International Journal of Innovative Research and Scientific Studies, 8(5) 2025, pages: 1747-1758

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

The perceived effort expectancy on assistive technology: A comparative analysis among the pre-ageing and ageing population

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Abstract

Age stereotyping leads to the digital divide, which assistive technology aims to overcome. There is a need to address such stereotyping in terms of the capabilities and effort expectancy of assistive technology, based on cognitive, physical, and social capabilities. This research examines the variation in response for the constructs of cognitive, physical capabilities, and social presence, as well as effort expectancy. An effective model was also developed using the ANN for future work. This study focused on the effort expectancy of assistive technology and the factors of cognitive, physical, and social changes caused by aging. Data was collected through a structured questionnaire derived and adopted from previous studies from pre-aging (45 to 60 years of age) and aging (60–75 years of age) users. It was found that there was no significant difference in the responses among the pre-aging and aging respondents when it comes to cognitive and physical aspects, as many perceive themselves to be younger than their actual chronological age. However, social factors were responded to differently among the two groups due to different social needs and self-determination of the aging respondents. The findings offer a new affective model that can be explored in the near future, which can provide practical implications for technology developers, designers, and policymakers aiming to improve the accessibility and usability of technology for aging individuals.

Keywords: Assistive technology, Cognitive, Physical, Pre-aging and Aging Users, Social.

DOI: 10.53894/ijirss.v8i5.9271
Funding: This study received no specific financial support.
History: Received: 12 June 2025 / **Revised:** 14 July 2025 / **Accepted:** 16 July 2025 / **Published:** 13 August 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Study conception and design, Haris Bin Abd Wahab (HBAW); material preparation, data collection, data analysis, manuscript drafting, Mansoor Ali Mohamed Yusoof (MAMY); manuscript review, comments, suggestions for improvements, Kumarashwaran Vadevelu (KV). All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Technological advancements offer tangible benefits in personal and social lives, but they also create an environment where there is a constant requirement to keep pace with rapidly changing technology. Individuals without a solid foundation in technology will struggle to keep up with those who have access to and are utilizing these technologies. The need to stay current eventually leads to the technological divide, which in the age of information technology has resulted in the "digital divide." [1-4] Many researchers consider the digital divide a social justice issue, as the lack of digital skills and access prevents disadvantaged groups from benefiting from the information technology revolution.

While some of the digital divide is due to people who do not have access to or face challenges in using technology, the divide can also occur over time. Aging can lead to an individual's inability to use technology, which is becoming more challenging due to biological changes and shifts in social structures [5].

For some, ageing is all about older people in rocking chairs or nappies, which creates a negative paranoia of ageing in society Gendron et al. [6]. Neugarten [7] identifies two basic strategies related to ageing. The first one is to consider ageing as a new challenge and opportunity by formulating various positive ways of coping with ageing, without withdrawing from social life and limiting life satisfaction. The second one is to accept ageing in negative ways, such as withdrawing from participating in society into a closed circle of family life or solitude. Here, an individual may accept the fact that they are old and view the ageing process as a negative aspect of life, where it is a disadvantage for the individual and others related to them.

One attempt to reduce the technological gap is to incorporate assistive technology (AT) that supports older users in accessing and using digital technology. AT is a term that describes technology designed to support people, especially older adults and those with disabilities or long-term conditions, to compensate for their functional difficulties or decline [8]. AT aims to support the ageing community both physically and emotionally [9]. There is a critical need for research to explore how users' capabilities, such as cognitive, physical, and social factors, specifically impact the acceptance and use of AT among aging adults, especially during the transitional phase from pre-aging to aging, to bridge the digital divide effectively and support healthier aging.

As aging results in a reduction in the functioning and capability of the EIAT, the intention to use ATs depends on whether they can achieve ease of use or reduce the effort needed to use ATs as intended. When it comes to ease of use, the ATs, there is a need for researchers and developers to understand the acceptance and usage of AT for aging users, considering the deteriorating cognitive and physical capabilities of older individuals. Despite various theories explaining technology acceptance and use, there is limited research on users' capabilities, such as cognitive, physical, and social, which are viewed differently among users based on their age. The common pretext is that these three capabilities decline with aging and can have a significant impact on the acceptance of AT.

This research examines the impact of ageing-related capability factors on the acceptance of AT, encompassing cognitive, physical, and social aspects for different age groups. The research aims to answer the question of the differences in cognitive, physical, and social aspects that influence the intention to use AT among different age groups. We have grouped the adult users into two age groups: pre-aging (45 to 60 years of age) and aging (60 to 75 years of age). Data was collected through a structured questionnaire derived and adopted from previous studies.

The remainder of the paper is organized as follows: Section 2 provides the background, underlying theories, and conceptual framework of this study. Section 3 presents the details of the methods adopted to achieve the aim of this research. Section 4 presents the results of the data analysis, which include demographic and SEM analysis, while Section 5 offers detailed discussions of the results. Section 6 examines an effective model to explain the perceived effort expectancy for AT, while Section 7 concludes the findings.

2. Literature Review

Digital divide is described as "the differences in accessing and usage of digital technologies by various social groups and communities" [10]. Digital divide can be defined as the differentiation in access to information and communication technologies between individuals, enterprises, and geographic areas, as well as the possibility of using these technologies for various purposes. The gap can manifest in several forms within a society due to demographic characteristics (such as age, gender, disability, and others), personality traits (for example, intelligence level, behavior, and motivation), and the level of competence in using IT [11].

The digital divide is essentially digital inequality caused by the lack of access to computer technology, which impairs pre-existing inequalities as well as establishes new ones [12]. Researchers have identified the digital divide across four fundamental levels. The first pertains to the use and adoption of the internet [13] while the second concerns the unequal distribution of technological access among different groups [14]. Digital technology is often assumed to be homogeneous, although it is becoming increasingly complex and fragmented [15].

Over the last few decades, digital technology has become an integral part of the lives of older adults [16]. Yes, technology plays a key role in the lives of older people, including everyday devices such as smartphones, fitness trackers, and electric bicycles [16]. Technology development now includes the needs of aging users [17]. For aging users, the common forms of digital assistive technology include robotics and mobile or computer-based applications [18].

According to [9], when aging, there are three main problem categories: sensory problems, motor problems, and cognitive problems. Many technological breakthroughs, such as Artificial Intelligence, speech-based interaction, and affective computing, benefit aging users. However, there is a disconnection between developers and aging users regarding the degree of capability and ability required to use the assistive technologies (AT) [19]. Such disconnection affects the acceptance and usage of AT.

2.1. Ageing and Technology Stereotyping

The process of aging is viewed differently across Western and Eastern cultures [20-22]. In Western culture, being old and aging is a disadvantage as old people are vulnerable, subject to social isolation, financially dependent, and have worsening health conditions [20, 21]. Ageing stereotypes affected both the young and the old, with both positive and negative impacts [23]. Gendron et al. [6] ageing is often associated with infantilized older persons in rocking chairs or nappies, creating a negative paranoia of ageing. Such a negative perception results in a lack of respect and the assumption that older people are an economic liability [24].

Age stereotypes are primarily the products of the cognitive construction of age-related social norms, which are unable to tolerate the possibility of individuals who deviate from such norms [25]. Using age as an identity, such as chronological age, indicates the stages of human life as an indicator of life stages, including childhood, adolescence, adulthood, and old age, allowing a person to highlight and amplify their resistance or association with a particular age concept and category. Despite criticisms, chronological age remains the established and normalized means of conceptualizing age in both quantitative and qualitative research [26]. However, demographic realities resulting from humans having longer lifespans and decreasing birth rates [27] and working longer years [28] as well as other modern aspects of life such as advances in digitization, may reduce the chronological age in practice.

The notion that older adults use less computer-based technology is often attributed to the fear of embarrassment that reveals an inability to use the technology, which ultimately confirms the stereotyping that society seeks to avoid [29]. In summary, aging leads to a reduction in the cognitive and physical capabilities of individuals. The declining capabilities of older individuals diminish their ability to use technologies designed for mass usage, such as smartphones or computers. The aging stereotyping fuels the gap in technology based on the pretext that EIAT are technology-averse. However, there are common alternative findings that defy the regular stereotyping of EIAT and technology, such as the use of mobile apps, which show that EIAT are keen to adopt smartphones [30].

In recent times, older people are more digitally aware today due to the need to obtain information and stay in contact with family [31] using devices such as mobile phones or smartphones [9]. Digital AT is aimed at enhancing the welfare and lives of older people, but users can be either the elderly themselves or their caregivers, particularly for health monitoring using sensors [32].

2.2. Theoretical Framework

The Human Activity Assistive Technology Model or HAAT [33, 34]. The capability of individuals in using technology is an important element in the development of technology, including AT. Individuals in their later years display similar usage patterns, reflecting the experience and use of certain types of technology in their formative years [35]. For example, the Internet and smartphones can be used to develop and maintain social relationships, thereby increasing older adults' interest in information technology [36].

Based on the HAAT model, it can be summarized that the ability of aging users to use assistive technology (AT) relies on their cognitive, physical, and social abilities, which in turn influence the level of effort needed to use the AT. As such, the focus of this research is on the ability of aging users to enjoy ease of use when using Ats Figure 1 illustrates the framework of this research, which focuses on the ability and ease of effort.

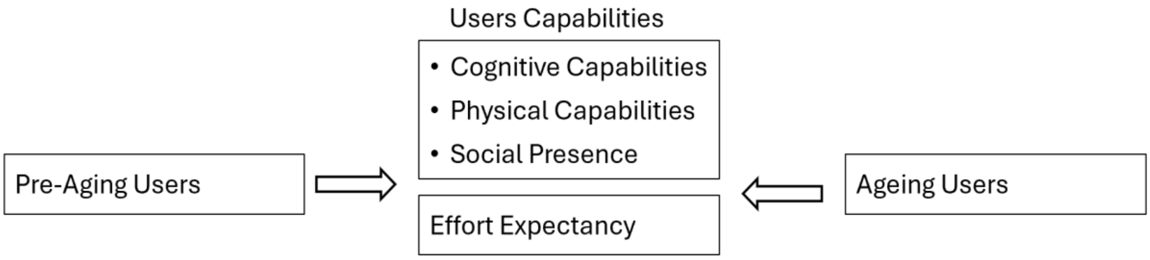

Figure 1.
The conceptual framework of this research.

Based on Figure 1, we hypothesize that the pre-aging and aging groups will view the elements of Cognitive Capabilities (COG), Physical Capabilities (PHY), Social Presence (SOCI), and Effort Expectancy (EE) differently. Individuals with a greater cognitive age (perceiving themselves as older) are less efficient, have less attentional capacity, and process information more slowly, despite their chronological age [37]. The cognitive capabilities of any individual decline with time [38], which can affect the use of devices that require visual and motor neuron input, such as typing or interacting with touchscreen devices like smartphones [39]. Cognitive overload occurs when an individual needs to analyze a large amount of complex or difficult information that requires more time to make sense of it [40]. Previous studies have shown that an increase in cognitive load requires users to exert more effort when using technology [38].

The physical deterioration that accompanies aging increases the challenges in accessing hardware features or digital content, caused by limitations in mobility and decreased visual capacity [41]. The adverse effect of ageing is the biophysical changes [42] that result in a steady loss of motor and sensory nervous system functions. As such, older individuals often find it challenging to adopt and use technologies that require physical effort. Combined with the waning of physical and cognitive abilities, such as hearing, vision, speech, locomotion, and memory capabilities, the ability to use technology decreases [43]. Poor physical functioning, particularly in sensory organs and motor control, affects the acceptance of technology, especially when there is an increasing requirement for effort in using those technologies.

With the decline in cognitive and physical abilities, aging users tend to depend on younger users for support and assistance. For example, the Internet and smartphones can be used to develop and maintain social relationships, thereby increasing older adults' interest in information technology [36]. Since it is not unusual for humans to engage with technology as if it were a social entity, we can expect that this effect is exacerbated when technology takes the form of an embodied character and interacts in a social manner using natural language and non-verbal human behaviors.

A person who lacks confidence in his/her abilities and skills would not make the effort to accomplish a task, and he/she would show less persistence in overcoming any potential obstacles than those with high confidence in their abilities and skills [44]. Although not explicitly mentioned, aging can determine the level of confidence and self-efficacy.

Increasing age may negatively impact the acceptance of technology [45]. While both Performance Expectancy and EE play a role in affecting technology acceptance among older adults, EE is a significant challenge uniquely associated with aging due to declines in physiological functions [45]. EE is associated with difficulties in processing complex stimuli and allocating attention to relevant information on the job, both of which may be necessary when using software systems [46]. Age may affect the EE among older adults, due to reduced cognitive abilities [47] and the increase in age weakens the relationship between EE and behavioral intention. This is because older users tend to perceive the complexity of technology more, while younger people tend to perceive the usefulness of technology more [48]. Shen [45] it was suggested that aging-related physiological decline, such as vision and hearing loss, and cognitive decline, such as memory impairment, are likely to have a significant impact and uniquely contribute to predicting EE and acceptance of technology.

3. Data and Methodology

This study examines the differences in aging-related factors that influence the acceptance of AT among the pre-aging and aging populations. The research’s theoretical foundation synthesizes constructs from technology acceptance among the pre-aging and aging populations, focusing on a common technology that benefits both groups, thereby forging a comprehensive understanding of aging-related factors on technology acceptance. This study enables bridging the current literature gaps, equipping stakeholders with invaluable insights, and paving the way for a digital metamorphosis among the aging population.

The target respondents are Malaysians who are pre-ageing (40 to 55 years of age) and ageing (55–70 years of age). This classification was based on the agreement among researchers that ageism has different effects on different age groups [49, 50]. The research will be conducted in the Klang Valley, home to over eight million Malaysians. Klang Valley is an ideal place for conducting this kind of research as it is Malaysia’s most congested and developed central city [51]. It is the most suitable geographical location for studying AT due to the high penetration of the Internet [52] which enables the online administration of the survey. Additionally, research on AT was conducted in the Klang Valley, revealing a high degree of awareness of AT among residents [53].

This study employs convenience sampling methods, focusing on individuals classified as pre-aging and aging. Several existing studies on technology adoption have used convenience sampling [47, 54].

3.1. Instrumentation

In this study, the constructs and items from the instrument used in the previous study are adapted to the current study's context, a common approach in instrument development, as existing instruments have been evaluated for validity and reliability [55]. The items include cognitive age [56] cognitive load [40] and intelligence [57] for cognitive capabilities. Hearing/speech [58, 59], Visual [58] and hand movement [60] are related to physical capabilities. Social inclusion [61] and social isolation [62] are related to social aspects, and effort expectancy [63] is related to the overall experience.

The operationalization of the instrument was based on a five-point Likert scale. Respondents need to rate each statement in the survey with the five-point Likert scale from (1) “strongly disagree” to (5) “strongly agree.” For a positive statement, the scores given by the respondents will be taken as they are. However, for negative statements, the score given by the respondents will be adjusted using the following formula: 6 - n, where n refers to the score given by the respondent.

3.2. Ethical Consideration

The research instrument and the data collection method have been reviewed and approved by the Universiti Malaya Research Ethics Committee (UMREC). The participants are not forced to participate in the research. If the participant feels uncomfortable with the survey, they may withdraw from the study at any time. Researchers do not share the respondents’ information with third parties. The researchers did not ask sensitive questions about physical or mental disabilities from the respondents.

3.3. Data Collection

The survey was administered online and through physical distribution to older respondents (age 55 and above). For the online survey, the researchers shared a link via social media platforms known to them and requested that they share the link with their contacts, thereby increasing the broadcasting range. At the end of the survey, respondents are encouraged to forward the link to the survey page to any family members or friends who are over 40 years old. The physical distribution of the survey for older adults is mainly because many of them may lack access to or have difficulties accessing the online survey [64]. It is important to ensure a balance between the pre-aging and aging groups, as the pre-aging group is more likely to complete the online survey.

3.4. Data Analysis Technique

Employing the analytical capabilities of SmartPLS 4, the study meticulously evaluates the data using the Measurement Invariance of Composite Models (MICOM) procedure [65], which is a crucial step in comparing constructs across different age groups in this study. When using structural equation modeling, comparison across time or groups can be misleading if measures are not invariant [66]. The MICOM procedure has gained widespread dissemination. MICOM has been applied in various research areas, including cultural intelligence, tourism, employee well-being, and digitalization, among others [66].

MICOM is used to assess whether the measurement model holds invariantly, meaning it measures constructs equivalently across groups [65], which is crucial for ensuring valid comparisons of constructs like Cognitive Presence (COG), Effort Expectancy (EE), Physical Capabilities (PHY), and Social Presence (SOCI) across different age groups.

Another new and novel approach in this research is the use of an ANN for predicting an effective model that can examine the intention to use AT among different age groups effectively. To explore the non-linear interactions and the potential hidden patterns within the constructs, the study progressed to employing Artificial Neural Networks (ANN) [67]. The architecture of the ANN was designed to reflect the complexity of interactions while maintaining interpretability. The network included an input layer (a neuron representing each of the predictor variables: cognitive presence, physical capabilities, social presence, and EE), hidden layers (two hidden layers), and an output layer (two neurons, one for each outcome variable).

Training the ANN involved using backpropagation with a gradient descent optimization algorithm. The model parameters, including the learning rate and the number of epochs, were selected based on preliminary experiments to optimize the convergence rate without overfitting. Once trained, the model's performance was evaluated using unseen test data. This step was crucial to assess the generalizability of the model. Key performance metrics such as Mean Squared Error (MSE) for regression outputs and accuracy metrics for classification outputs (if applicable) were calculated. With ANN, we developed a conceptual framework that most effectively explains the intention to use AT among different age groups based on the data collected from the respondents.

4. Findings

4.1. Demographics Analysis

Table 1 depicts the demographic composition of the two groups of pre-aging and aging users, indicating a balanced composition in terms of gender, level of education, and income.

Table 1.
The demographic composition of the two groups of pre-aging ang aging users.

Demographic	Category	Pre-Aging	Aging	Total
Gender	Male	119 (30.43%)	92 (23.53%)	234 (59.9%)
	Female	115 (29.41%)	65 (16.62%)	157 (40.1%)
Level of education	Diploma and lower	15 (3.8%)	35 (9.0)	50 (12.8%)
	Bachelor's degree	64 (16.4%)	33 (8.4%)	97 (24.8%
	Master's degree	135 (34.5%)	77 (19.70%)	212 (54.2%)
	Ph.D.	20 (5.1%)	12 (3.1%)	32 (8.2%)
Level of income	None	0 (0.0%)	1 (0.3%)	1 (0.3%)
	Less than RM 2000	22 (5.6%)	82 (21.0%)	104 (26.6%)
	RM 2,000 to 4,000	32 (8.2%)	15 (3.8%)	48 (12.0%)
	RM 4,000 to 6,0000	54 (13.8%)	29 (7.4%)	83 (21.2%)
	More than RM 6,000	126 (32.2%)	30 (7.7%)	156(9.9%)

Table 2.
Measurement Model Statistics (Higher Order Construct).

Construct	Items	OL	VIF	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted
COG	AGE	0.922	3.384	0.899	0.904	0.937	0.832
	INT	0.943	3.907				
	LOAD	0.915	2.896				
PHY	PHM	0.917	3.168	0.828	0.828	0.897	0.745
	PSH	0.852	1.770				
	VIS	0.878	2.655				
SOCI	SIN	0.919	1.360	0.865	0.872	0.897	0.557
	SIS	0.811	1.360				

Note: EE→ Effort Expectancy, IUAT→ Intention to Use AT, COG→ Cognitive, PHY→ Physical, SOCI→ Social.

4.2. Measurement Model Statistics

Table 2 shows the measurement model statistics for the constructs. It becomes evident that all constructs display good reliability, with Cronbach's alpha and composite reliability values exceeding the acceptable threshold of 0.7, indicating that the constructs consistently measure the intended underlying phenomena [67]. The AVE values are also above the commonly accepted level of 0.5, indicating satisfactory convergent validity.

4.3. Measurement Invariance of Composite Models

Table 3 presents the Multigroup Analysis (MGA) of age using the Measurement Invariance of Composite Models (MICOM) procedure. This finding underscores a high level of construct correlation consistency across different age groups, indicating stable construct relationships even when subjected to permutations.

Table 3.
MICOM.

	Original correlation	Correlation permutation mean	5.0%	Permutation p-value	Support
COG	1.000	1.000	0.999	0.173	Yes
EE	0.999	1.000	0.999	0.164	Yes
PHY	0.999	0.999	0.998	0.395	Yes
SOCI	1.000	0.994	0.979	0.830	Yes

Note: EE→ Effort Expectancy, COG→ Cognitive, PHY→ Physical, SOCI→ Social.

At a p-value of 0.05 it indicates no significant divergence between the observed correlations and those generated through permutation. This supports the hypothesis that this study's measurement model remains invariant across groups. The confirmation of measurement invariance across age groups is critical, suggesting that this study's constructs are robustly and consistently measured, irrespective of age.

4.3.1. Mean

In conducting a multigroup analysis, two pivotal steps were undertaken: examining mean differences and exploring variance differences among the constructs [65]. From Table 4, the analysis revealed negligible to slight negative differences in the means across constructs, with permutation p-values suggesting no statistically significant differences [67]. Specifically, the permutation means differences hovered around zero, and the confidence intervals included both negative and positive values, indicating a lack of systematic mean differences between the groups for constructs such as COG, EE, PHY, and SOCI.

Table 4.
Mean.

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p-value	Support
COG	-0.069	0.005	-0.188	0.203	0.499	Yes
EE	-0.131	0.008	-0.190	0.193	0.182	Yes
PHY	-0.069	0.006	-0.194	0.206	0.508	Yes
SOCI	-0.036	0.008	-0.188	0.208	0.726	Yes

Note: EE→ Effort Expectancy, COG→ Cognitive, PHY→ Physical, SOCI→ Social.

4.3.2. Variance

Interestingly, variance differences presented a different scenario. All variables exhibit significant variance differences, as indicated by permutation p-values above 0.05 [68]. This finding indicates that the variability in participants' perceptions of technology might significantly differ across age groups, suggesting a divergence in how these experiences or expectations determine technology acceptance, as indicated in Table 5.

The lack of significant mean differences across most constructs suggests that, on average, all variables are perceived similarly across age groups. However, the significant variance points to a diversity in the variables that have a significant influence on effort expectancy and technology acceptance, underscoring the importance of not only considering average perceptions but also the variability within those perceptions in technology design and implementation for different age groups [69].

Table 5.
Variance.

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p-value	Support
COG	0.819	0.006	-0.353	0.394	0.000	No
EE	0.605	0.002	-0.384	0.404	0.007	No
PHY	0.660	0.009	-0.329	0.373	0.000	No
SOCI	0.859	-0.004	-0.393	0.396	0.000	No

Note: EE→ Effort Expectancy, IUAT→ Intention to Use AT, COG→ Cognitive, PHY→ Physical, SOCI→ Social.

4.3.3. Bootstrap MGA

The significant p-values and t-values found in this study corroborate these findings, suggesting that cognitive and social factors are critical determinants of effort expectancy and, by extension, the intention to use technology, irrespective of age. Conversely, the lack of significant findings for SOCI -> EE in the 56-70 age group raises interesting considerations. Literature suggests that physical capabilities may have a varied impact on technology acceptance, potentially influenced by age-related declines in physical functions [70]. The absence of significant p-values in this age group may reflect the complex relationship between physical abilities and technology use, where the significant influence of physical capabilities on effort expectancy and IUAT may not be as straightforward as cognitive and social factors, as shown in Table 6.

Table 6.
Bootstrap MGA.

		t value (Group_40-55)	t value (Group_56-70)	p-value (Group_40-55)	p-value (Group_56-70)	Support
H1	COG -> EE	2.989	3.487	0.003	0.000	Yes
H2	PHY -> EE	17.499	7.787	0.000	0.000	Yes
H3	SOCI -> EE	5.862	1.140	0.000	0.254	No

Note: EE→ Effort Expectancy, COG→ Cognitive, PHY→ Physical, SOCI→ Social.

5. Discussion and Conclusions

This study highlights the critical importance of considering age-specific factors in the design and implementation of assistive technologies. The consistent role of cognitive and physical factors across age groups underscores the need for interventions that enhance the perceived ease of use and social support for technology use among older adults. However, the nuanced impact of physical capabilities suggests that tailored strategies may be necessary to address the unique challenges faced by individuals in the 56- to 70-year-old age bracket. This differentiation is crucial for developing effective technology acceptance strategies that cater to the diverse needs and capabilities of Malaysia's aging population.

The bootstrapping results emphasize the complexity of technology acceptance dynamics among aging populations. For cognitive and physical capabilities, there is no perceptual difference in the users' cognitive ability between the two groups. Both groups understand the role of cognitive skills required to use AT. The findings also reveal that respondents in both groups feel that their cognitive capabilities are adequate when accepting and using AT. This finding is explained in Berkowsky et al. [71], where it is noted that if technology is considered valuable and important, participants will learn it regardless of the difficulty level. Older adults are more likely to consider adopting technology if they perceive it as useful and believe it will have a positive impact on their lives. It also shows that AT design has the cognitive capability that matches the current capabilities of both groups of users, resulting in no significant difference in the responses among the groups.

Most respondents perceive themselves to be younger than their actual chronological age, showing higher levels of self-confidence, self-respect, innovativeness, as well as a willingness to try new innovations and accept change [72, 73]. The result shows the misleading stereotyping of older users based on their chronological age. The result also supports the STAM model, which suggests that an older adult's self-perceived characteristics play a vital role in technology adoption and acceptance [74].

The findings also reveal that respondents in both groups feel that their current physical ability is adequate when accepting and using assistive technology (AT). One reason why the uniformity in responses among the two groups could be the lack of physical disability among the respondents. In the natural process of aging, older adults usually show different levels of sensory decline, with most experiencing auditory and visual decline. However, with increased use of sensory aids, such as hearing devices, glasses, screen readers, large-screen mobile phones, and so on, such sensory decline can reduce cognitive loads and increase the use of Ats [75].

The older group disagrees that social influence is important for perceived EE, which does not align well with the existing work, as highlighted in Mannheim et al. [76] where older adults often depend on younger generations for support in accepting and using technology. The results show that the pre-aging group feels they will need the support of young people when using technology as they age. However, the aging group did not agree that they needed the support of young people when using technology. This finding was supported in Berkowsky et al. [71] where technology was considered valuable and important; participants would learn it with or without support, regardless of the difficulty level. On the other hand, a study by Semlambo et al. [54] found that social influence is perceived differently by young and older users.

Older adults are more likely to consider adopting technology if they perceive it as valuable and believe it will positively impact their lives. An interesting justification for this was found in Berkowsky et al. [71], where older users stated that being old means they have plenty of time to learn about technology and become accustomed to it, thereby increasing the acceptance and usage of AT. Again, the responses from the older users are based on their perception of their capabilities in using technology such as AT. This coincides with their perception of cognitive and physical capabilities in using AT.

5.1. Designing an Effective Acceptance Model for AT

The result of the Bootstrap MGA Difference analysis provided insights into the direction and significance of the differences between the two age groups regarding the impact of COG, PHY, and SOCI on EE. The results indicated no significant differences between the groups for all items, as shown by the 1-tailed and 2-tailed p-values, which did not reach the conventional threshold of statistical significance ($p < 0.05$). These findings suggest that the relationships between these constructs and outcomes do not significantly differ between the 40-55 and 56-70 age groups.

The interpretation of the results from the repeated runs of the ANN model, as detailed in Table 7 below, focuses on the variations in training and testing mean squared error (MSE) and root mean squared error (RMSE) across runs. These variations offer insights into the stability and generalizability of the model under different initialization conditions and training iterations.

The results presented illustrate the performance of two stages in an Artificial Neural Network (ANN) model where a set of independent variables (AGE, INT, LOAD, PHM, PSH, VIS, SIN, SIS) first predict Effort Expectancy (EE). Here is a detailed interpretation of the performance metrics across both stages of this model:

Stage 1: EE as Dependent Variable

Training and Testing Efficiency: The model achieves relatively high efficiency in both training and testing phases, with efficiency mostly hovering above 86% in training and 83% in testing. This high efficiency indicates that the ANN model can effectively capture and utilize the relationships between the diverse set of predictors and EE.

Error Rates: The training error rates range from approximately 9.7% to 13.2%, and the testing error rates range from approximately 12.6% to 16.5%. These error rates, although modest, highlight areas where the model's predictions deviate from the actual outcomes, suggesting room for model optimization and potential issues with overfitting.

Stage 2: IUAT as Dependent Variable

Training and testing efficiency: In this stage, the model shows a slight decrease in efficiency compared to the first stage, especially in the testing phase.

Table 7.
The variations in training and testing mean squared error (MSE) and root mean squared error (RMSE) across runs.

EE as dependent					**IUAT as Depended**				
Run	**Training Efficiency (%)**	**Testing Efficiency (%)**	**Training Error Rate (%)**	**Testing Error Rate (%)**	**Run**	**Training Efficiency (%)**	**Testing Efficiency (%)**	**Training Error Rate (%)**	**Testing Error Rate (%)**
Run 1	89.2	86.7	10.8	13.3	Run 1	88.4	84.5	11.6	15.5
Run 2	87.5	84.2	12.5	15.8	Run 2	86.9	83.3	13.1	16.7
Run 3	88.1	85.9	11.9	14.1	Run 3	87.5	85	12.5	15
Run 4	90.3	87.4	9.7	12.6	Run 4	85.7	82.9	14.3	17.1
Run 5	86.8	83.5	13.2	16.5	Run 5	89.1	85.6	10.9	14.4
Run 6	89	86.1	11	13.9	Run 6	87.2	83.8	12.8	16.2
Run 7	88.7	85	11.3	15	Run 7	88.3	84.7	11.7	15.3
Run 8	87.4	84.8	12.6	15.2	Run 8	86.5	82.1	13.5	17.9
Run 9	90.1	87	9.9	13	Run 9	87.9	85.2	12.1	14.8
Run 10	88.3	85.5	11.7	14.5	Run 10	85.3	81.7	14.7	18.3

From Table 7, based on the best run using the ANN, the practical framework for explaining the perception of AT among the elderly in Malaysia, as determined by the identified factors, is presented in Figure 2 below. The new model is based on low-level variables, which include all components of Cognitive Presence (Chronological Age, Cognitive Load, and Intelligence), all components of Social Presence (social inclusion and social isolation), and physical hand movement as independent variables. The other two components of Physical Capabilities (Visual and Speech & Hearing) are now moderating variables.

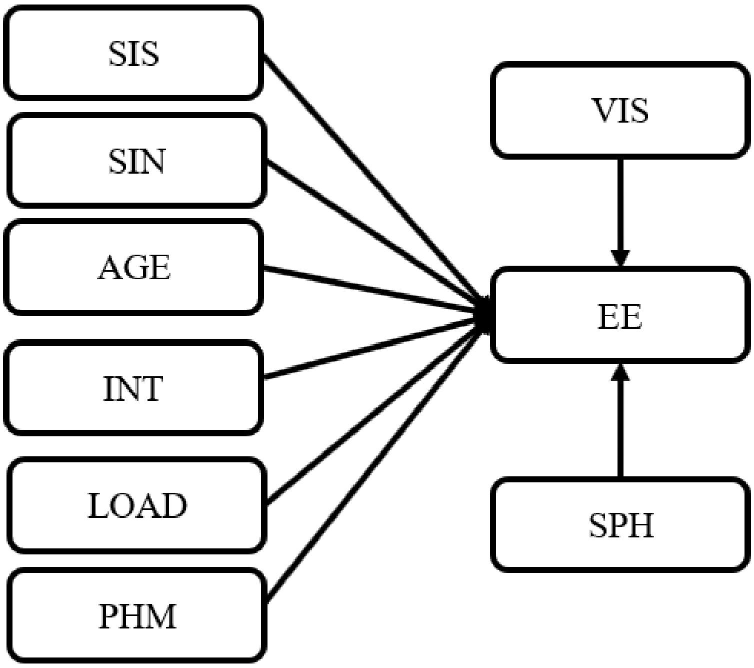

Figure 2.
The design of an effective acceptance model for AT among the EIAT.

5.2. Conclusion

One significant finding in this research is that the existing stereotype that older users are technologically adverse is rejected. While both cognitive and physical abilities are critical for perceived effort expectancy, as they are necessary for interacting with technology, particularly computers and mobile devices, the responses from the pre-aging and aging groups did not differ significantly. This indicates that both groups understand the role of cognitive and physical factors in the acceptance and use of assistive technology (AT). The findings also reveal that respondents in both groups feel that their current cognitive and physical capabilities are adequate when accepting and using AT. Most aging respondents perceive themselves to be younger than their actual chronological age, exhibiting higher levels of self-confidence, self-respect, innovativeness, and a willingness to try new innovations and accept change.

Based on the best-performing model using ANN, the new model is based on low-level variables, which are all components of Cognitive Presence, Social Presence, and Physical Capabilities. The ANN model's performance in this study highlights its potential in deciphering complex relationships within behavioral data. However, it also underscores the necessity for meticulous model tuning and validation to ensure reliable predictions that can effectively inform technology adoption strategies. This analysis provides valuable insights into the dynamics of technology acceptance and points towards areas where further research and model development could be beneficial for future work in this domain.

5.3. Implications for the Study

Model Generalization: The consistency in training and testing efficiency across both stages indicates that the model is generally robust, but it also shows signs of potential overfitting, as evidenced by higher testing errors.

Complexity of behavior prediction: The increased difficulty in accurately predicting EE suggests that user intention is influenced by other factors, possibly emotional or contextual, that may also play significant roles and should be considered in further model refinements.

Need for Model Optimization: The results advocate for continuous model tuning, possibly through hyperparameter optimization, incorporation of regularization techniques, or even exploring different model architectures. Additionally, feature engineering that includes interaction effects or higher-order terms may capture complex relationships more effectively.

Strategic Implications: For practical applications, understanding the role of EE is crucial. Interventions aimed at improving effort expectancy could be strategically designed to enhance overall technology adoption among the targeted aging populations.

5.4. Research Limitations and Future Works

In summary, this study has limitations that should be taken into consideration when interpreting its findings. The potential for socially desirable responses by participants may have influenced the results. Additionally, the variables used were validated in a Western-based sample, which may limit their generalizability to non-Western contexts.

The study was also conducted in the context of pre-ageing and ageing users in Malaysia residing in the Klang Valley. Respondents from the Klang Valley have the highest adoption of technology across different age groups, including both young and old, as well as those with disabilities. The findings of this research will thus be limited to its relevance to other pre-ageing and ageing users. The target respondents are the pre-ageing (40–55 years) and ageing (55–70 years).

For future directions, the proposed model by ANN can be tested to determine the strength of the model in assessing EE among AT users. A longitudinal study could be conducted to understand the impact of aging on the actual use of technology and the capability over time. Researchers can confirm the consistency of the constructs over time and their linkages through such a study, as well as continuously gauge the impact of modifications. Furthermore, additional research studies should be conducted to validate and reinforce the findings of this study.

Secondly, future research could benefit from including non-users of digital technology in the study population. Additionally, a larger sample size would enable researchers to validate the study findings further and explore additional perspectives. To better understand the causes and consequences of users' capabilities in various digital environments, it would be helpful to undertake comparable research in other countries that may have different technology uptakes.

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