 0.10 is acceptable for RMSEA (Chau, 1997; Chen, Curran, Bollen, Kirby, & Paxton, 2008; Kline, 2010; Hair et al., 2013; Hoyle 2011; Hu & Bentler, 1999). The p value is very close to fit. However, a $\chi 2$/degree of freedom (df) is sufficiently acceptable.

Table 5

Model fitness and recommended values for ATM

Fit Measures	Recommended Values	Validated Model
Chi-square (χ^2)	P≥0.05	63.35(0.053)
Degrees of Freedom		36
χ^2/Degree of freedom (df)	≤3.00	1.7597
RMSEA	<0.06	0.086
Normed Fit Index (NFI)	≥0.90	0.91
Goodness of Fit Index (GFI)	≥ 0.90	0.92
Adjusted Goodness of Fit Index (AGFI)	≥ 0.80	0.81
Relative Fit Index (RFI)	≥ 0.80	0.81
Incremental Fit Index (IFI)	≥ 0.90	0.96
Comparative Fit Index (CFI)	≥ 0.90	0.95

6. Discussion

From a SEM analysis, the observed squared multiple correlation coefficient (R^2) explains the amount of variance that the independent constructs contribute to developing the conceptual significance of the dependent construct. From our ATM model (Figure 2), PAC and ECSI explain 51% variance of the dependent construct as per the conceptual definition of TT measured by the scale items shown in Appendix A. Therefore, these two significant constructs contribute significantly in developing elderly people's trust in an autonomous system. The analysis also revealed that TUR and PBA do not make a significant contribution in encouraging trust in elderly people towards machines as an autonomous homecare system. Again, in comparison to ECSI, PAC makes a greater contribution in forming trust. It accounts for 0.53 as the standardized loading value. The significance of this value is that a unit change on perception of PAC can cause a 0.53 unit positive change on perceptual beliefs of trust in an autonomous system if the contribution of ECSI remains constant.

This result clearly demonstrates that for elderly people, the main issues for developing trust in an autonomous homecare system as an alternative to human support are the ability to use the system and feelings of empathetic interaction with the system. If they believe that they can control autonomous homecare support and can find some empathetic social interaction with artificial machine intelligence, they have a potential psychological motivation and cognitive heuristic attitude to generate trust in the system. At that initial stage, they do not care about risk or probable uncertain behavior of a technology governed by ambient intelligence, or a belief in personal benefit and accomplishment. In terms of general psychological and cognitive behavior, elderly and disabled people are more dependent on personal ability for using modern technology and are more eager to be attached to those people and things that demonstrate a caring behavior in their lonely life, something comprehensively supported by a technology adoption model (Davis, 1989), social learning theory (Bandura, 1986), a GAM model (Shareef et al., 2011), and adoption of mobile health (Dwivedi et al., 2016). Eagerness for empathy is also supported by many marketing and psychological studies (Bagozzi, 2007; Gefen et al., 2003; Jarvenpaa, Tractinsky, & Vitale, 2000; McAllister, 1995). From an analysis of the ATM model, we postulated two more relations that contribute to developing a belief in personal ability and control of machine technology. Individual characteristics and personality and caring feelings of machines can promote a perception of personal control and ability to use the system. These two facets are also supported by UTAUT (Venkatesh et al., 2012), Dwivedi et al. (2016) and psychological theory (Bandura, 1986; Burger & Cooper, 1979; Heider, 1958). When elderly people perceive their own detachment from society, their belief of self-control is substantially governed by their personality and feelings of benevolence (Gefen et al., 2003; McAllister, 1995; McKnight et al., 2002).

From our ATM model (Figure 2), the constructs TT and SCBA, as hypothesized, show potential contribution for developing BI, as per the conceptual definition measured by the scale items of behavioral intention (see Appendix A) to use an autonomous homecare system controlled by ambient intelligence. These two significant constructs contribute significantly in developing elderly people's intention for acceptance in using autonomous system. Again, compared to individual personality, general trust contributes more to encouraging use. It accounts for 0.57 as the standardized loading value; contribution of SCBA is 0.28.

Therefore, trust is the dominant factor for elderly and disabled people as to whether to accept an autonomous homecare system managed by ambient technology. Because such systems for elderly and disabled people are an emerging possibility, even if they are still not familiar with this alternative to human support, they are profoundly guided by a need to trust an apparently uncommon system. Trust literature has ample evidence that accepting any social system is substantially dependent on the possibility of developing perception of trust in a system (Hancock et al., 2011; Körber et al., 2018; McAllister, 1995; Satterfield et al., 2017; Schaefer et al., 2016). Several behavioral studies have theoretical support about this contribution of trust in developing behavioral intention (Gefen et al., 2003; Jarvenpaa et al., 2000; McKnight et al., 2002; Schaefer et al., 2016). Psychological theory like social learning (Bandura, 1986) also supports this finding. Nevertheless, personal characteristics and self-concept also have an impact on whether to pursue this intention (Dwivedi et al., 2016; Mishra & Morrissey, 1990; Shareef et al., 2019).

As expected and hypothesized, perception of PBA through adoption of an autonomous homecare system governed by ambient intelligence is impacted by both psychological and cognitive feelings. Consequently, both PCP and PPP contribute to forming a belief in personal gain by using ambient technology instead of traditional human support and nursing. Similarly, from our proposed hypotheses, PCC and PPC—that is, both logical and emotional feelings about the beliefs of complexity of homecare autonomous system operated by ambient intelligence—have almost equal contribution to forming perceptions of PAC in the uncommon and unfamiliar system replacing human support.

However, findings from the analysis show that developing beliefs of TUR concerning a new ambient intelligence-driven autonomous system is streamlined only by PPR. Rational analysis about ambient intelligence does not provide any impact of PCR on developing belief of uncertainty about an autonomous homecare system. Hence, this hypothetical relation is insignificant. Shedding light on recent studies about ambient technology and autonomous systems (Bloss, 2011; Broekens et al., 2009; Clifford & Clifton, 2012; Clifton et al., 2012), it can be inferred that the elderly and disabled have been accumulating enough knowledge for many years about this new trend of using intelligent technology that can be employed without human support. Rhetorically, they understand that concern about the unreliability of ambient intelligence does not have any justified reference (Hancock et al., 2011; Körber et al., 2018; Satterfield et al., 2017). It is a purely psychological phenomenon that is due to unfamiliarity with the application of autonomous systems and longstanding expectations of receiving human support in old age (Rashidi & Mihailidis, 2013; Schaefer et al., 2016). Consequently, there is no justified sense of risk about autonomous systems, and so PCR makes no potential contribution to forming a belief of reliability and uncertainty about intelligent machine systems. A summary of the hypotheses is presented in Table 6.

Table 6

Summary of results

Hypothesis	Status
H_1: Personal ability and control (PAC) of users has an impact on developing trust (TT) in an autonomous system.	Significant
H_{1a}: Perceived cognitive complexity (PCC) of users has an impact on developing personal ability and control (PAC) of an autonomous system.	Significant
H_{1b}: Perceived psychological complexity (PPC) of users has an impact on developing personal ability and control (PAC) of an autonomous system.	Significant
H_2: Perception of technological uncertainty and reliability (TUR) has an impact on developing trust (TT) in an autonomous system.	Not significant
H_{2a}: Perceived cognitive risk (PCR) of users has an impact on developing perception of technological uncertainty and reliability (TUR) of an autonomous system.	Not significant
H_{2b}: Perceived psychological risk (PPR) of users has an impact on developing perception of technological uncertainty and reliability (TUR) of an autonomous system.	Significant
H_3: Personal benefit and accomplishment (PBA) of users has an impact on developing trust (TT) in an autonomous system.	Not significant
H_{3a}: Perceived cognitive performance (PCP) of users has an impact on developing personal benefit and accomplishment (PBA) from an autonomous system.	Significant
H_{3b}: Perceived psychological performance (PPP) of users has an impact on developing personal benefit and accomplishment (PBA) from an autonomous system.	Significant
H_4: Perception of empathetic cooperation and social interaction (ECSI) has an impact on developing trust (TT) in an autonomous system.	Significant

H_5: Self-concept and behavioral attitude (SCBA) of users has a direct impact on behavioral intention (BI) toward an autonomous system.	Significant
H_6: Trust (TT) of users has a direct impact on behavioral intention (BI) toward an autonomous system.	Significant

6.1.Theoretical and Managerial Implications

These findings provide clear direction for academics working on elderly people's behavior toward autonomous technology. We conclude that an autonomous homecare system driven by ambient intelligence can be logically explained by the trust disposition model, ATM. This is a very parsimonious model that can reflect two important issues to be met to generate trust among elderly people. Elderly people must have control on using any system in the absence of human support while maintaining a more solitary life in a retirement house home. The system must be easy to learn and operate. It should also be designed in such a way that can create and impart social feelings. It should develop psychological benevolence and a certain level of attachment and social interaction.

While accepting modern technology and machine intelligence as an alternative system, many studies (Bloss, 2011; Broekens et al., 2009; Clifford & Clifton, 2012; Clifton et al., 2012; Rashidi & Mihailidis, 2013) have confirmed that users typically search for the relative benefits from a new system. Users also perceive a certain level of risk in adopting a new technology that encourages them to avoid any virtual environment. These conceptual paradigms, traditionally accepted by academics, are also supported by many technology adoption-related theories (Bagozzi, 2007). However, academics should understand that advancement and application of modern technology and ambient intelligence has been underway for many years, and now all people, including the elderly, are quite familiar with the application of ambient intelligence in their daily life. Pragmatically and heuristically, benefits and risks of using modern technology are well evaluated, determined, and established. These overarching issues are explained in multiple research studies (Hancock et al., 2011; Körber et al., 2018; McAllister, 1995; Satterfield et al., 2017). Consequently, when generating trust of autonomous homecare systems driven by ambient intelligence, risk and benefits are not the key issue for elderly people. This identification clearly provides a new stream of research for academics.

For practitioners, this study has several interesting findings. Nowadays, many companies across the world are engaged in designing different kinds of autonomous homecare systems driven by ambient intelligence, such as a robotic dog called AIBO and autonomous vacuum cleaners and lawnmowers. Assistive healthcare systems and products are included under these autonomous homecare systems. This assistive social support has created a new area of marketing for autonomous systems to provide healthcare and social services to elderly and disabled people. Software designers, information technology experts, marketing managers, and government policy makers are expecting to solve this problem through autonomous systems that can smartly and intelligently provide all required supports.

This study and its findings can provide specific guidelines to designers and marketing managers of autonomous homecare systems. Designers should understand that elderly people are happy and willing to accept autonomous homecare systems, replacing the use of human support in old age. However, designers must address two essential aspects. For self-service, users must have full control of the system. They must know how to operate and derive benefits from these products. That means that utilization capability is the most important criterion for elderly and disabled people to develop necessary trust. Fundamentally, this trust is the primary and essential issue for accepting these systems over ever more costly and scarce human support.

However, the need for benevolence and social attachment can never be denied or ignored when considering elderly people who gradually become detached from family orientation and relocate to retirement housing. An autonomous homecare system is meant to be operated without active human support. However, a major and substantial difference between machine intelligence and human service providers is that living human beings can create a scope of social interaction and feelings of attachment and affection toward the elderly. Traditionally, it is believed, machine intelligence cannot develop affection and benevolence or create a scope of social attachment and interaction. That is a serious challenge for designers and marketers of autonomous homecare systems driven by ambient intelligence. A need for feeling and caring, and a sense of belongingness and social attachment amidst a lonely life are vital criteria (Burger & Cooper, 1979), particularly for elderly people who are gradually becoming detached from traditional family routines and social life. Therefore, ambient intelligence must ensure that this ubiquitous psychological need is not abandoned in order for users to perceive these systems as trustworthy.

Present condition of Covid-19 pandemic where social isolation is a potential issue, practitioners must think designing an effective system of autonomous healthcare. For getting continuous assistive social support, application of this ambient intelligence is almost mandatory for the elderly people at this new era. However, since trust is a potential factor for acceptance of autonomous system, the findings of this research can provide deep knowledge to the practitioners while designing an effective system. Since trust is a very complicated issue (Gefen et al., 2003), both psychological status and thinking process of elderly people should be integrated and focused while designing an acceptable system to support daily routine life.

This is both an interesting and challenging issue for practitioners. Nevertheless, this attribute must be incorporated into the design of autonomous homecare systems. Elderly people become physically and mentally detached at a certain age, yet we cannot deny dependency on healthcare support from family members and professional agencies. However, their urge for independence, self-actualization, and social esteem related to maintaining their previous standard of life is significant. The elderly, due to disabilities, require a certain level of specialized services, including:

- Emergency physical support
- Regular physical support
- Internal and personal autonomy enhancement support (self-esteem)
- Social interactive support (social esteem and relatedness)
- Internal affective support (detachment and depression)
- Special comfort support

Practitioners and academics must understand these issues and provide proper prioritization when conducting future research, and design an ambient intelligence as a strong and prolific alternative of human interaction.

6.2.Limitation and Future Research Direction

This is an especially new kind of research. It is an exploration of the application of ambient intelligence as an alternative source of human service. As a result, it contains some limitations. It should be conducted among many elderly people with different requirements, as well as different levels and magnitudes of service, so that a generalized concept can be confirmed.

This study was conducted only in Canada. Due to differences in service and support, the perceptions and expectations of elderly people in other countries might be different. Culture might have a compounding impact on this kind of social and family product that can displace the traditional concept of service providers (Doney, Cannon, & Mullen, 1998). Future researchers might investigate elderly people's trustworthiness by collecting data from countries with a different cultural background.

Because different kinds of autonomous homecare systems having different degrees of ambient intelligence, this trustworthiness model (ATM) might be affected. This research did not categorize the autonomous homecare system, and so future researchers might also investigate categorized homecare autonomous systems and identify this ATM model for a specific type of autonomous homecare product. Cultural attributes can be an issue for trustworthiness. Future researchers should consider this issue. Future studies could also consider the effect of various moderators such as personality characteristics and the level of previous experience of using the technology.

7. Conclusion

Elderly people gradually become physically and mentally detached, and more dependent on healthcare support from family members and professional agencies. Yet most maintain a desire for some level of independence (Acampora et al., 2013; Heerink et al., 2010; Nehmer et al., 2006).

To understand the requirements of autonomous support, this study argues that all unknown modern technological systems, particularly those for elderly people who are not familiar and traditionally reliant on family support, developing trust can be a potential hurdle for accepting an autonomous homecare system (Hancock et al., 2011; Körber et al., 2018; Schaefer et al., 2016). However, behavioral patterns greatly influenced by trust vary significantly for any new technology as a social system, especially on matters like personal image, self-concept, and personality (Dwivedi et al., 2016; Jarvenpaa et al., 2000; Mishra & Morrissey, 1990). To resolve these issues and postulate a comprehensive model of elderly and disabled people's predisposition to accepting ambient technology as a replacement for human support, this current study set its twofold objectives to reveal the factors that contribute to generating trust in an autonomous system controlled by ambient intelligence. Secondly, this study attempted to reveal how trust and personal characteristics can encourage intent for adopting an autonomous system.

To resolve these objectives, this study identified 23 preliminary measuring items of six first-order constructs: PCC, PPC, PCR, PPR, PCP, and PPP. It further identified 28 measuring items of five second-degree constructs (four with behavioral intent through trust and one directly with behavioral intent): PAC, TUR, PBA, ECSI, and SCBA. After relating the study's hypotheses, it proposed a comprehensive trust disposition model (Figure 1).

To investigate and understand the proposed relations, the authors designed an experiment and extensive empirical study among elderly and disabled people in retirement homes and rehabilitation centers in Ontario, Canada. After collecting data, SEM was conducted to verify the reliability and validity of collected data and cause-effect relationships. Out of four direct relationships assumed to contribute to developing trust, the analysis identified that PAC and ECSI have a significant relationship. Bisecting this finding, we streamlined our concept, positing that for elderly people to trust and accept an autonomous homecare system governed by ambient intelligence, they must believe that they can both operate it and perceive social interactivity from it.

At the same time, this study has identified some potential factors that do not have any impact on trust development. Previous literature has claimed that uncertainty is an important issue for whether users will trust any technological innovation (Broadbent et al, 2009; Kachouie et al., 2014; Rijsdijk et al., 2007). Users experience both cognitive and psychological risks from using any ambient intelligence when human support is absent. Behavioral and technology adoption researchers (Bagozzi, 2007; Davis, 1989; Dwivedi et al., 2016; Fishbein & Ajzen, 1975; Moore & Benbasat, 1991; Rogers, 2003; Shareef et al., 2011; Thompson et al., 1991) have postulated that users traditionally seek comparative advantage when adopting any new technological system that replaces human support. This return of investment can reflect both cognitive and psychological benefit. However, findings of this research clearly deny that these issues have any potential impact on developing elderly people's trust in an autonomous system that replaces traditional behavior.

This identification can be argued under the implied conceptual direction of social learning theory (Bandura, 1986). For the past few decades, diffusion of technology has accelerated and its application has increased among all groups of people (Broekens et al., 2009; Clifton et al., 2012). Conscious users, including elderly and disabled people, have become familiar and comfortable with the extensive application of intelligent machines (Bloss, 2011; Broekens et al., 2009; Rashidi & Mihailidis, 2013). Through societal and individual experience, elderly people heuristically understand that scarcity of human medical support at the micro level, particularly in retirement homes, is significant and will gradually become obsolete in future, or at least be very costly (Clifford & Clifton, 2012; Clifton et al., 2012; Nehmer et al., 2006; Such, 2017; Summary Report, 2015). This cognitive and psychological realization will have a severe impact on their mental development. When the elderly are provided with an autonomous homecare system as an alternative to human support, they strongly require, at minimum, two essential attributes from that system. These are: they must have the ability to control and use the system, and they must derive some level of empathetic caring and social interaction from the system. If these two essential needs are fulfilled, they are more inclined to find intrinsic motivation to develop trust in using these autonomous homecare systems. This situational understanding is supported by a psychological phenomenon reflected by attribution theory (Gordon & Graham, 2006; Heider, 1958). Eagerness to perceive a certain level of social interaction and attachment with affection are core human traits supported by psychological drive theory (Seward, 1956).

However, in this context, it is noteworthy to remark that individual personality—personal characteristics, motives, and self-concept—is also an important factor for influencing behavioral intent. Employing self-perception theory (Bem, 1972), it is suggested that personal speculation ultimately dictates behavior. This finding has strong support from existing literature and theories related to behavior (Shettleworth, 2010; Wang & Wu, 2008), cognitive (Moskowitz, 2005; Shareef et al., 2011) and psychological trends (Bandura, 198; Hughes, 2011) for the acceptance of any ambient technology.

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APPENDIX A

Scale Items with standardized **Factor Loading from CFA for Independent and Dependent Variables**

Item	Loading value
Perceived Cognitive Complexity (PCC)	
PCC1: I know I can operate this type of autonomous system	0.90
PCC2: I know from my knowledge that this is easy for me to accomplish my tasks by autonomous system	0.91
PCC3: I have ability to manage and control autonomous system to seek service as I require	0.78
PCC4: I have knowledge to use this autonomous system to fulfill my desired tasks	0.85
Perceived Psychological Complexity (PPC)	

Item	Loading value
PPC1:I have feelings that I can operate this type of autonomous system	**0.84**
PPC2: I have feelings that this is easy for me to accomplish my tasks by autonomous system	**0.82**
PPC3: I have mental strength to manage and control autonomous system to seek service as I require	**0.89**
PPC4: I have knowledge to use this autonomous system to fulfill my desired tasks **(DROPPED)**	**0.33**
Personal Ability and Control (PAC)	
PAC1: Learning how to use autonomous system is easy for me.	0.83
PAC2: I think I have ability to control autonomous system to accomplish my daily tasks	0.85
PAC3: I find seeking service from autonomous system to accomplish my daily tasks easy for me.	0.88
PAC4: It is easy for me to become skillful at seeking, receiving, and interacting with autonomous system **(DROPPED)**	0.18
PAC5: Handling autonomous system to accomplish my daily tasks should not be a problem for me	0.75
PAC6: I feel it is possible for me to accomplish my daily tasks through autonomous system instead of human assistance	0.88
Perceived Cognitive Performance (PCP)	
PCP1: I can seek autonomous system anytime to accomplish my daily tasks.	0.87
PCP2: I can get more time to do my daily tasks using autonomous system.	0.94
PCP3: Autonomous system can save my time for continuous use.	0.77
PCP4: Using autonomous system provides me good value for the money.	0.89
Perceived Psychological Performance (PPP)	
PPP1: I feel autonomous system more helpful to accomplish my daily tasks.	0.87
PPP2: Using autonomous system provides me feelings of more benefits for the money.	0.90

Item	Loading value
PPP3: I feel convenience using autonomous system to accomplish my daily tasks.	0.91
Personal Benefit and Accomplishment (PBA)	
PBA1: I find autonomous system useful in my daily life.	0.89
PBA2: Using autonomous system provides me more scopes to accomplish my daily. **(Dropped)**	0.46
PBA3: Using autonomous system helps me accomplish my daily tasks more quickly.	0.94
PBA4: Using autonomous system is more convenient to accomplish my daily tasks	0.91
PBA5: Using autonomous system increases my performance.	0.91
Empathetic Cooperation and Social Interaction (ECSI)	
ECSI1: Using autonomous system is fun.	0.78
ECSI2: Using autonomous system is enjoyable.	0.52
ECSI3: Using autonomous system cannot decrease my scope to be attached with society.	0.88
ECSI4: Using autonomous system cannot decrease my scope to interact socially.	0.82
ECSI5: Service of autonomous system gives me feelings of caring **(DROPPED)**	0.35
ECSI6: I find good feelings while seeking service from autonomous system to accomplish my daily tasks	0.89
ECSI7: Company of autonomous system while accomplishing my daily tasks is entertaining	0.91
Perceived Cognitive Risk (PCR)	
PCR1: I know from my knowledge that service provided by autonomous system to accomplish my daily task is accurate.	0.76
PCR2:I know from my knowledge that interaction with autonomous system to accomplish my daily tasks is clear	0.64
PCR3: I know from my knowledge that outcome from the interaction with autonomous system to accomplish my daily tasks is not uncertain due to the absence of direct personnel.	0.89
PCR4: I know from my knowledge that technology used to operate	0.73

Item	Loading value
autonomous system is reliable	
Perceived Psychological Risk (PPR)	
PPR1: I have feelings that service provided by autonomous system to accomplish my daily task is accurate.	0.90
PPR2: I have feelings that technology used to operate autonomous system is reliable	0.89
PPR3: I have feelings that interaction with autonomous system to accomplish my daily tasks is clear **(DROPPED)**	0.36
PPR4: I have feelings that outcome from the interaction with autonomous system to accomplish my daily tasks is not uncertain due to the absence of direct personnel.	0.82
Technological Uncertainty and Reliability (TUR)	
TUR1: I believe service provided by autonomous system to accomplish my daily task is accurate.	0.89
TUR2: I believe interaction with autonomous system to accomplish my daily tasks is clear**.**	0.75
TUR3: I believe technology used to operate autonomous system is reliable.	0.91
TUR4: I can get reliable assistance from autonomous system to accomplish my daily tasks when I have difficulties.	0.92
TUR5: I believe outcome from the interaction with autonomous system to accomplish my daily tasks is not uncertain due to the absence of direct personnel.	0.91
Self-Concept and Behavioral Attitude (SCBA)	
SCBA1: I like autonomous system to accomplish my daily tasks. (**DROPPED)**	0.36
SCBA2: I prefer autonomous system to accomplish my daily tasks.	0.85
SCBA3: I have interest for technology governed autonomous system to accomplish my daily tasks.	0.81
SCBA4: My personal behavior is congruent with the characteristics of autonomous system.	0.75
SCBA5: Autonomous system fits well with the way that I like to accomplish my daily tasks	0.52
Trust (TT)	

Item	Loading value
TT1: I have general faith on autonomous system engaged for me to provide service.	0.68
TT2: I have general faith that autonomous system is overall reliable.	0.80
TT3: I have general faith that service of autonomous system is overall reliable.	0.74
TT4: What I do through this autonomous system controlled by ambient intelligence is guaranteed.	0.68
TT5: I have general faith that autonomous system is safe to interact to accomplish my daily tasks.	0.73
Behavioral Intention (BI)	
BI1. I like to use autonomous system.	0.70
BI2. I intend to use autonomous system in future.	0.70
BI3. I will always try to use autonomous.	0.71
BI4. I plan to inform my friends and relatives to use autonomous system.	0.66