Machine Autonomy for Rehabilitation of Elderly People: A Trade-off between Machine Intelligence and Consumer Trust

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Abstract

This is an exploratory study with the objective to understand elderly people's expected behavior to accept and use machine autonomy controlled by ambient intelligence. It was conducted on a proposed theoretical framework, the expected trust model for machine autonomy (ETM4MA). A detailed survey was collected among elderly people living at home with their family members in a developing country, Bangladesh. Based on the results obtained from structural equation modeling (SEM) on the sample, it was observed that elderly people's acceptance of automation systems driven by ambient intelligence as a substitute for caregiving support directly from human beings was linked to their concerns about emotional belongingness and social interaction as well as their ability to use the technology. Thus, in developing trust in this machine autonomy, their expectations around personal ability and the feeling of caring are two important issues for elderly people. To form the behavioral intention to accept this machine autonomy, trust plays a crucial role; however, this might vary depending on the differences in personality and behavioral attitude.

Keywords: Automation, human behavior, trust, machine autonomy, human psychology, elderly people

1. Introduction

The rehabilitation of elderly people, including their daily routine and healthcare activities, is experiencing some trends and changes throughout the world and thus facing new challenges recently (Shareef et al., 2021a). Researchers working on issues related to elderly people, including their support to perform daily routine activities, have recognized the significant and steady increase of elderly people in all countries, particularly in the developed countries. For instance, globally, at present, there is one older adult (age 65 and above) in every 11 persons, and this is higher in the developed countries. In Europe and North America, this ratio will be one in every four persons by 2050 (Unifor, 2020). On the other hand, human resources for overall homecare support services, including healthcare, are becoming scarce and costly (Shareef et al., 2021b). This alarming situation is only going to worsen, as clearly indicated during the pandemic outbreak in 2020 (Borges et al., 2021; Dwivedi et al., 2021).

However, modern technology driven by ambient intelligence is showing future hope by providing an effective alternative, termed the automation system in this study. Automation systems, such as smart home devices (Mejia & Kajikawa, 2017; Shareef et al., 2021a), are modern technologies controlled by ambient intelligence that can assist in providing personal services that were previously supplied by human beings directly (Edwards et al., 2019; Kachouie et al., 2014; Pullig et al., 2002). There are many types of automation systems that can provide different levels of support to elderly people in their daily life activities and healthcare tasks, such as automated vehicles, automated vacuum cleaners, washing machines, alarm clocks, robots, etc.

Elderly people are typically partially or completely dependent on external support services provided by either family members or professional workers. They need support and assistance from external people to manage their daily life tasks and medical requirements (Di Vaio et al., 2020; Körber et al., 2018). Researchers working on ambient intelligence and automation systems (Bloss, 2011; Caselli et al., 2021; Hancock et al., 2011) have postulated that different kinds of automation, allowing for different degrees of autonomy, can be an excellent alternative in providing homecare support to elderly people. Since this support is currently being provided by a limited supply of support workers, automated service can reduce the cost and effort of providing homecare services. In addition, particularly in the developing countries where providing human support is still fairly inexpensive and in which the family traditionally assumes the responsibility to support elderly family members in their daily life activities and healthcare needs, family members are increasingly seeking better social and economic status in the job market and are thus unable to provide elderly support to the same extent as before (Garza, 2012; Körber et al., 2018). Therefore, a severe scarcity is currently arising around the provision of this support. Several researchers with expertise in analyzing health services and family structure (Dwivedi et al., 2016; Shareef et al., 2021b) predict that the majority of elderly people in the near future will not receive adequate homecare support from family members or external sources due to the changing pattern of economic status and the inadequacy of resources.

Software experts and marketing companies dealing with advanced technology and automation systems controlled by ambient intelligence are designing and offering many types of automation systems that can meet the requirements of elderly people having difficulties performing daily routine tasks and obtaining adequate healthcare support (Anderson & Perrin, 2017). However, there are several serious challenges and barriers to introducing these systems into the lives of elderly people who are habituated to receiving their required services from internal family members or external workers (Neves et al., 2019). Several scholarly articles (Anderson & Perrin, 2017; Körber et al., 2018) have reported on the extensive empirical studies conducted on the adoption behavior of elderly people to obtain daily routine and healthcare assistance from machine-driven automation systems in lieu of traditional human assistance and have identified that elderly people present considerable resistance in this regard. Elderly people are apparently not ready to replace traditional human support with machine autonomy. The question this paper addresses is why. What are the reasons behind this powerful resistance on the part of elderly people to accepting automated assistance?

The recent research on technology, homecare support, and consumer behavior has been mostly engaged in studying technology adoption behavior in the light of performance expectancy, effort expectancy, and convenience (Chen et al., 2021; de Visser et al., 2020; Dwivedi et al., 2016; Han & Timmermans, 2022; Pillai et al., 2020; Shareef et al., 2011). These studies have focused on general technology adoption behavior (Shareef et al., 2021b). However, in analyzing human psychology (de Visser et al., 2020; Körber et al., 2018; Schaefer et al., 2016) and the emotional patterns of elderly people (Lewis et al., 2018), researchers have agreed that the resistance of elderly people to accept machine autonomy cannot be explained merely in terms of technology adoption behavior and thus cannot be understood by analyzing only the cognitive aspect of their ability to adapt (Ferguson et al., 2019; Pal et al., 2018). Importantly, the psychological resistance of elderly people in adopting machine autonomy is deeply rooted in their lack of trust in the reliability of modern technology to meet their unique needs (Satterfield et al., 2017). Heuristically speaking, in proposing an automation system to replace traditional human support to meet the daily support and healthcare needs of elderly people, a comprehensive review and analysis are essential to predict elderly people’s behavior to adopt such an automation system. Since machine autonomy substitutes for human interaction in providing these services, the behavioral intention of elderly people to adopt such technology is influenced by their thinking and perceptions regarding the uncertainty of machines and their psychological feelings around the loss of empathy (Shareef et al., 2021b). In considering the factors of human psychology reflected in the attachment theory (Hazan & Shaver, 1994) and the logical thinking reflected in the UTAUT2 model (Venkatesh et al., 2012) and mobile health adoption behavior (Dwivedi et al., 2016), this argument is justified. Bandura's social learning theory (1986) also provides justification for this argument.

Resistance to accepting different kinds of machine autonomy to assist in daily life, including healthcare, depends on many behavioral factors (Dwivedi et al., 2021; Pal et al., 2018; Shareef et al., 2021b; Sipior, 2020). At the same time, there are several practical reasons that can serve as encouragement for elderly people to accept machine autonomy. This study will first identify the emotional and cognitive factors that can create resistance to the behavioral intention to adopt machine autonomy. Then, based on this finding, it will propose a theoretical framework to understand elderly people's behavioral intention to adopt machine autonomy. The explicit focus of this study is to understand the factors that influence elderly people to use different kinds of autonomous systems to assist in their daily routine activities, including healthcare tasks, and thus support their rehabilitation. The research addresses the following objectives, the meeting of which can contribute toward the implementation of machine autonomy as homecare support for elderly people:

1. Identify the factors behind elderly people's resistance to accepting machine autonomy.

2. Propose an integrated theoretical framework to predict the adoption behavior of elderly people to accept machine autonomy.

This study is extremely important for both the developed and developing countries, as the resources directed at providing homecare and healthcare services to elderly people are becoming alarmingly scarce, and thus an effective, more cost-effective alternative is needed. However, without an understanding of the overall acceptance behavior of elderly people, such efforts will not be effective and successful. Therefore, this study has the potential to contribute substantially to the marketing, technology, and human behavior research around this issue.

Researchers in the cultural diversity field have revealed that the adoption behavior of people in the developed countries is significantly different from that of people in the developing countries (Baydoun & Willett, 1995; Dwivedi et al., 2021; Malhotra et al., 2005; Shareef et al., 2016b; Winkler et al., 2008). In analyzing the technology adoption patterns of many developed and developing countries, Nourbakhsh et al. (2012) concluded that, comparatively speaking, the developed countries are at an advanced stage in adopting new technology. Considering the attachment theory (Hazan & Shaver, 1994) in terms of the differences in emotional attachment and family bonding between elderly people of the developed and developing countries, it can be argued that in replacing traditional human support with machine autonomy, elderly people and their caregivers in the developing countries might exhibit a difference in attitude compared to the developed countries (Borges et al., 2021; Dwivedi et al., 2021; Na et al., 2023). The implementation of automation systems driven by ambient intelligence among elderly people in the developing countries is a crucial issue nowadays (Dwivedi et al., 2021; Pal et al., 2018; Sipior, 2020). Thus, understanding their adoption behavior through a theoretical framework is an important undertaking. In the developing countries, family members still feel the responsibility to support their elderly family members in executing their daily life activities and to provide healthcare support (Garza, 2012; Huda, 2022; Körber et al., 2018; Mazumder et al., 2020). Nevertheless, even in the developing countries where human support, particularly from female members, is still not very costly, people are increasingly turning away from the home to the job market, and consequently, a severe scarcity is developing around the provision of these services (Bilkis, 2020; Huda, 2022; Na et al., 2023; Sipior, 2020; Sowa et al., 2021). Researchers with expertise in machine autonomy working on family composition and work-life balance (Dwivedi et al., 2016; Huda, 2022; Shareef et al., 2021b) predict that due to the changing pattern of economic status and the inadequacy of healthcare resources, the majority of elderly people in the developing countries will not receive adequate support to perform their daily routine activities and meet their healthcare needs from family members or external sources. Therefore, research on the application of homecare autonomous systems as a cost-effective alternative for elderly care in the developing countries has significant value. Analyzing elderly people's behavioral intention to adopt machine autonomy in the developing countries can potentially contribute to the existing literature in this area (Adamuthe & Thampi, 2019; Behkami & Daim, 2012; Dwivedi et al., 2021; Erzurumlu & Pachamanova, 2020).

Nevertheless, most of the scholarly studies about elderly people's adoption behavior of machine autonomy have been conducted in the developed countries (Shareef et al., 2021b; Sipior, 2020; Sowa et al., 2021; Vlačić et al., 2021). In addition, in those studies, the elderly people studied were used to living in support care homes where they were already detached from their regular family members. According to attachment theory, the group dynamics of elderly people in such settings are quite different from those of elderly people who live with their regular family members. Therefore, there is a potential research gap in understanding the adoption behavior of elderly people who live with their family members in the developing countries. This study has the following differences from the previous studies in this general area:

1. It has been conducted in a developing country.
2. The study respondents are used to living with their family members.
3. The study respondents are used to performing all their daily routine activities, including meeting their healthcare needs, with the help of family members.
4. The theoretical framework attempts to capture the expectation of gaining family benefits (not only personal benefits) by using machine autonomy, which is a unique aspect.

Therefore, this study has significant scope to contribute to the existing literature on elderly people's adoption behavior of machine autonomy in their daily life and healthcare activities.

The next section reviews the literature on consumer behavior and ambient intelligence. The following section develops the theoretical framework of this research to understand elderly people's adoption behavior. The research design is then proposed, followed by the statistical analysis to reveal cause-effect relations. The subsequent section includes the findings and discussion, which is followed by the limitations of this study and suggestions for future research. The managerial and theoretical implications are stated in the next section, and then the conclusion is drawn.

3. Literature review

Over the last decade, the manufacturing and application of smart home appliances has been steadily growing (Yoon & Jang, 2012). Thus, a huge scope of opportunity is predicted for these ambient, intelligence-driven automation systems to be used in homecare support, including healthcare provision, particularly for elderly and disabled people (Di Vaio et al., 2021; Lu et al., 2019; Martinez-Martin et al., 2020; Pachidis et al., 2019). The population of elderly people is increasing rapidly in societies worldwide, leading to huge shortages and increasing costs of homecare resources. Consequently, in the near future, a significant number of the elderly will not receive standard homecare support to execute their daily tasks, including healthcare services to meet their urgent needs (Liu et al., 2021; Rantanen et al., 2017). A feasible solution to this problem is the extensive application of automation in modern homecare systems, which will also provide healthcare services to replace the services directly provided by human beings (Borges et al., 2021; Burström et al., 2021; Collins et al., 2021; Di Vaio et al., 2020; Duan et al., 2019; Dwivedi et al., 2016; Pal et al., 2018).

Among the many services that can be provided by machine autonomy controlled by ambient intelligence, smart home appliances are the main items of home automation that can assist elders to meet their needs automatically without seeking human support (Blue Frog Robotics, 2021; Cecchinato et al., 2015; Na et al., 2023). However, many behavioral psychologists and consumer behavior experts (Clifton et al., 2012; Dwivedi et al., 2016; Goraya et al., 2020; Kachouie et al., 2014; Micceri, 1989; Shettleworth, 2010; Shareef et al., 2011; Shareef et al., 2016a) are very skeptical about elderly people's willingness to break with their traditional values and habits in accepting ambient, intelligence-driven automation systems as substitutes for human support. These researchers believe that these non-human assistive caregivers, i.e., automation systems, will face severe compound resistance from elderly people if machine autonomy is used to replace direct human support (Shareef et al., 2018). This resistance will develop from both the cognitive and emotional attitudes of elderly people (Golant, 2017; Gonzálezet al., 2012; Na et al., 2023). Therefore, any attempt to implement automation systems in homecare support for elderly people will clash with the factors of traditional beliefs, abilities, reliability, expectations, values, habits, culture, and emotional psychology (Shareef et al., 2021a). Researchers from behavioral psychology and consumer behavior (Lu et al., 2019; Martinez-Martin et al., 2020; Pachidis et al., 2019; Pal et al., 2018; Rantanen et al., 2017; Sjödin et al., 2020) have revealed a serious concern associated with this resistant behavior, which is the elderly's perception of risks and lack of trust regarding the functionality of these automation systems controlled by ambient intelligence

(Schaefer et al., 2016; Na et al., 2023). Researchers on homecare appliances and ambient intelligence (Borges et al., 2021; Burström et al., 2021; Cecchinato et al., 2015; Collins et al., 2021; Di Vaio et al., 2020; Duan et al., 2019; Dwivedi et al., 2021; Loureiro et al., 2021; Na et al., 2023; Pal et al., 2018; Sipior, 2020; Sowa et al., 2021; Vlačić et al., 2021) have argued that the lack of confidence in automation systems is the prime reason for elderly people's resistance to using them in their daily lives, including to provide healthcare support. Other important concerns are the fear of losing personal control over their daily activities and losing personal bonding and interaction with family members or external workers (Adamuthe & Thampi, 2019; Behkami & Daim, 2012; Erzurumlu & Pachamanova, 2020; Phillips & Linstone, 2016; Zhu & Porter, 2002). To meet their relational and cognitive needs, elderly people require human interactions in their daily life (Shareef et al., 2021b). Therefore, they are understandably wary and dubious that machine autonomy can replace their needed interaction with other human beings (Dwivedi et al., 2021; Golant, 2017; Loureiro et al., 2021; Sipior, 2020; Sowa et al., 2021; Vlačić et al., 2021).

4. Theoretical framework

Since automated homecare systems naturally represent a non-human support, before describing the expectations of elderly people driving their acceptance or rejection of them, it is important first to address the psychological issues that can help to evaluate the formation of trust in elderly people toward such systems.

Researchers (Schneider & Kummert, 2021; Wicks et al., 1999; Zhang et al., 2021) have identified trust as faith in the predictability of one's expectations regarding any subject. However, trusting behavior is a very complex phenomenon for researchers to study and analyze (Mayer et al., 1995). The researchers working on technology adoption behavior using, for example, the technology acceptance model (TAM) (Davis, 1989), the diffusion of innovation theory (DOI) (Rogers, 1995), and the unified theory of acceptance and use of technology (UTAUT2) (Venkatesh et al., 2012) did not explore the issue of trust when analyzing consumers' behavior (Dwivedi et al., 2016). The automation systems' reliability, capabilities, and association with empathy and belonging are also not considered by most behavioral models, including the e-government adoption model (GAM) (Shareef et al., 2011) and the mobile health model (Dwivedi et al., 2016). Therefore, it is concluded that the existing behavioral models dealing with technology adoption are not sufficient to integrate trustworthiness with other behavioral issues related to technology adoption. To incorporate this aspect in researching the adoption of an automation homecare system for elderly people, Shareef et al. (2021b) conducted an extensive study in Canada and postulated a comprehensive model called the automation trust model (ATM).

This model was developed in order to understand the behavioral intentions of elderly people to adopt automation systems that replace human support in providing assistance in their daily routine activities, including healthcare. This study was conducted in a developed country, Canada. The respondents were elderly people used to living in care homes and being separated from their family members. The ATM model was developed under the theoretical paradigms of consumer behavior; however, both cognitive and psychological risks were considered in this model. Unlike the present study, the ATM model considered the personal benefits that elderly people expected from the application of autonomous systems.

The present study proposes the following rationales for using a similar model to the ATM as a theoretical framework (Figure 1), with some modifications based on the new context:

1. The ATM model (Shareef et al., 2021b) was developed using a sample of elderly people in Canada, which is a developed country. Several researchers (Adamuthe et al., 2019; Heerink et al., 2010; Kachouie et al., 2014) have argued that due to cultural diversity and variations, any behavioral model tested in both a developed country and a developing country can provide deep insights for comparing, contrasting, and generalizing adoption behavior. This study has chosen the revised version of the ATM model as a reference for constructing a theoretical framework in a developing country context, namely Bangladesh, with some adjustments. The number of elderly people is increasing rapidly in Bangladesh, where around 13 million people are aged over 60, which is equal to almost 8% of the country's total population (Bangladesh Statistics Bureau, 2022; Barikdar et al., 2016). Moreover, this ratio is increasing due to an increase in life expectancy. It is anticipated that the proportion of elderly people will double in the next 20 years.

As a result, the need for essential homecare support is growing quickly in Bangladesh (Bilkis, 2020; Mazumder et al., 2020).

2. Several researchers working on machine autonomy (Adamuthe et al., 2019; Schneider & Kummert, 2021) have recognized that the adoption behavior of elderly people toward automation systems as an alternative to daily homecare and healthcare services provided directly by internal family members and external workers, i.e., human support, may vary depending on the status of the elderly people, who are either living with family or in care homes isolated from the family. This means that the behavioral intention to adopt an automation system by elderly people living in care homes may vary from those who live with their own family. Social psychologists (Hazan & Shaver, 1994; Schaefer et al., 2016) have also argued that due to differences in family bonding, mental status, group dynamics, and belongingness, elderly people who live with their own family might show different attitudes from those who are already isolated and living in care homes in adopting automation systems that replace direct human support and services. In the previous study (Shareef et al., 2021b) conducted in Canada, all the elderly people were used to living in care homes and the disabled people in different rehabilitation centers. In contrast, this study investigates elderly people's trust and behavioral intention with regard to the adoption of automated services using a sample of elderly people living with their own families so that the differences in behavior, if any, can be captured. Therefore, this study has the potential to contribute to the existing literature by comparing and contrasting the behavior of elderly people living with their family or living separately in care homes. Thus, this study can provide deep knowledge to generalize the grounded theory that is explored based on the revised version of ATM model shown in Figure 1.

3. Considering cultural diversity, technology familiarity, experience in using machine autonomy, and family bonding, the constructs and scale items of the ATM model have been modified to capture the expectations of elderly people living in a developing country. Reviewing the literature on machine autonomy and elderly people in Bangladesh, it is evident that elderly people in Bangladesh have barely any practical experience in using machine autonomy in their daily life (Bangladesh Statistics Bureau, 2022; Barikdar et al., 2016; Bilkis, 2020; Mazumder et al., 2020). Therefore, for the elderly people living in Bangladesh, the intended aim of this study

is to capture expectations of the elderly people from the autonomous system. This is an explicit difference from the study conducted in Canada. As mentioned, most of the elderly people who participated in this study are living with their own families, not separately in care homes. Hence, the theoretical framework that was used in Canada was modified and adjusted according to the present study's social orientation. All the constructs and conceptual definitions were primarily taken from the ATM model; however, these were revised and edited to reflect the objective, content, and context of the present study. These revisions were done with the help of several other studies and a focus group comprised of three university professors (Appendix B).

Expected personal ability and control (EPAC)

Managing technology-driven systems controlled by ambient intelligence is a challenging issue for elderly people. They are not familiar enough with this kind of automation, and they also may have cognitive and emotional deficiencies in managing and controlling technology-driven systems (Such, 2017). As a result, their expected personal ability and control (EPAC) might be an important factor in terms of their developing the trust to use automation systems in their daily life (Shareef et al., 2021b). Several technology adoption models, for instance TAM, DOI, UTAUT2, GAM, and mobile health adoption (Dwivedi et al., 2016) have strongly supported the idea that belief in one's ability and control can help people to develop trust in technology-driven systems. However, this perception of the ability to control is significantly influenced by cognitive and psychological complexity (Broekens et al., 2009; Such, 2017). Thus, in connection with the ATM model, this study proposes the following hypotheses:

H_1: Expected personal ability and control (EPAC) helps elderly people to develop trust (TR) in machine autonomy.

H_{1a}: Expected cognitive complexity (ECC) of elderly people influences expected personal ability and control (EPAC) toward machine autonomy.

H_{1b}: Expected psychological complexity (EPC) of elderly people influences expected personal ability and control (EPAC) toward machine autonomy.

Expected technological uncertainty (ETU)

When adopting and using any technology-driven system, the risk of uncertainty and reliable functionality is always an important issue from a human standpoint (Gefen et al., 2003; Rashidi

& Mihailidis, 2013). This perception of risks may deter people from accepting any new system controlled by ambient intelligence (Körber et al., 2018). Particularly, an automation system proposed to replace direct human support in homecare for elderly people is a potential issue of uncertainty and unreliability (Nehmer et al., 2006). Shedding light on the ATM model developed based on elderly people's perceptions in Canada, this study claims that expected technological uncertainty (ETU) can demotivate Bangladeshi elderly people to accept machine autonomy because of its potential negative impact on their trust development process (Bilkis, 2020; Huda, 2022). Behavioral researchers have revealed that this belief around uncertainty and unreliability is the result of both cognitive factors and psychological attitudes (Clifton et al., 2012; Satterfield et al., 2017). Therefore, this study proposes the following hypotheses:

H_2: Expected technological uncertainty (ETU) can influence elderly people to develop trust (TR) in machine autonomy.

H_{2a}: Expected cognitive risk (ECR) of elderly people influences expected technological uncertainty (ETU) of machine autonomy.

H_{2b}: Expected psychological risk (EPR) of elderly people influences expected technological uncertainty (ETU) of machine autonomy.

Family benefit and accomplishment (FBA)

The acceptance of an automation system by elderly people potentially allows for the replacement of direct human support in performing their daily life routines and meeting their healthcare needs (Dwivedi et al., 2016). Heuristically speaking, elderly people will be interested in developing their trust in machine autonomy if they perceive relative advantages and benefits from this replacement (Shareef et al., 2021b). Several behavioral theorists (Broekens et al., 2009; Satterfield et al., 2017; Sprott, 2008) have asserted that people will be persuaded to develop their trust in technology-driven systems if they expect they will provide them with personal as well as family benefits and accomplishments. The ATM model has examined the construct of personal benefit and accomplishment (PBA) in Canada to understand the trust development process of elderly people in accepting an automation system to replace direct human support. Since Bangladeshi elders in this study are living with family members, instead of PBA, the construct can be family benefit and accomplishment (FBA) (Barikdar et al., 2016; Huda, 2022; Mazumder et al., 2020). However, researchers have revealed that the expectation of benefits and accomplishments from technology-driven systems controlled by ambient intelligence has both logical and emotional aspects (Shareef et al., 2018a). As such, this study proposes the following hypotheses:

H_3: Expectation of family benefit and accomplishment (FBA) helps elderly people to develop trust (TR) in machine autonomy.

H_{3a}: Expected cognitive performance (ECP) of elderly people influences expected family benefit and accomplishment (FBA) of machine autonomy.

H_{3b}: Expected psychological performance (EPP) of elderly people influences expected family benefit and accomplishment (FBA) of machine autonomy.

Expected empathetic cooperation and social interaction (EECSI)

In replacing traditional human support with machine autonomy, this issue is a potential concern for anyone who is habituated to deriving human support and social interaction from their family (Acampora et al., 2013; Heerink et al., 2010). However, scholarly studies on automation systems and their adoption behavior by elderly people (Erzurumlu & Pachamanova, 2020; Phillips & Linstone, 2016) have postulated that for elderly people, the perception of empathetic human interaction is a very important consideration in replacing human support with automation. Researchers working on human trust and its antecedents (Goeldner 2015; Hancock et al., 2011; Khaksar et al. 2016; Körber et al., 2018; Schaefer et al., 2016; Søraa et al., 2021) have affirmed that belongingness and social interaction are the dominating factors in creating trust in adopting any technology-driven systems. The ATM model has postulated that if machine autonomy does not have the ability to provide feelings of empathetic cooperation and social interaction, elderly people might lose their trust and thus behavioral intention to adopt the technology. This study proposes the following hypothesis with specific regard to elderly people in Bangladesh:

H_4: Expected empathetic cooperation and social interaction (EECSI) helps elderly people to develop trust (TR) in machine autonomy.

Self-concept and personality & image (SCPI)

In analyzing human behavior in terms of developing the trust to accept complex technology-driven systems, many behavioral researchers agree that an individual’s characteristics and overall personality and self-image play an important role in their perception processes (Burger & Cooper, 1979; Chiang et al., 2022; Shareef et al., 2020). In analyzing people's behavior to accept mobile health instead of direct physical healthcare support, for example, Dwivedi et al. (2016) postulated that self-image and personality have a strong influence on the trust development process. Behavioral theories (Fishbein & Ajzen, 1975) also assert that personal beliefs can dictate behavioral standards. In using the ATM model to analyze Canadian elders' perceptions, it was found that self-concept and behavioral attitudes associated with personality and image can influence human behavior as well as the development of trust toward unknown technology-driven systems. Therefore, it can be argued that self-concept and personality & image (SCPI) can influence the attitude of trustworthiness toward autonomous systems. This study proposes the following hypothesis in this regard:

H_5: Self-concept and personality & image (SCPI) of elderly people influences the behavioral intention (BI) toward machine autonomy.

Trust (TR)

Trustworthiness is an important issue in accepting automation systems controlled by ambient intelligence (Jarvenpaa & Todd, 1997; Lu et al., 2019; Martinez-Martin et al., 2020; McKnight & Chervany, 2002). Acceptance of any technologically advanced system by consumers potentially depends on their trustworthiness in the system (Schneider & Kummert, 2021). In different contexts, although the conceptual paradigms of trust vary, several scholarly studies have argued that behavioral intention to adopt any system substantially depends on people's trust in the system (Borges et al., 2021; Collins et al., 2021; Na et al., 2023; Pal et al, 2018). Researchers working on virtual systems and machine autonomy have revealed that while adopting any virtual system and machine autonomy replacing human support, the behavioral intention to adopt the system is highly connected with their trust in it (Chiu et al., 2017; Dwivedi et al., 2021; Hooda et al., 2022; Sowa et al., 2021). The ATM model revealed strong support for the idea that if elderly people have trust in machine autonomy, they might be interested in accepting automation to replace direct human support. Thus, this study proposes the following hypothesis:

H_6: Trust (TR) helps elderly people develop behavioral intention (BI) toward machine autonomy.

Based on the aforementioned hypotheses, the proposed theoretical framework is shown in Figure1.

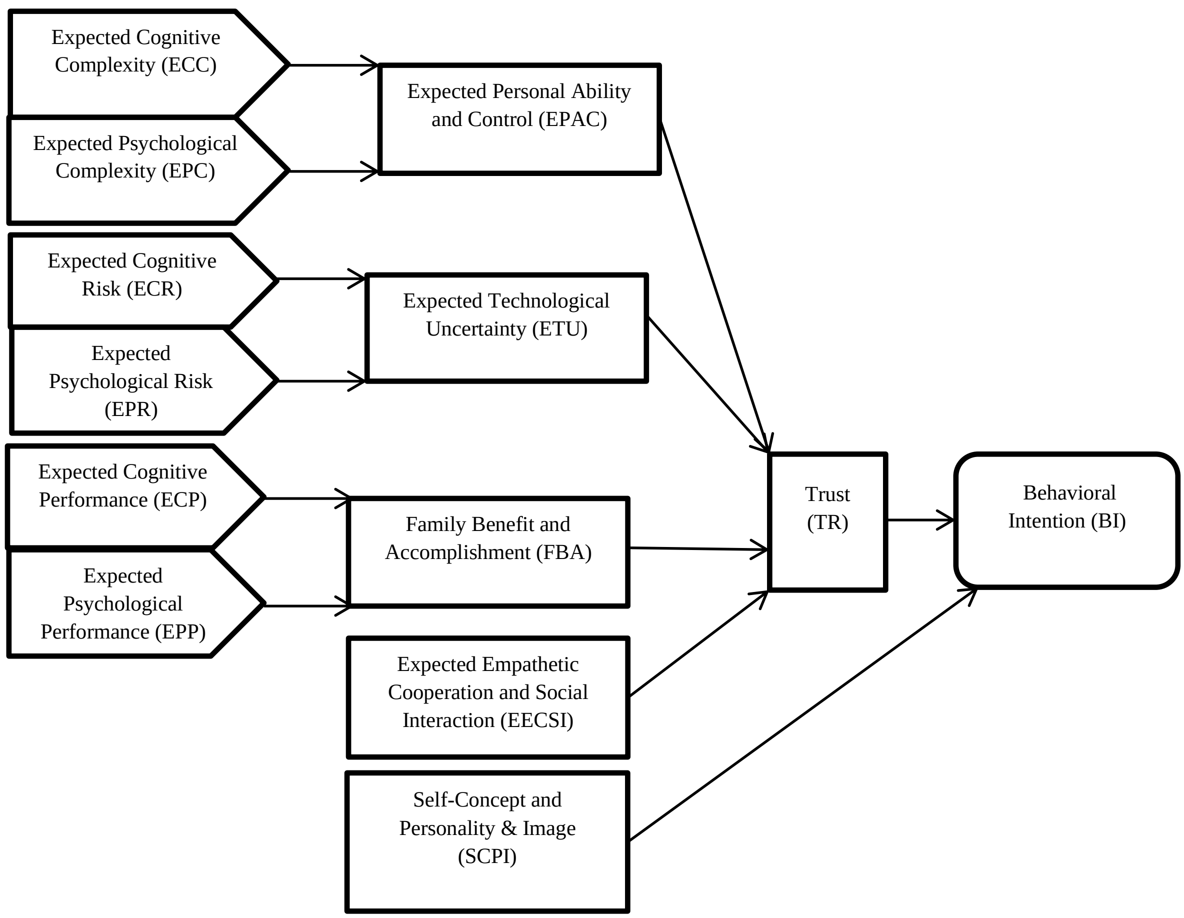

Fig. 1. Expected trust model for machine autonomy (ETM4MA) (Revised from Shareef et al. 2021b)

5. Research methods

This research was conducted first through an experiment and then through an empirical survey. The study was designed to be conducted in Bangladesh in three major districts (Dhaka, Chattogram, and Rajshahi) to assimilate cultural differences so that generalized recommendations could be made (Mazumder et al., 2020). The purpose of conducting the investigation in these districts was to propose a generalized theoretical concept that could be derived from a pragmatic assumption.

The proportion of elderly people in Bangladesh is steadily increasing. Approximately 13 million people are aged over 60, which is equal to almost 8% of the country's total population (Bangladesh Statistics Bureau, 2022), and this ratio is increasing due to the increase in life expectancy. It is anticipated that the proportion of older people will double in the next 20 years (Bilkis, 2020). As a result, the need for essential homecare support is growing rapidly in the country. In Bangladesh, there are many elderly people who cannot maintain their regular life activities without assistance from others (Huda, 2022). For many of their daily routine tasks, they require close assistance. Traditionally, so far, homecare support to elderly people in Bangladesh has mostly been provided by family members (Barikdar et al., 2016; Huda, 2022; Mazumder et al., 2020). However, this scenario is changing quickly. Due to the busy urban life, no family member can offer continuous assistance. This presents an acute problem for disabled and elderly people in Bangladesh (Huda, 2022). In addition, the medical resources in Bangladesh are quite limited with respect to the need, and medical services are very costly and therefore not affordable for the majority of the elderly population. In this regard, the automated system can assist them in performing daily routine tasks and meeting their healthcare needs (Barikdar et al., 2016; Bilkis, 2020; Huda, 2022; Mazumder et al., 2020). However, no comprehensive study has been conducted in Bangladesh to understand the requirements of an automation system to serve the elderly and disabled population in Bangladesh (Huda, 2022). Therefore, the situation of the elderly people in Bangladesh, particularly in the major cities of Dhaka, Chattagram, and Rajshahi, where people are extremely busy and do not have enough time to provide health support to their family members, offers an excellent opportunity for research aimed at capturing the requirements of such an automation system (Bilkis, 2020; Huda, 2022).

This research was designed to investigate and identify the critical factors that contribute to the adoption of environment-friendly automation systems by the demand-side stakeholders, i.e., end users of the homecare system. The survey questions are categorized in such a way to ensure that the responses from the elderly people are based on concrete, impartial, and past specific experiences or future expectations. The specific methodology this study follows is described below.

The study was designed to follow two sequential steps: First, an experiment was conducted to demonstrate the possible applications of machine autonomy to assist elderly people in performing their daily routine and healthcare activities. Since several studies conducted in Bangladesh (Bilkis, 2020; Huda, 2022; Mazumder et al., 2020) have revealed that most elderly people in Bangladesh do not have enough experience to use autonomous systems, an experiment was designed to show some examples of machine autonomy and their applications for elderly people. The sample of elderly people was selected randomly from the database provided by the respective city departments. It was collected from three major cities in Bangladesh (mentioned previously). In this study, all the elderly people who participated had a minimum age of 65 (both male and female). A video about the application of homecare robots and smart vacuum cleaners was prepared by a marketing company and displayed to the elderly people. It was shown in their residences for about 45 minutes. Two weeks after this experiment, a questionnaire-based survey was conducted on the selected sample of elderly people. The methodology and sample selection criteria used in this study are depicted in the flowchart shown in Figure 2.

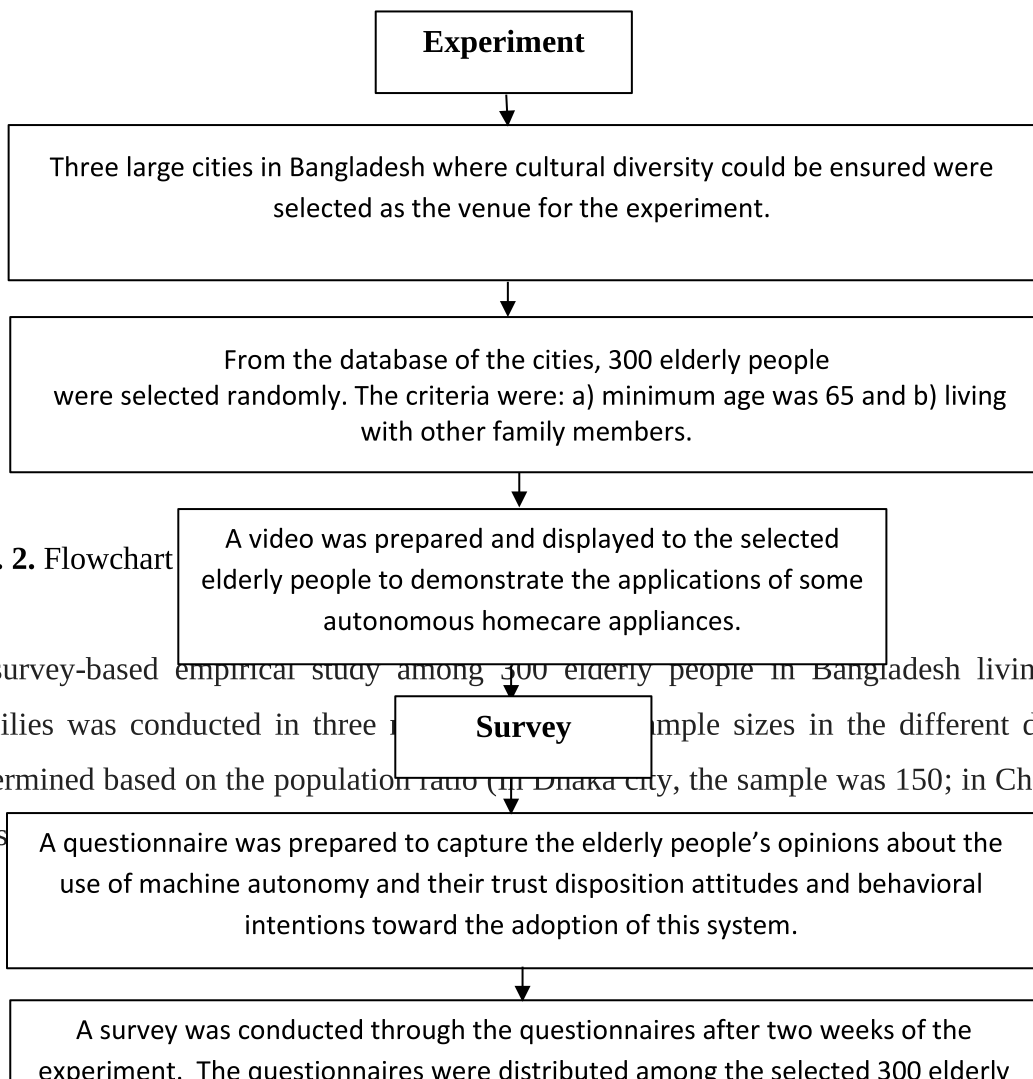

Fig. 2. Flowchart

A survey-based empirical study among 300 elderly people in Bangladesh living with their families was conducted in three r... mple sizes in the different districts were determined based on the population ratio (in Dhaka city, the sample was 150; in Chattagram and Rajs... sh have little practical experience using an automation system, the survey questions were designed to capture their expectations about automation based on the video display. Out of the 300 participants, questionnaires were mailed with return postage to 150 people, while the 150 remaining questionnaires were delivered manually. This was done to minimize method bias. The complete survey and experiment took around three months. The questionnaires were then collected manually or by mail. Responses from 212 elderly people were received, representing a response rate of 70.67%.

The survey items were measured by a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). Social science research has indicated that the Likert scale measurement is appropriate to capture the behavioral intention of elderly people due to its minimal effort and convenience (Chyung et al., 2017; Weber et al., 2014). All the scale items were taken from the study conducted by Shareef et al. (2021b) in Canada and some other studies (Davis, 1989; Dwivedi et al., 2016; Gefen et al., 2003; Rogers, 2003; Shareef et al., 2011). However, the measuring items were edited and revised with the help of a focus group comprised of three university professors with expertise in conducting this kind of survey. The reason for this modification was to reflect the specific purpose of this study.

This study also conducted interviews with 45 family members from the three cities (spouse, son, daughter, and close relatives). The objective of these interviews was to understand the trust disposition attitude of family members toward automation. They were asked a straightforward question measured on a Likert scale (Always-1, Mostly-2, Sometimes-3, Mostly Not-4, Never-5):

Do you provide an automation system (any kind) to your elderly family members in place of human support?

The mean of the revealed answers was 2.69. Therefore, they were more inclined to answer “mostly” and “sometimes.” Based on the outcome of the interviews, the family members’ attitudes toward this system were very scattered.

6. Statistical analysis

The demographic factors of the elderly people showed a significant difference in several areas. This analysis was done to understand the respondents' general demography for the three cities (Table 1).

Table 1
General characteristics

Traits	**Respondents**
Mean Age	72.9 (years)
Gender	57:43 (Men versus Women)
Time of receiving support (partial or full) from family members or external people (Mean)	5.3 years
Average education	College degree
Average family income	9,450 USD annually
Children	3 numbers
Smart phone usage experience	49.8%
Computer usage experience	16.7%

5.1. Reliability and validity of the sample and analysis

To validate the sample and acceptability of the constructs and scale items, a two-step approach to perform the sequential analysis was conducted following the suggestion of Anderson and Gerbing (1988). The objective was to obtain a cause-effect model with sufficient model fitness. In this regard, at first, confirmatory factor analysis (CFA) was conducted to verify the measurement model (Zhou, 2012). The scale items and the respective constructs were primarily taken from the ATM model, but the measurement indicators were modified and adjusted based on the context of the present research. Then, to verify the cause-effect relations of the proposed constructs, a structural model analysis was conducted. CFA was performed to examine the construct, discriminant, and convergent validity of the scale items and their respective constructs.

5.2. Confirmatory factor analysis (CFA)

CFA was done for the six first-order constructs, with 23 measurement items: Expected Cognitive Complexity (ECC), Expected Psychological Complexity (EPC), Expected Cognitive Risk (ECR), Expected Psychological Risk (EPR), Expected Cognitive Performance (ECP), and Expected Psychological Performance (EPP). Similarly, CFA was done for the five second-degree constructs, with 28 measurement items. These were Expected Personal Ability and Control (EPAC), Expected Technological Uncertainty (ETU), Family Benefit and Accomplishment (FBA), Expected Empathetic Cooperation and Social Interaction (EECSI), and Self-Concept and Personality & Image (SCPI). At the same time, CFA was performed to validate the two dependent constructs Trust (TR) and Behavioral Intention (BI), with nine indicators.

As expected, the 11 independent constructs and the two dependent constructs, with their underlying measurement items, were found acceptable as per the recommendations of the published literature (Fornell & Larcker, 1981; Kline, 2015). The authors recommended that any scale items be retained if their contribution is at least 0.50. Otherwise, it will be assumed that the scale item does not have a significant contribution to the respective construct. Following the suggestion, eight items were dropped, as shown in the Appendix (similar to the original framework, with some changes). Since the average variances extracted (AVE) for the retained measurement items of all the factors have values at least 0.50 or above, the convergent validity of the items was confirmed (Fornell & Larcker, 1981). To validate the discriminant validity of the independent and dependent constructs, the guiding principle is that the largest shared variance between the factors should be lower than the least AVE value for each factor and its measures (Hair et al., 2013). This was confirmed. However, for further verification of the discriminant validity, Fornell & Larcker (1981) suggested that the variances of any two variables should be higher than the squared correlations between the two variables. It was revealed that 0.734 is the lowest AVE (as shown in Table 2), which is greater than the highest squared correlation between two variables (as shown in Table 2). Therefore, this study can safely claim the discriminant validity of the variables (Table 2). The model fitness and loading pattern of the CFA results also showed that the scale items could properly measure their respective construct. This finding confirms the construct validity (Chau, 1997).

Table 2

Convergent and discriminant validity

	ECC	EPC	EPAC	ECP	EPP	FBA	EECSI	ECR	EPR	ETU	SCPI
ECC	**0.871**										
EPC	0.0163	**0.734**									
EPAC	0.2702	0.114	**0.793**								
ECP	0.0084	0.013	0.00068	**0.822**							
EPP	0.0029	0.0077	0.0005	0.3677	**0.891**						
FBA	0.0024	0.0158	0.00002	**0.632**	0.3262	**0.822**					
EECSI	0.1332	0.0899	0.29268	0.0005	0.0004	0.0011	**0.798**				
ECR	0.0002	0.0002	0.0067	0.0045	0.0023	0.0093	0.0033	**0.756**			
EPR	0.0129	0.0009	0.0064	0.0228	0.0014	0.0088	0.0065	0.0512	**0.882**		
ETU	0.0066	0.0523	0.0329	0.0088	0.0164	0.0024	0.0253	0.0082	0.2878	**0.810**	
SCPI	0.2727	0.0001	0.2642	0.0027	0.0001	0.0014	0.1651	0.0009	0.0343	0.0029	**0.854**

The reliability of the constructs was an important issue to check before proceeding further. This examination was done through the verification of the composite reliability score. Following the recommendations of Fornell and Larcker (1981) and Hair et al. (2013), the reliability of any construct should be accepted if the composite reliability is greater than the benchmark of 0.70. It was found acceptable, as shown in Table 3. The study also calculated the mean of the constructs to reveal the actual status of the respondents under each construct (Table 3).

Table 3

Examination of the composite reliability (CR) and average of the constructs

Constructs	**CR Values**	**Average Score**
ECC	.928	3.582
EPC	.800	3.765
EPAC	.876	4.232
ECP	.934	2.681
EPP	.912	3.021
FBA	.862	2.545
ETU	.911	3.670
ECR	.865	3.845
EECSI	.901	4.101
EPR	.801	3.444

SCPI	.833	3.32
TR	.865	3.02
BI	.777	4.01

5.3. Structural model: Cause-effect relationships

The structural portion of the model was statistically analyzed through LISREL to investigate the cause-effect relationships between the dependent and independent variables (both first-order and second-order constructs simultaneously). In the first attempt, after several iterations, the revealed model fitness parameters, including the root mean square error of approximation (RMSEA) (0.145), chi-square (84.33), and P-value (0.00001), indicate that the model did not fit with the survey data as per the proposed relationships.

For model improvement, the analysis had two specific suggestions in terms of the cause-effect relations. The model suggested that for better fitness, there should be relations between SCPI and EECSI with EPAC. For significance, this means that the expected ability and control (EPAC) of the autonomous system among elderly people depends on their expectation of the scope of emotional and social belongingness (EECSI) with the machine autonomy in terms of its replacement of active human support. However, this expectation of control (EPAC) also depends on their own personality and image (SCPI). Before introducing these two relations with EPAC, their correlations and supporting theories were verified. These explanations are illustrated in the next section. Among the four cause-effect relations of the independent constructs EPAC, FBA, EECSI, and ETU with trust (TR), it was found that EPAC and EECSI are significant at the 0.05 level, and even at the 0.01 level, and thus, the corresponding hypotheses are accepted (Table 4). Both the constructs EPAC and EECSI had potential contributions to developing the perceptions of trust among elderly people. However, the model derived through the statistical analysis of SEM rejected the inclusion of ETU and FBA in the ATM model, as their contributions to developing the perception of trust (TR) are negligible and thus, should be removed. The hypotheses were rejected. As per the proposed theoretical framework, TR and SCPI have a potential effect to influence the adoption of machine autonomy (BI). Thus, both hypotheses are accepted. All the six hypotheses related to the first-order construct were examined through SEM. All the first-order constructs were found significant at the 0.05 level except for ECR. This means that the expectation of cognitive risk (ECR) to form the perception of expected technological uncertainty (ETU) is not significant. Its contribution is negligible (Table 4).

Table 4

Validity of hypotheses and loading values in SEM

Original Hypothesis	Status	Loading Value
H_1: Expected personal ability and control (EPAC) helps elderly people to develop trust (TR) in machine autonomy. H_{1a}: Expected cognitive complexity (ECC) of elderly people influences expected personal ability and control (EPAC) toward machine autonomy. H_{1b}: Expected psychological complexity (EPC) of elderly people influences expected personal ability and control (EPAC) toward machine autonomy.	Accepted Accepted Accepted	0.43 0.21 0.23
H_2: Expected technological uncertainty (ETU) can influence elderly people to develop trust (TR) in machine autonomy. H_{2a}: Expected cognitive risk (ECR) of elderly people influences expected technological uncertainty (ETU) of machine autonomy. H_{2b}: Expected psychological risk (EPR) of elderly people influences expected technological uncertainty (ETU) of machine autonomy.	Rejected Rejected Accepted	0.03 0.02 0.58
H_3: Expectation of family benefit and accomplishment (FBA) helps elderly people to develop trust (TR) in machine autonomy. H_{3a}: Expected cognitive performance (ECP) of elderly people influences expected family benefit and accomplishments (FBA) of machine autonomy. H_{3b}: Expected psychological performance (EPP) of elderly people influences expected family benefit and accomplishments (FBA) from machine autonomy.	Rejected Accepted Accepted	0.04 0.56 0.19
H_4: Expected empathetic cooperation and social interaction (EECSI) helps elderly people to develop trust (TR) in	Accepted	0.41

machine autonomy.		
H_5: Self-concept and personality & image (SCPI) of elderly people influences behavioral intention (BI) toward machine autonomy.	Accepted	0.18
H_6: Trust (TR) helps elderly people to develop behavioral intention (BI) toward machine autonomy.	Accepted	0.59
New Hypotheses		
Self-concept and personality & image (SCPI) of elderly people influences the expected personal ability and control (EPAC) toward machine autonomy.	Significant	0.24
Expected empathetic cooperation and social interaction (EECSI) of elderly people influences the expected personal ability and control (EPAC) toward machine autonomy.	Significant	0.29

Finally, the accepted theoretical framework is shown in Figure 3.

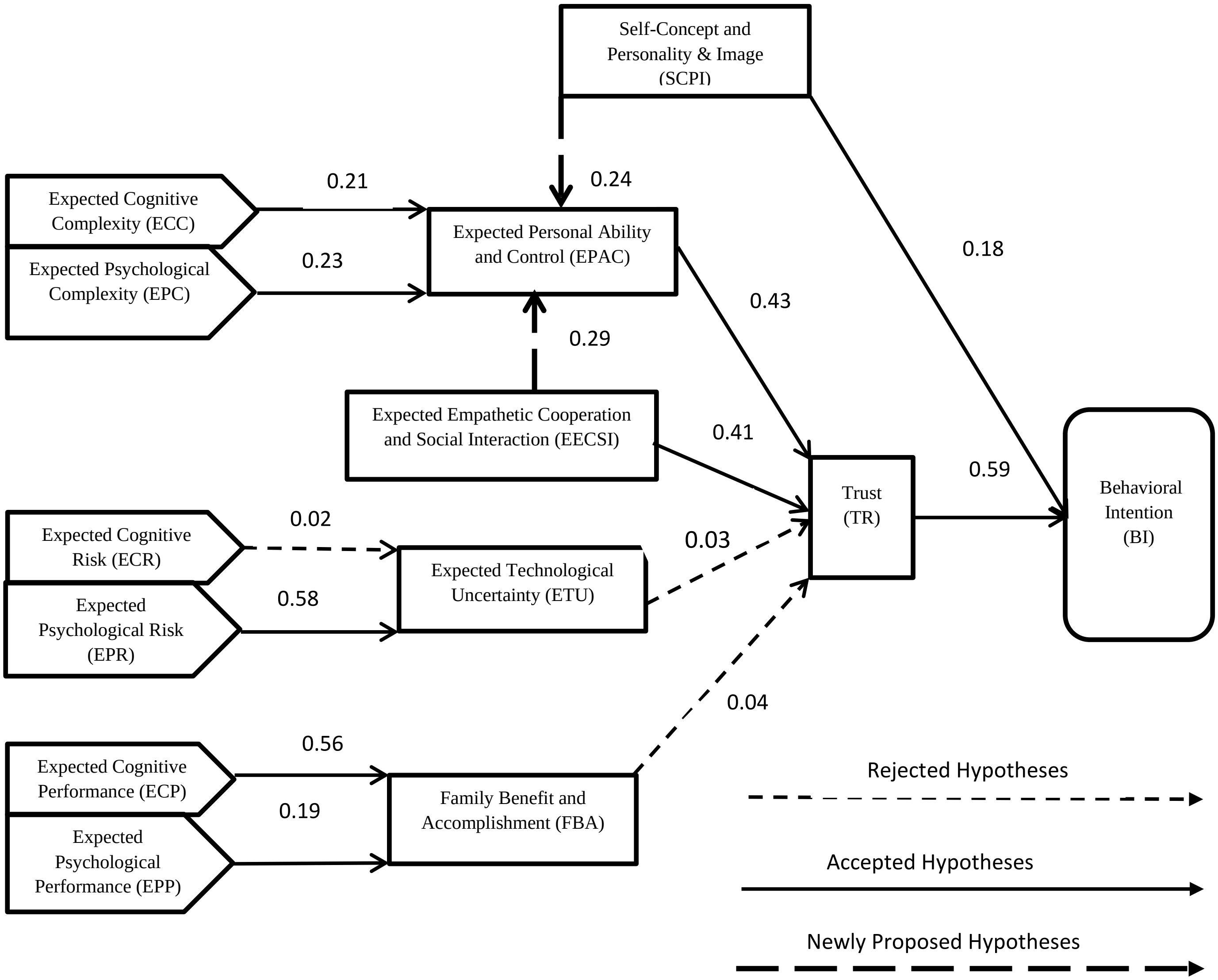

Fig. 3. Expected trust model for machine autonomy (ETM4MA)

At this stage, it is revealed that the model fitness parameters, such as goodness of fit index (GFI), comparative fit index (CFI), adjusted goodness of fit index (AGFI), incremental fit index (IFI), normed fit index (NFI), relative fit index (RFI), RMSEA, chi-square, and P-value have a good fit with the data, and thus cannot be rejected. The model fitness parameters in comparison to the recommended literature (Chau, 1997; Chen et al., 2008; Kline, 2015; Hair et al., 2013; Hoyle 2011; Hu & Bentler, 1999) are shown in Table 5.

Table 5

Model parameters and prescribed values

Fit Measures	**Prescribed Scores**	**Scores of the Present Study**
Chi-square (χ^2)	P ≥ 0.05	67.49 (0.06114)
Degrees of Freedom (df)		36
χ^2/(df)	≤ 3	1.8747222
RMSEA	< .06	.068
CFI	≥ .90	.96
NFI	≥ .90	.93
GFI	≥ .90	.92
RFI	≥ .80	.84
(IFI	≥ .90	.97
AGFI	≥ .80	.85

7. Findings and discussion

A revised theoretical framework of the ATM model, which was revealed based on a sample of a developed country, Canada, was tested in this study in a developing country, Bangladesh. Based on the country context, cultural differences, familiarity with machine autonomy, and experience in using modern technology, this study proposed the *expected trust model for machine autonomy (ETM4MA*) as the theoretical framework. Another difference was in the social composition of the respondents, elderly people. In Canada, all the respondents were used to living in care homes. However, in the current study, the elderly people who participated in the survey live with their own families. This group dynamic may have a potential impact on the adoption behavior of elderly people in relation to group behavior as well as perceptions and expectations (Shareef et al., 2020). Shedding light on attachment theory, psychologists Hazan and Shaver (1994) illustrated that based on the scope of bonding with other known family members, people may exhibit different emotional behavior in group dynamics. Reflecting on the core idea of this theory, elderly people may have an urge for social bonding and emotional attachment with their caregivers. As a result, when the issue of replacing human support with machine autonomy arises, they are more prone to expect empathetic cooperation from this autonomous system. In this aspect, elderly people try to avoid any risks and fear of uncertainty. Attachment theory suggests that the finding of this study to ensure the feeling of belongingness from machine autonomy is a very common need of elderly people in terms of group dynamics.

Several researchers (Hajiheydari & Ashkani, 2018; Hooda et al., 2022; Lin et al., 2020; Wang et al., 2015) have determined that the family composition, technology availability, and trustworthiness behavior of the population of developing countries are sometimes different. On the other hand, Nourbakhsh et al. (2012) revealed from an extensive empirical study that the technology adoption behavior of people in the developing countries showed a similar trend. In addition, some studies on machine autonomy and family culture postulated that in terms of family bonding, availability of resources, and trustworthiness, the behavioral attitudes of elderly people in the developing countries might have potential similarities (Dwivedi et al., 2021; Lin et al., 2020: Loureiro et al., 2021; Tran et al., 2022). In that sense, the findings of this study can be an excellent indication of the behavioral intentions of elderly people in the developing countries to adopt machine autonomy.

The study reveals that the independent constructs EPAC and EECSI have a 52.3% ($R^2 = 0.523$) variance of the dependent construct TR. This means that if elderly people have an expectation that they have the ability to use machine autonomy controlled by ambient intelligence to perform daily life routines and healthcare activities, in which they were previously assisted by internal family members or external workers, and if they find enough psychological and social belongingness with this automation system, they will be disposed to trust the system. It can thus be postulated that the expectation of one's ability to use, control, and accomplish daily routine activities through machine autonomy that provides a sense of empathy and social interaction can foster the behavioral attitude to trust the system.

This identification broadly is a replication of the previous study. However, there is a potential difference between the two studies in terms of the contributions of the constructs to develop the perception of trust. In the previous study conducted in Canada, it was found that the development of trust depends on the ability to use automation and expected empathy provided by this automation system while replacing human contact. However, in that study, the contribution of perceived ability is much higher (0.53) than the contribution of the scope of empathetic and social relation, which is only 0.28. The point to be noted here is that the elderly people in that study were living entirely in care homes (detached from their family members). However, in this present study conducted in Bangladesh among elderly people who live solely with their family members, the contributions of both EPAC and EECSI are almost equal (EPAC: 0.432 and ECSI: 0.414). This means that people in a developing country who live with family members give much more priority to emotional and social belongingness in replacing direct human support with machine autonomy while performing daily routine activities and meeting their healthcare needs. Yet, it is true that the most important issue for elderly people to replace direct human support with machine autonomy is their expected physical and mental ability to use the system independently.

This finding has a strong foothold in many general technology adoption models, for instance TAM (Davis, 1989), GAM (Shareef et al., 2011), mobile health adoption (Dwivedi et al., 2016), DOI (Rogers, 1995), and social learning theory (Bandura, 1986). The need of elderly people to feel a sense of belongingness and affection as well as social interaction is an important issue to consider when replacing direct human contact and service with machine autonomy controlled by ambient intelligence. In the light of different social, psychological, and consumer behavior studies (Bandura, 1986; Hazan & Shaver, 1994; Jarvenpaa et al., 2000; Shareef et al., 2021a), it can be inferred that elderly people's acceptance of automation systems to assist in their daily routine activities and healthcare services in lieu of direct human (mostly family members in developing countries) support is based on their trust in the provision of similar human contact and interaction. Heuristically and pragmatically, elderly people expect that a similar feeling of belongingness, or at least benevolence, should be provided by this alternative system of support, i.e., machine autonomy. The theory of attachment (Hazan & Shaver, 1994) also asserts that in group dynamics, the need for empathy and social interaction is a predominant feature.

From the ETM4MA model, it is revealed that elderly people's expectation in their ability to manage and use an automation system (EPAC) is potentially dependent on their own judgment of compatibility with the machine autonomy, i.e., their personality and characteristics, as represented by the construct SCPI. However, EPAC is accompanied by the sense of caring expected from an automation system (EECSI), which is supported by the theories of attachment and social learning. Scholarly articles on social psychology (Burger & Cooper, 1979; Heider, 1958; Shareef et al., 2021a) and consumer behavior (Dwivedi et al., 2016; Venkatesh et al., 2012) also show strong support in favor of these findings. Unlike the study conducted in Canada, this study revealed that the expected scope of emotional caring and social interactivity (EECSI) has a higher contribution in developing the expectation of ability and control to use machine autonomy, even though it is higher than the effect of self-concept and image governed by one's personality (SCPI). From the study in Canada, the contributions of perceived empathy and personality to form the belief in one's ability and control are 0.26 and 0.30, respectively. However, for the similar constructs, the values of the study conducted in Bangladesh are 0.289 and 0.238, respectively (Figure 2). Therefore, broadly, it can be inferred that for Bangladeshi elderly people, the contribution of the appeal for personal and emotional caring and psychological belongingness is much more prominent than with the Canadian elderly people. However, it is noteworthy that the Canadian elderly people (sample of that study) were living in care homes, whereas the elderly people of this Bangladesh study were living in their own homes with their own family members.

Like the elderly people in Canada, the Bangladeshi elderly people exhibit the same behavioral attitudes in developing trustworthiness in terms of the expected uncertainty of technology (ETU) and expected family benefit and accomplishment (PBA) from this technology to develop trustworthiness toward machine autonomy. Due to the advancements and wide applications of smartphones, the Internet, social media, and other communication technologies, people in any country, including elderly people, are somehow habituated and familiar with this machine autonomy. Consequently, irrespective of developed or developing countries, elderly people do not find any uncertainty or any unexpected new benefits from the use of these new technologies. However, for both the samples, the feeling of uncertainty (either due to perceptions or expectations) stems from the belief in psychological risk (PPR) only; the belief in cognitive risk (PCR) is not significant in this case. This is very justified as people are now quite familiar with automation systems, particularly the application of modern technologies such as smartphones and the Internet. Therefore, analytically, they do not see any risk; it is solely their mental obsession. Like the sample from a developed country, this sample from a developing country showed the same significant relations of personal characteristics represented by personality and image (SCPI) and trustworthiness (TR) with behavioral intention (BI); however, for the Bangladeshi sample, the contribution of personality and image (SCPI) to form behavioral intention (BI), and thus its effect, is much less. For the Canadian sample, it is 0.28, and for the Bangladeshi sample, it is 0.18. The effect of trust (TR) is very close (Canadian sample and Bangladeshi sample are 0.57 and 0.59, respectively).

Therefore, a couple of issues are potentially important for Bangladeshi elderly people to accept the usage of automation in their life in place of their caregiving (mostly family support in Bangladesh) support directly from humans. In developing trust in this machine autonomy, the expected personal ability and control and the expected feeling of caring are two important issues for elderly people. Also, in their behavioral intention to accept automation systems, trust plays a crucial role; however, this might vary depending on differences in personality and behavioral attitudes (supported by Trimpop et al., 1997). From analyzing the trust literature (Gefen et al., 2003; McKnight et al., 2002; Schaefer et al., 2016; Shareef et al., 2020) and social learning theory (Bandura, 1986), it is quite evident that for human behavior, particularly in group dynamics, trust plays a crucial role in motivating elderly people to accept machine autonomy controlled by ambient intelligence.

Another important finding revealed from the interviews with the family members, including the elderly people, was that they unanimously agreed that the encouragement of family members is an important factor for elderly people to develop trust in machine autonomy. Therefore, "influence from peers/family members" can be proposed as an important predictor of behavioral intention to adopt machine autonomy. For future researchers, this can be a significant issue to consider.

In summary, the following findings can be highlighted:

- The independent constructs of expected personal ability and control (EPAC) and expected empathetic cooperation and social interaction (EECSI) explain a 52.3% ($R^2 = 0.523$) variance of the dependent construct trust (TR).
- Personal ability and control (EPAC), which is developed considering both cognitive and psychological risks, helps elderly people to develop trust (TR) in machine autonomy.

- Perception of technological uncertainty (ETU), which is developed considering only psychological risk, does not significantly influence elderly people to develop their trust (TR) in machine autonomy.
- Perception of family benefit and accomplishment (FBA), which is developed considering both cognitive and psychological risks, does not significantly influence elderly people to develop their trust (TR) in machine autonomy.
- Expected empathetic cooperation and social interaction (EECSI) helps elderly people to develop their trust (TR) in machine autonomy. EECSI has also an impact on the expected personal ability and control (EPAC) toward machine autonomy.
- Self-concept and personality & image (SCPI) of elderly people has an impact on the behavioral intention (BI) as well as on the expected personal ability and control (EPAC) toward machine autonomy.

6.1. Limitation and future work direction

The respondents of this study were living with their own families. Living in care homes without regular interaction with family members might create differences in their behavioral attitudes toward accepting the automation system. Therefore, this is a limitation of this study. Future researchers can consider doing similar research among elderly people living in care homes without the regular attachment and support of family members. In addition, the moderating effects of age, gender, income, and educational level of elderly people were not investigated in the scope of this research. This is another limitation of the study. These effects can be explored in future studies. The trust disposition attitude of other family members toward machine autonomy as well as their encouragement around its adoption should be considered in future research. This study did not try to exclude the elderly people from the collected sample who did not have past experience using machine autonomy. This is also a limitation. Therefore, future researchers could collect samples of elderly people with experience using machine autonomy to understand their behavioral intentions.

8. Implications

The findings of this study have several potential implications for both academics and practitioners. The proposed expected trust model for machine autonomy (ETM4MA) is used in this study as the theoretical framework. The model is distinct in capturing the perceptions of elderly people around their adoption of machine autonomy in comparison to traditional technology adoption models or the ATM model, for several reasons:

1. Similar to any technology adoption model, including the ATM model, it uses traditional constructs, such as the ability to use the technology and its perceived personal benefits. However, in addition to these features, this model attempts to capture the family benefits that can be obtained through the use of machine autonomy in assisting elderly people with daily activities, including meeting their healthcare needs. This has significant implications for both academics and practitioners because machine autonomy not only provides personal support but also simultaneously reduces the amount of assistance required by elderly people from caregivers or family members.
2. A major and potential difference between human support and machine autonomy are the feeling of empathy and the scope of social interaction. These aspects were also intended to be captured through this theoretical framework.
3. The effects of personality and self-image on technological uncertainty were also incorporated into this model.
4. Overall, this is a comprehensive model in which both affective and cognitive risks were captured.

There is a significant difference between the two samples of the respective models, namely, the automation trust model (ATM) and the expected trust model for machine autonomy (ETM4MA). For the ATM model, Canadian elderly people (sample of that study) were living in care homes whereas, for the ETM4MA model, Bangladeshi elderly people (sample of this study) were living in their own homes with their family members. Since the Canadian elderly people in the study were receiving direct support from external people, their willingness to use machine autonomy might have been greater, as they were already to some extent detached from their family and friends (Shareef et al., 2021b). Unlike that sample, the Bangladeshi elderly people (sample of the current study) were living with their family members, and thus their need and desire for empathy and social interaction in substituting family support with machine autonomy might have been more pronounced (Dwivedi et al., 2021; Loureiro et al., 2021; Sipior, 2020).

The potential difference between these two studies is that for the Bangladeshi elderly people, the appeal for personal and emotional caring and psychological belongingness was much more prominent than that of the Canadian elderly people. For the Bangladeshi sample, the contribution of personality and image (SCPI) toward forming behavioral intention (BI), and thus its effect, is much less than in the Canadian sample. The two studies also revealed a significant difference in terms of the perception of risks. Affective risks play a more vital role for elderly people living in a developing country in comparison to elderly people living in a developed country. It has also been revealed that elderly people in the developed countries are more concerned about cognitive aspects, for instance their personal ability and control in using the technology. This finding shows the difference between the two samples in terms of culture and technology familiarity. In addition, elderly people in a developing country such as Bangladesh are more concerned about affective attitudes, for instance, the scope of empathy and social interaction. However, irrespective of developed or developing countries, elderly people do not experience any uncertainty or find any unexpected new benefits from the use of these new technologies.

The specific theoretical and managerial implications of this model are discussed next.

7.1. Theoretical Implications

After obtaining the results from a sample of elderly people in a developing country and contrasting it with a similar sample from a developed country, it can be postulated that the expected trust model for machine autonomy (ETM4MA) shown in Figure 2 can support the following grounded theory:

The expected belief in the ability to control and use an autonomous system is a potential issue for elderly people in terms of developing their trust. However, the expected presence of emotional and social belongingness has an overarching impact on this trust development process in replacing direct human (family) support with an automated system. Thus, the development of behavioral intention to adopt this system is highly influenced by trustworthiness; however, *personal characteristics, including compatibility with the technology, have an important role to play in this context.*

This finding makes a major theoretical contribution to behavioral psychology, consumer behavior, and the adoption of an automation system. The results revealed several differences from the study conducted in a developed country in terms of the factors involved in adopting an automation system. Particularly, elderly people in the developed countries are more concerned with cognitive aspects, for instance personal ability and control. On the other hand, elderly people in a developing country like Bangladesh are more concerned about affective factors, for instance expected empathetic cooperation and social interaction. Therefore, researchers of consumer behavior can understand from the findings that the observational learning of people cannot be generalized. The effect of cognitive and affective attitudes is potentially different for people from different cultural backgrounds.

Researchers working on cultural diversity can find strong evidence from this study that consumer behavior in adopting complex technological systems is significantly different for citizens in advanced countries than in underdeveloped countries. The urge for family belongingness and social attachment is potentially more important for people in developing countries. This identification can contribute to the literature on family and culture. Behavioral psychology, for instance attachment theory, can find strong support that group dynamics are closely connected to family bonding, and thus, the trust disposition attitude can be quite different for people living with different group dynamics. Behavioral psychologists can also benefit from an important finding of this study. For people living in a developing country, the formation of trustworthiness behavior is more influenced by affective attitude than cognitive attitude, which is almost the opposite for people in a developed country. Emotion thus plays a crucial role in shaping the minds and attitudes of people in the developing countries.

In addition, academics can gain the clear insight from this study that the behavioral intention of elderly people to use automation systems in the developed and developing countries is potentially different. The expectation of one’s ability to use and control automation systems is more impacted by the cognitive beliefs of elderly people living in care homes in a developed country, whereas the same expectation is more affected by psychological and emotional factors for the elderly people living with family members in a developing country. Any research dedicated to understanding the behavioral patterns of elderly people should therefore recognize that in attempting to replace the support of direct human interaction with machine autonomy, the urge for emotional and social belongingness and benevolence must be considered. This issue is clearly more important for the elderly people living in developing countries.

Moreover, researchers and academics who are exploring the social behavior and cultural diversity of the developing and developed countries can learn from these findings that there is a certain difference in behavioral intention and trustworthiness in the light of individual personality. Self-image and personality have a more prominent effect on the development of behavioral intention in elderly people living in a developed country than elderly people living in a developing country. Therefore, academics can further understand that group behavior is substantially influenced by individual personality. In this regard, researchers in artificial intelligence and technology marketing can derive a clear guideline from this study for understanding the issues that have a profound impact on shaping consumer behavior to accept complex technology-driven systems controlled by ambient intelligence. In this respect, they need to connect the systems' compatibility with people's personality. This requirement of compatibility is more important for people in the developed countries than in the developing countries.

7.2. *Managerial implications*

Practitioners can take significant learning from the findings of this study. For example, marketers who want to promote their products and are eager to understand consumer behavior can benefit from the outcomes of this study. Elderly people who are living in either care homes without family members or in their own homes with family members mostly execute their daily routine activities and healthcare tasks with the help of direct human contact and support. Pragmatically, this support and contact provides a necessary feeling of social empathy and interactivity, which is a potential requirement for elderly people in adopting service technology. Practitioners must understand that future automation systems should be designed in such a way that elderly and disabled people will not feel separated from vital human contact in using automation systems.

At the same time, an automation system controlled by ambient intelligence, such as a robotic system, should be designed in such a way that elderly people can experience touch and the feeling of emotional empathy from this machine autonomy. These are essential features in elderly people's inclinations to accept and use automation systems in place of human contact and interaction. Conducting SEM on the collected sample, the study found that to accept any kind of machine autonomy, the ability to use it is the prime issue for elderly people, since their technical knowledge is not adequate. Proper training in this regard is thus mandatory. A significant difference between human-supported homecare services and automation is the level of empathy. Accepting an automation system for homecare services for elderly people is highly dependent on the ability and scope of the automation system to provide empathy. This issue is extremely important and should be considered in designing technology for automation.

The designers of automation systems can also learn from the findings that a precondition of elderly people to accept any kind of machine autonomy is the development of trust in this system. However, the development of trust is a complex issue, and the perception of trustworthiness is substantially dependent on the belief of elderly people that they have the ability to use and control the machine autonomy. Several behavioral models, including TAM, GAM, DOI, mobile health model (Dwivedi et al., 2016), and the UTAUT2 model (Venkatesh et al., 2012), have suggested that the ability to use and operate any unknown modern technology and its perceived or expected benefits are key factors in developing trustworthiness in the system.

Researchers in consumer behavior and trust have explored this phenomenon extensively and agreed that if people perceive that an unknown technology-driven system can increase their skill and efficiency, and it is reliable and trustworthy, they will exhibit a favorable attitude toward the system. Therefore, simplicity and ease of understanding and use are important factors for manufacturers to consider in pursuing the behavioral intention of elderly people to use an automated care system in lieu of direct human support, which is increasingly becoming scarce and costly.

9. Conclusion

This is an exploratory study with the aim of understanding elderly people's behavior to accept and use machine autonomy controlled by ambient intelligence. In this regard, a detailed empirical study was conducted with elderly people living at home with their family members in a developing country, Bangladesh. It was conducted based on a theoretical framework termed as the expected trust model for machine autonomy (ETM4MA), which was tested among elderly people in a developing country, namely Bangladesh, who are living at home with their family members. This model is an extension and revision of the previous automation trust model (ATM), which was tested among the elderly people in a developed country living in care homes and separated from family members. The present study incorporated the findings from the previous study but extended them to capture the views of elderly people in developing countries. Therefore, it can be claimed that the present study is much more generalized and can be replicated in different populations where elderly people might be either associated with or detached from family members.

The results of this study have major implications for families and healthcare systems in terms of technology adoption, organizational change, social values, quality of service, economic capability and digital divide, political commitment, and less hazardous, disabled-centric health services. Generally, there are ongoing efforts to replace the services directly provided by human beings (for instance, human-controlled homecare services) with automation, based on its relative advantages. However, this study clearly found that elderly people in Bangladesh are interested in using automation systems to replace traditional human-supported services only if they include specific features. Therefore, policymakers should take these requirements into deep consideration in the provision of different preliminary homecare automation systems for elderly people.

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APPENDIX A

Measuring indicators with loading values from CFA

Indicators	**Scores**	**Source**
Expected Cognitive Complexity (ECC)		Primary source: Shareef et al, 2021b And other sources: Davis, 1989; Dwivedi et al., 2016; Gefen et al., 2003; Rogers, 2003; Shareef et al., 2011
ECC1: I am able to manage machine autonomy	0.79	
ECC2: From my thinking, I know that it will be possible for me to complete my activities by automation system	0.90	
ECC3: I think I am able to operate automation system to accomplish my activities as I need **(DROPPED)**	0.42	
ECC4: I think I am able to use this automation system to fulfill my desired tasks	0.88	
Expected Psychological Complexity (EPC)		
EPC1:I expect that I can operate this type of automation system	0.87	
EPC2: I expect that it will be possible for me to complete my activities by automation system	0.81	
EPC3: I hope to operate automation system to complete my activities as I need	0.85	
EPC4: I expect to use machine autonomy to complete my activities	0.83	
Expected Personal Ability and Control (EPAC)		
EPAC1: Knowing how to use machine autonomy is not difficult.	0.78	

Indicators	Scores	Source
EPAC2: I hope I have skill to manage automation system to complete my everyday activities	0.93	
EPAC3: I expect using automation system to complete my everyday activities is not difficult.	0.82	
EPAC4: This will not be difficult for me to interact with automation system	0.78	
EPAC5: Handling automation system to complete my everyday activities is not a problem. **(DROPPED)**	0.39	
EPAC6: I expect I am able to complete my everyday activities through automation system without taking human support	0.81	
Expected Cognitive Performance (ECP)		
ECP1: I am able to use machine autonomy anytime to complete my everyday activities.	0.86	
ECP2: I am able to get more time to complete my everyday activities using machine autonomy. **(DROPPED)**	0.40	
ECP3: Automation system can save my time for continuous use.	0.78	
ECP4: Using automation system can provide me good value for the money.	0.84	
Expected Psychological Performance (EPP)		
EPP1: I feel that automation system will be more helpful to complete my everyday activities.	0.81	
EPP2: Using automation system will provide me feelings of more benefits for the money.	0.78	
EPP3: I will feel convenience to use automation system to complete my everyday activities.	0.92	
Family Benefit and Accomplishment (FBA)		
FBA1: I expect that automation system will be useful in my daily family life.	0.83	
FBA2: Automation system will provide my family with higher facilities to complete my everyday activities.	0.78	
FBA3: Automation system will help my family to complete my everyday activities quickly.	0.91	
FBA4: Machine autonomy will be easier for my family to complete my everyday activities.	0.93	
FBA5: Automation system will provide with more benefits to my	0.44	

Indicators	Scores	Source
family. **(Dropped)**		
Expected Empathetic Cooperation and Social Interaction (EECSI)		
EECSI1: Machine autonomy will be entertaining.	0.76	
EECSI2: Machine autonomy will be enjoyable. **(DROPPED)**	0.42	
EECSI3: Using automation system will not reduce my opportunity to interact with the society.	0.85	
EECSI4: Using automation system will not reduce my opportunity to interact with my family.	0.80	
EECSI5: Service of automation system will give me a sense of belongingness	0.89	
EECSI6: I expect to get better attachment while taking support from machine autonomy to complete my everyday activities.	0.92	
EECSI7: Attachment of automation system while completing my everyday activities will be fun. **(DROPPED)**	0.39	
Expected Cognitive Risk (ECR)		
ECR1: From my learning, I can understand that support provided by machine autonomy to complete my everyday activities will be perfect. **(DROPPED)**	0.38	
ECR2:I know from my knowledge that interaction with automation system to accomplish my daily tasks will be clear	0.68	
ECR3: I know from my knowledge that outcome from the interaction with automation system to accomplish my daily tasks will not be uncertain.	0.82	
ECR4: I know from my knowledge that technology used to operate automation system will be reliable	0.76	
Expected Psychological Risk (EPR)		
EPR1: I have feelings that service provided by automation system to complete my everyday activities will be perfect.	0.93	
EPR2: I have feelings that automation system will be reliable.	0.84	
EPR3: I have feelings that using machine autonomy to complete my everyday activities will be trustworthy.	0.54	
EPR4: I have feelings that interaction with machine autonomy to complete my everyday activities will not be uncertain.	0.85	
Expected Technological Uncertainty (ETU)		

Indicators	**Scores**	**Source**
ETU1: I believe support provided by automation system to complete my everyday activities will be perfect.	0.83	
ETU2: I believe automation system will be reliable**.**	0.72	
ETU3: I believe using machine autonomy to complete my everyday activities will be trustworthy.	0.86	
ETU4: If I have problems, I expect to get accurate service from machine autonomy to complete my everyday activities.	0.89	
ETU5: I believe interaction with machine autonomy to complete my everyday activities will not be uncertain. (**DROPPED)**	0.47	
Self-Concept and Personality & Image (SCPI)		
SCPI1: I like machine autonomy to complete my everyday activities.	0.52	
SCPI2: I will prefer machine autonomy to complete my everyday activities.	0.83	
SCPI3: I have interest for machine autonomy to complete my everyday activities.	0.88	
SCPI4: My personal behavior will be congruent with the characteristics of machine autonomy.	0.79	
SCPI5: Machine autonomy will fit well with the way I like to complete my everyday activities.	0.51	
Trust (TR)		
TR1: I have general faith that automation system will provide quality service.	0.69	
TR2: I have general faith that automation system will be overall reliable.	0.68	
TR3: I have general faith that service of automation system will be overall reliable.	0.70	
TR4: What I do through machine autonomy will be guaranteed.	0.76	
TR5: I have overall confidence that automation system is safe to interact with to complete my everyday activities.	0.67	
Behavioral Intention (BI)		
BI1. I prefer to use machine autonomy.	0.87	
BI2. I hope to use machine autonomy.	0.73	
BI3. I will use machine autonomy.	0.77	
BI4. I expect to encourage my close ones to use machine autonomy.	0.68	

APPENDIX B

Construct	Definition	Source
Expected personal ability and control (EPAC)	Expected level of ability and control to use machine autonomy personally to execute daily routine activities	Primary source: Shareef et al, 2021b And other sources: Davis, 1989; Dwivedi et al., 2016; Gefen et al., 2003; Hancock et al., 2011; Körber et al., 2018; McKnight et al., 2002; Rogers, 2003; Satterfield et al., 2017; Schaefer et al., 2016; Shareef et al., 2011
Expected cognitive complexity (ECC)	Expected analytical and practical realization about ability and control to use machine autonomy personally to execute daily routine activities	
Expected psychological complexity (EPC)	Expected emotional evaluation about ability and control to use machine autonomy personally to execute daily routine activities	
Expected technological uncertainty (ETU)	Expected level of assurance to avail assistance from machine autonomy without human support whenever it is required	
Expected Cognitive Risk (ECR)	Expected analytical and practical realization about potential threats to use machine autonomy	
Expected Psychological Risk (EPR)	Expected emotional evaluation about potential threats to use machine autonomy	
Family Benefit and Accomplishment (FBA)	Expected level of achievements users believe their family will receive by using machine autonomy	
Expected Cognitive Performance (ECP)	Expected analytical and practical realization of getting benefits users believe their family will receive by using machine autonomy	
Expected Psychological Performance (EPP)	Expected emotional evaluation of getting benefits users believe their family will receive by using machine autonomy	
Expected Empathetic Cooperation and Social Interaction (EECSI)	Expected level of scope and availability about mental and social attachment machine autonomy can provide	
Self-Concept and Personality & Image (SCPI)	Overall evaluation of own characteristics about the level of compatibility with machine autonomy	
Trust (TR)	Overall confidence about the credibility and reliability to use machine autonomy personally to execute daily routine activities	