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Why Do Older Adults Feel Negatively about Artificial Intelligence Products? An Empirical Study Based on the Perspectives of Mismatches

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Abstract: Artificial intelligence products (AIPs) for older adults enhance the functions of traditional products and improve the quality of their lives. However, AIPs are not popular among this population, and limited attempts have been made to investigate these users' negative tendencies regarding AIPs. This study explores the causes of avoidance and exit behaviors toward AIPs among older people from both a functional and socio-emotional mismatch perspective. Data were collected from 1102 older AIP users to verify the research model and hypotheses. The results indicate that perceived control and expectation disconfirmation affect the functional mismatch, while public stigma has the greatest impact on the socio-emotional mismatch. Furthermore, the results highlight a mixed influence of the functional and socio-emotional mismatches on negative behaviors. This study explores older people's negative tendencies toward AIPs, comprehensively considering the functions of AIPs and the socio-emotions they evoke. Thus, it provides new empirical evidence for the systematic relationship between the functional mismatch and the socio-emotional mismatch and fills the research gap on the influence on the subsequent behaviors of older adults. Additionally, this study sheds light on the specific methods of designing, developing, and promoting AIPs.

Keywords: artificial intelligence products; negative tendencies; emotional mismatch; older people

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1. Introduction

The new generation of information technology has initiated a digital society in which the prominent application of artificial intelligence (AI) benefits humankind. Indeed, the adoption of AI has received considerable attention in almost all sectors, from healthcare to manufacturing [1]; in particular, AI products (AIPs) in elderly care that are equipped with assisted decision-making, automatic response, and intelligent service features are emerging, enhancing the functions of traditional products and improving the quality of the users' lives [2].

The new generation of conversational artificial intelligence represented by the large language model shows impressive natural language understanding and text generation ability [3], bringing the dawn in the field of voice assistants and robotic companions for older adults. However, there still remain many problems to be solved in the practice of AIPs in the field [3] of assistive technology for older people. In a recent large-scale promotion of AIPs in the Anhui Province, China, many older people shelved or abandoned AIPs after short-term usage, and follow-up surveys revealed attitudes of avoidance or resistance toward AIPs among these users. Furthermore, related studies also confirmed that these tendencies are prevalent among this population with different types of AIPs (e.g., ambient assisted living systems [4], healthcare monitoring products [5], and intelligent monitoring systems [6]). Thus, exploring the reasons for these negative tendencies of AIPs, rather than the reasons for adoption, could be more important. This will promote the deep integration of AI with human lives and solve social problems brought by AI.

Previous research has shown that the mismatch between the requirements of older people for the products they use and the AIPs' actual functions, along with the mismatch between their expectations and the socio-emotions the AIPs evoke, explain the failure of the AIP promotion [7,8]. For one thing, a decline in autonomy and a rise in expectations of independence with increasing age become the root of many conflicting events in the lives of older adults [9]. The assisted decision-making and intelligent service functions that AIPs possess, to a certain extent, reduce the opportunities for older people to make their own decisions and deviate from their actual needs, which has resulted in a negative attitude toward AIPs. Additionally, AIPs offer social significance to users while meeting their functional needs [10]. However, a mismatch can occur between users' expectations of AIP and the social evaluation they receive from using it, influenced by algorithmic bias, ageism, and stigma [11]. Accordingly, it is necessary to explore the behaviors of the avoidance and exit of AIPs among older people by considering both the functional mismatch and the socio-emotional mismatch.

Existing studies have mostly focused on a single dimension of products, such as the functions of products or the socio-emotions they evoke. For example, a research paradigm based on product functional design discusses participatory design [12], inclusive design, and accessible design for older adults by considering human–computer interaction [13]. However, these studies fail to spotlight the functional mismatch caused by the perceived intrusiveness and control of AIPs, along with the impact of the mismatch. In addition, several studies have been conducted from the socio-emotional perspective, for example, research on the mechanisms by which public stigma affects the resistance to AIPs of older people [14], research on how to dispel negative stereotypes of older people being unhealthy and technologically illiterate [7], and on the reasons for the negative feelings that arise (e.g., self-stigma and inferiority) when older people use AIPs [15]. While these studies focus on the causes of the socio-emotional mismatch, they lack empirical evidence connecting this mismatch to subsequent behavior.

In conclusion, no systematic research to date has explored the causes of the mismatches between AIPs and older people, and research gaps still exist on the impact of the mismatches on subsequent behavior by older users. Thus, this paper poses the following research questions to systematically understand the causes of functional mismatch and socio-emotional mismatch, along with the mechanisms that affect the negative AIP usage behavior of older people.

RQ1: What factors influence the functional mismatch and socio-emotional mismatch in the use of AIPs among older people?

RQ2: What are the differences in the mechanisms by which this functional mismatch and socio-emotional mismatch influence the negative use behavior among older people?

To address these issues, we construct a research model based on the cognition–affect–conation (CAC) pattern to investigate the causes of the avoidance and exit behaviors toward AIPs among older adults from the perspectives of the functional mismatch and socio-emotional mismatch in order to support future deep application of AIPs. In the next section, this paper reviews the existing literature and presents the research hypotheses. The third section describes the research methodology. The fourth section explains the data analysis and presents the results. Discussion, implications, and limitations are reported in section five. Finally, the last section presents conclusions.

2. Literature Review and Hypothesis Development

2.1. The Cognition–Affect–Conation Pattern

The CAC pattern describes the effect of external stimuli on an individual's emotions and intentions [16]. Cognition is the intellectual, spiritual, or rational state of an individual. Affect is the responses and preferences of the individual to external stimuli on the basis of cognition. Conation is a behavioral tendency to make comprehensive decisions based on cognition and affect. The essence of the CAC framework is the process of "information processing → preference formation → behavioral tendencies (actual behavior)" [17]. The CAC framework illustrates the direct influence of cognition on affective outcomes (e.g., attitudes or satisfaction) to motivate individual behavior [16].

The CAC framework, which is often used to study consumer behavior, provides a multi-level perspective to understand the mechanisms by which individuals' cognition about products is translated into actions through effect and enables examination of the impact of technology in the decision-making process of consumers [18]. Furthermore, the CAC framework is already being used as the foundation of other theories that can effectively explain the consumer adoption and usage behavior of new technologies [19]. According to previous studies, the CAC framework is well suited to explain the impact of new technologies on individual behavioral intentions, in both the functional and socio-emotional perspectives, for example, students' continuance intention on using mobile social network sites [20] or users' continued use and purchase intentions toward augmented reality technology [19]. At the same time, the CAC framework is able to explain the mechanism that generates negative usage behaviors of technologies and products, such as the avoidance of social media [16] or passive usage [21]. Therefore, using the CAC framework to study older people's avoidance and exit behaviors towards AIPs is appropriate.

2.2. Negative Effects of AIPs for Older People

AIPs are a new generation of information technology products that can interact with the environment and are designed to mimic human intelligence [22]. AIPs for older people, such as ambient assisted living systems and healthcare monitoring devices, provide potential solutions and new opportunities to reduce the burden of elderly care and improve the quality of their lives [23]. However, AIPs equipped with assisted decision-making and intelligent services often result in negative emotions because they do not match the actual needs of older people. In addition, the designers of AIPs have difficulty accurately analyzing and understanding the emotions of older people due to a lack of training data from this population, leading to negative tendencies toward AIPs among older people. Specifically, it is not always beneficial for older people to be overloaded with advice and assistance [24]. The gradual loss of independent living skills with increasing age makes older people more eager to make decisions on their own, so the frequent advice from the AIPs is often seen as an interruption or intrusion [25]. Furthermore, AIPs lead to negative effects on older people's self-esteem, perceived control, and psychological cognition [26,27]. Therefore, we review the current research to further identify and confirm the negative effects of AIPs on older people (Table 1).

Table 1. Negative effects of AIPs on older people.

	Research Objects	Research Subjects	Negative Effects	Reference
1	ICT and older people	The impact of digital participation on the quality of life of older people	Perceived control; feelings of shame; privacy disclosure; social isolation	[28]
2	AI	The ethical issues of geriatric technology in elderly care	Discrimination; dehumanization	[5]
3	AI and IoT	The influence of AI on life assistance and health monitoring of older people	Perceived control; perceived intrusiveness	[23]
4	AI	Opportunities and challenges	Prejudice; discrimination	[6]
5	AI and expert systems	Expectations of AI	Expectation disconfirmation	[29]
6	Virtual personal assistant	Active aging	Perceived intrusiveness	[30]
7	AI and robotics	Lessons from intelligent products for older people	Non-availability; emotional reaction; discrimination; loss of autonomy	[31]

Table 1. *Cont.*

	Research Objects	Research Subjects	Negative Effects	Reference
8	AI	Aging in place	Perceived control; non-availability; lack of technical literacy	[32]
9	Intelligent wearable system	Status and challenges	Stigma; feelings of shame; perceived intrusiveness	[33]
10	Intelligent assistive technology	The emotional experiences and attitudes	Perceived control; lack of literacy; stigma; feelings of shame	[15]
11	Geriatric technology	Reasons for negative behavior of older people	Social isolation; addiction	[34]
12	Geriatric technology	The acceptance of geriatric technology	Technology anxiety	[35]
13	Assistive equipment	The ethical discussion of technologies in the community	Stigma; feelings of shame; private anxiety; perceived control; perceived intrusiveness	[36]
14	Autonomous vehicles	External and internal factors for acceptance	Stigma; stereotype	[37]
15	Wearable devices and sensors	Quantified self	Stigma; feelings of shame; perceived control	[38]
16	Advanced technology (AI and robotics)	Psychological barriers to digital society	Technology anxiety	[39]
17	Assistive technology	Barriers to technology adoption	Perceived uselessness; stigma; not being independent	[4]

Notes: ICT = information and communications technology; IoT = Internet of Things.

As Table 1 shows, the negative effects of AIPs are diverse, including technical, social, and psychological aspects. AIPs have functional properties, indicating that some negative effects can be categorized as being in the functional dimension [40]. In addition, the social attributes of AIPs, such as the expectations of individuals and the perceptions of others, show a more social, psychological, and emotional dimension than other types of products [41]. Therefore, we divide the negative impact of AIPs into two aspects: a functional mismatch and a socio-emotional mismatch.

2.3. Functional Mismatch of AIPs

User experience, the satisfaction of requirements, and expectation confirmation are the basic principles of modern product design [42]. For older people, the core design principle of age-friendly products is to meet their relevant needs based on their physiological and psychological characteristics [43]. In the "pre-smart" era, safety, usability, and attractiveness were the key factors considered by older people when choosing products [44]. However, the design of AIPs focuses more on having functions, such as assisted decision-making and intelligent services, all accomplished using big data and intelligent algorithms [45]. Although current AIPs for older people meet the design principle of "satisfaction of requirements", the current design philosophy may be flawed; as a result, the products deviate from the expectations and experiences of older people [46].

The physical deterioration caused by aging can make daily life progressively more difficult for older people. AIPs for older adults were originally designed to help them overcome these difficulties and maintain their autonomy and independence. However, these AIPs often trigger negative emotions by not matching the actual needs of the users [47]. First, the perceived intrusiveness of the AIPs becomes a social issue because the AIPs tend to acquire information and preferences of individuals to provide personalized services and achieve targeted functions [48]. Older people are more concerned than others about this invasion of personal privacy and security enough that they resist using AIPs [32].

Additionally, privacy concerns make it difficult for older people to enjoy the personalized, high-quality services offered, and ultimately, older users have more negative emotions about the functions of the AIPs. Second, older people expect to be assisted by AIPs. However, when the AIP offers too many reminders and suggestions, the user feels increasingly controlled by it; this phenomenon is more obvious for older people who are eager to live independently, which leads to a series of negative comments on the functions of the AIPs by older people [33]. In addition, older people tend to misunderstand or have excessive expectations about the actual functions of AIPs due to their lack of information technology literacy [49]. However, AIPs have difficulty meeting these expectations, leaving a mismatch between the AIP functionality and the user requirements [50]. Therefore, we propose the following hypotheses about AIPs and older users.

H1. *Perceived intrusiveness can significantly affect the functional mismatch.*

H2. *Perceived control can significantly affect the functional mismatch.*

H3. *Expectation disconfirmation can significantly affect the functional mismatch.*

2.4. Socio-Emotional Mismatch of AIPs

Except for functional attributes, the AIPs possess many social attributes, such as a user image, social evaluation, and memories related to products [51]. Thus, the socio-emotional mismatch of individuals toward products is often determined by social evaluation and individual responses that AIPs evoke [52]. For older people, AIPs often amplify negative feelings that are inconsistent with the social identification expected from using them, influenced by digital ageism and algorithmic bias. For one thing, the use of age-friendly products is in itself a reflection of public stigma (the prejudice and discrimination endorsed by the general population that affects a person) [4,53]. Although people are sympathetic to older adults, implicit discrimination is unavoidable. In particular, the AIPs are often connected to the relatives of the users or their communities or hospitals. Not only does this connection make more people aware of the aging and weakness of the user, but it also reinforces the stereotypes and stigma. Therefore, older people feel more negatively about the social significance of the AIPs based on social feedback and evaluations. For another, the internalization of public stigma among older people increases, namely, self-stigma (the harm that occurs when the person internalizes the prejudice) [53], influenced by ageism and implicit discrimination based on big data [15]. This increase in self-stigma affects an older user's capability of independent living and social participation. And the pressure brought by the stigma is likely to form a vicious circle that makes it difficult for older adults to reconstruct their positive self-image and reduces their social adaptability, leading to a socio-emotional mismatch. Additionally, in the information and communications technology field, technology anxiety has an equal effect on the socio-emotional mismatch [54]. Since older people cannot understand the logic of AIPs and the operation mechanism of digital society reflected by this logic, they are anxious about the social isolation implied by the use of AIPs, which leads to further socio-emotional mismatch. Based on all these factors, we propose the following hypotheses.

H4. *Self-stigma can significantly affect the socio-emotional mismatch.*

H5. *Public stigma can significantly affect the socio-emotional mismatch.*

H6. *Technology anxiety can significantly affect the socio-emotional mismatch.*

2.5. Avoidance and Exit Behavior

According to previous studies, the primary reason for avoidance or exit behavior is a mismatch between products and the requirements of consumers [40], including a functional mismatch and a socio-emotional mismatch [55]. In the digital society, older adults are using

AIPs actively or passively, but this does not mean that older people accept or prefer to use the AIPs [56]. Specifically, according to Ho's research, despite the good applied value of AIPs in elderly care, biases based on functional and socio-emotional mismatch could lead to avoidance behavior of AIPs among older people [57]. In addition, Ploug and Holm's research showed that AI bias and discrimination in disease diagnosis and treatment, as well as patient preference for face-to-face treatment, can significantly increase exit tendency by older people [57]. Dwivedi et al. pointed out that functional mismatch and socio-emotional mismatch remained major challenges that prevent the promotion of AIPs among older people [6]. In summary, we argue that a functional mismatch and socio-emotional mismatch in the use of AIPs can lead to avoidance and exit behaviors among older people. Therefore, we hypothesize as follows.

H7. *Functional mismatch can significantly affect the avoidance behavior of older people.*

H8. *Functional mismatch can significantly affect the exit behavior of older people.*

H9. *Socio-emotional mismatch can significantly affect the avoidance behavior of older people.*

H10. *Socio-emotional mismatch can significantly affect the exit behavior of older people.*

We examined older adults' avoidance and exit behaviors toward AIPs from the perspectives of two mismatches based on the CAC framework. As shown in Figure 1, we propose that the perceived intrusiveness, perceived control, and expectation disconfirmation of AIPs affect the functional mismatch; self-stigma, public stigma, and technology anxiety affect the socio-emotional mismatch. The functional mismatch and socio-emotional mismatch can lead to the avoidance and exit behaviors of older people toward AIPs.

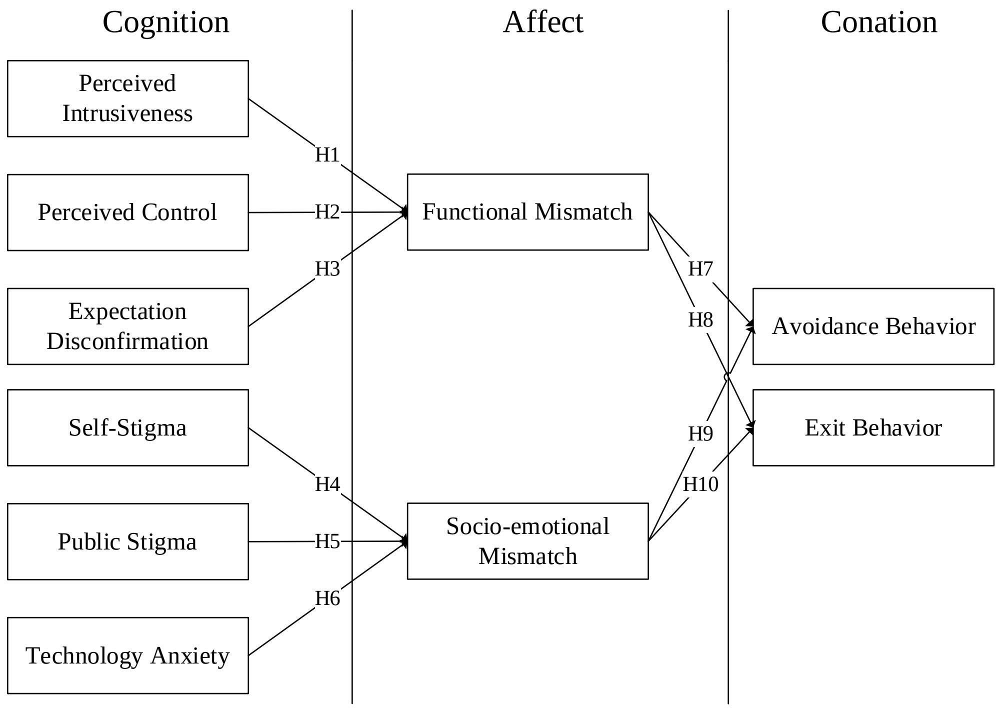

Figure 1. Research model.

3. Materials and Methods

3.1. Survey Instruments

All scales were based on previous studies and modified to fit the current research context. All measurement items adopted a seven-point Likert scale where 1 represents negative (strongly disagree or strongly agree), and 7 represents positive (strongly agree or strongly disagree), with the exception of the control variables. The measurement items of perceived control were adapted from Lachman and Weaver [58]; the items of perceived intrusiveness were adapted from Xu et al. [59]; the items of public stigma and self-stigma were adapted from Vogel [60]; the items of technology anxiety were adapted from the results of Jeng, Pai, and Yeh [61]; the items of expectation disconfirmation were adapted from Lin, Wu, and Tsai [62]; the items of functional mismatch and socio-emotional mismatch were adapted from Chen's research [15]; and the measures of avoidance and exit behaviors were adapted from Ogbanufe and Gerhart [63]. Table 2 shows the variables and indicators.

Table 2. Variables and indicators.

Variable	Measurement Items	Reference
Perceived Control	PC1: I feel like I'm losing the territory that I used to control. PC2: I feel like I lack control over the outside world (other people, situations). PC3: I can set clear, realistic, and meaningful goals. PC4: Something (human or machine) exerts too much control over me.	[58]
Perceived Intrusiveness	PI1: I am concerned that AIPs are collecting too much information about me. PI2: I feel that as a result of my using an AIP, others know about me more than I am comfortable with. PI3: I believe that as a result of my using an AIP, information about me that I consider private is now more readily available to others than I would want. PI4: I feel that as a result of my using an AIP, information about me is out there that, if used, will invade my privacy.	[59]
Self-Stigma	SS1: It makes me feel inferior to use an AIP. SS2: When I use an AIP, my view of myself is more negative. SS3: My self-image feels threatened when I use an AIP. SS4: Using an AIP makes me feel like there is something wrong with me.	[60]
Public Stigma	PS1: Using an AIP carries a social stigma. PS2: It is a sign of weakness and aging to use an AIP. PS3: People tend to like others less when those others are using an AIP. PS4: It is advisable for me to hide that I use an AIP.	
Socio-emotional Mismatch	SM1: AIPs cannot satisfy my emotional needs. SM2: AIPs cannot match my emotional needs. SM3: I cannot say that AIPs please me. SM4: AIPs have no positive impact on my affection.	[15]
Functional Mismatch	FM1: AIPs can not meet my daily needs. FM2: AIPs don't fit my daily needs. FM3: I cannot say that AIPs help me in my life. FM4: AIPs have not changed my life.	
Expectation Disconfirmation	ED1: My experience with using the AIP was worse than what I expected. ED2: The service level provided by the AIP was worse than what I expected. ED3: Overall, most of my expectations about using the AIP were not confirmed.	[62]
Technology Anxiety	TA1: I feel stressed when I use a new AIP. TA2: I am worried that the new AIP will affect my life. TA3: I fear that AIPs will change my life. TA4: I'm afraid that I don't have enough ability to use AIPs.	[61]
Avoidance Behavior	AB1: The transition to AIPs is stressful for me. AB2: I feel comfortable not continuing to use AIPs. AB3: I like using the original product instead of AIPs.	[63]
Exit Behavior	EB1: I won't be using the AIPs as much as I used to. EB2: After using an AIP for a while, my interest in continuing to use it gradually decreases. EB3: I'm going to stop using my AIPs, but that doesn't mean I'm going to give them up altogether.	

3.2. Sample and Data Collection

This study collected firsthand data using a questionnaire survey to verify the conceptual model. Potential respondents were individuals over 60 years old who had used at least one kind of AIP. Given that some measurement items were not available in Chinese, the English items were first translated into Chinese by one author who was proficient in both languages. The items were then tested by two experts in AI and behavioral sciences and seven PhDs in related areas. To ensure the quality of the questionnaire, 50 copies of a pre-survey questionnaire were distributed offline. All 50 were collected. Some respondents were interviewed, and the questionnaire was revised according to their suggestions.

The formal questionnaire was collected in March–April 2022 with the assistance of the Civil Affairs Bureau of Hefei (Hefei, Anhui Province, China). With the help of community workers, we distributed questionnaires to older people who had participated in a previous, large-scale promotion of AIPs. Since the current average retirement age in China is 55 years old, when people retire, their behavior and psychology have become de facto elderly people. In the relevant research on the elderly and artificial intelligence, a large number of scholars also set the age of the research object as 55 years old [35,64,65]. In the previous promotion activities, the target of distribution was also 55 years old. Therefore, the study set the starting age of respondents as 55 years old.

Relevant training was given to all volunteers before the distribution. Each questionnaire took about 30 min to complete; for those participants who had difficulty reading and writing, the questionnaires were completed using an oral question-and-answer format with the assistance of volunteers. In addition, demographic information such as the respondent's age, gender, and educational level were required in the questionnaire. A total of 1574 questionnaires were collected, and after eliminating the invalid questionnaires, 1102 valid questionnaires were received, with an effective rate of 70.01%. The statistical characteristics of the sample are shown in Table 3.

Table 3. Respondents' sample statistics.

Measure	Item	Count
Age	55–59	212 (19.24%)
	60–69	515 (46.73%)
	70–79	237 (21.50%)
	>80	138 (12.53%)
Gender	Male	585 (53.09%)
	Female	517 (46.91%)
Education	Primary school	116 (10.53%)
	Junior middle school	477 (43.28%)
	High school	353 (32.03%)
	Undergraduate	156 (14.16%)
AI used (multi-choice)	Healthy	670 (60.80%)
	Accompanied	784 (71.14%)
	Monitored	836 (78.86%)
	Walking-aided	539 (48.91%)

4. Data Analysis and Results

We used partial least squares (PLS) methods for data analysis in an exploratory study to simultaneously assess the reliability and validity of construct measures and to estimate the relationship between constructs. In addition, PLS imposes minimal restrictions on sample size and residual distribution. We followed a two-step approach when examining the measurement and structural models.

4.1. Measurement Model Testing

4.1.1. Common Method Biases and Multicollinearity

The variance inflation factor (VIF) was measured. The VIF can measure the severity of collinearity in multiple linear regression models. Although a VIF value of 3.3 or 5 is the best under ideal conditions, a large number of literatures also believe that in the study of PLS-SEM, a VIF less than 10 is sufficient [66,67]. According to Shrestha (2020), when the VIF value is between 5 and 10, it is still acceptable despite the challenging value [68]. In this study, the maximum value of the VIF was 7.295, which is less than the threshold value of ten, indicating that the model does not have a multicollinearity problem.

To ensure the fit validity of the model, the standardized residual root mean square (SRMR), unweighted least square difference (d_ULS), and geodesic difference (d_G) of the model were measured to determine how well the model fitted the data. SRMR should be less than 0.08, and SRMR, dULS, and dG should be less than 95% of the bootstrap difference. As shown in Table 4, the SRMR value is 0.034, which is less than the threshold value of 0.08. The values of SRMR, d_ULS, and d_G are all less than 95% bootstrap differences. Overall, the analysis showed that, with a 5% probability, the measurements were sufficient for empirical analysis.

Table 4. Test of fitting validity.

Index	Value	HI95	Result
SRMR	0.034	0.133	Support
d_ULS	0.828	12.439	Support
d_G	0.59	0.938	Support

To ensure that there is no common method bias in the samples, Harman's one-factor test was used for measurement in this study [69]. In Harman's one-factor test, when the ratio of the largest single factor to the variance is less than 50%, it is generally considered that common method bias is not supported [70]. SPSS22 was used for analysis, and the results showed that the maximum factor accounted for 27.785% (less than 50%), and the total factor (nine factors) accounted for 72.601%. In addition, this paper uses the marker variable method to test the common method biases [71]. The results show that each marker variable has no significant influence on the model variables. Therefore, the possibility of common method deviation in this study is small.

4.1.2. Reliability and Validity

To validate the measurement model, we assessed the reliability of the construct and two types of validity (convergent validity and discriminant validity). Table 5 shows the factor loading, combined reliability (CR), Cronbach's alpha, and average variance extracted (AVE) coefficient of the model. In this study, the minimum value of factor loading is 0.779, and the maximum is 0.96, both of which are greater than 0.7 [72]. As an effective indicator of the internal reliability of each dimension of the model, CR plays an important role in evaluating the model. In this study, the minimum value of CR is 0.897, and the maximum value is 0.972, which is greater than the recommended value of 0.7 [72]. Cronbach's alpha is an important measure of the internal validity of the model, and most of the literature suggests that the value needs to be greater than 0.7 [72]. The range of values in this study is 0.827–0.962, which is greater than the threshold value of 0.7, indicating good internal consistency of the questionnaire. The AVE took values ranging from 0.743 to 0.898, which are greater than 0.5, indicating that the observed items explain much more variance than the error term and that the validity of the model aggregation is relatively high [72].

Table 5. Reliability and validity.

Construct	Item	Loading	Cronbach's α	CR	AVE
Function Mismatch	FM1 FM2 FM3 FM4	0.941 0.941 0.943 0.877	0.944	0.960	0.857
Avoidance Behavior	AB1 AB2 AB3	0.897 0.939 0.922	0.908	0.942	0.845
Socio-emotion Mismatch	SM1 SM2 SM3 SM4	0.928 0.960 0.954 0.947	0.962	0.972	0.898
Technology Anxiety	TA1 TA2 TA3 TA4	0.921 0.905 0.912 0.917	0.934	0.953	0.835
Expectation Disconfirmation	ED1 ED2 ED3	0.857 0.912 0.885	0.861	0.916	0.783
Public Stigma	PS1 PS2 PS3 PS4	0.949 0.949 0.960 0.920	0.960	0.971	0.892
Perceived Intrusiveness	PI1 PI2 PI3 PI4	0.779 0.869 0.898 0.897	0.884	0.920	0.743
Perceived Control	PC1 PC2 PC3 PC4	0.918 0.928 0.948 0.935	0.950	0.964	0.869
Self-stigma	SS1 SS2 SS3 SS4	0.925 0.936 0.920 0.935	0.947	0.962	0.863
Exit Behavior	EB1 EB2 EB3	0.797 0.886 0.902	0.827	0.897	0.744

The results in Table 6 show that the square root of the AVE for each construct is greater than the correlation involving that construct, which confirms the discriminant validity. According to Hair, the heterogenic–parthenosexual correlation ratio (HTMT) is another method for evaluating discriminant validity [72]. The HTMT value is less than 0.85, indicating that the validity of the discrimination has been determined. In Table 7, all HTMT values are less than 0.85. In summary, the model has good reliability and validity.

Table 6. Fornell–Larcker criterion.

	FM	AB	SM	TA	ED	PS	PI	PC	SS	EB
FM	0.926									
AB	0.625	0.919								
SM	0.851	0.617	0.947							
TA	0.610	0.556	0.627	0.914						
ED	0.581	0.538	0.521	0.459	0.885					
PS	0.777	0.616	0.750	0.697	0.541	0.945				
PI	0.511	0.506	0.471	0.502	0.769	0.510	0.862			
PC	0.600	0.567	0.555	0.516	0.754	0.574	0.707	0.932		
SS	0.602	0.595	0.554	0.534	0.723	0.572	0.677	0.842	0.929	
EB	0.688	0.558	0.605	0.452	0.519	0.645	0.457	0.540	0.537	0.863

Notes: FM = Functional Mismatch; PI = Perceived Intrusiveness; PC = Perceived Control; ED = Expectation Disconfirmation; SM = Socio-emotional Mismatch; SS = Self-Stigma; PS = Public Stigma; TA = Technology Anxiety; AB = Avoidance Behavior; EB = Exit Behavior.

Table 7. HTMT.

	FM	AB	SM	TA	ED	PS	PI	PC	SS	EB
FM										
AB	0.675									
SM	0.842	0.660								
TA	0.644	0.599	0.655							
ED	0.644	0.608	0.572	0.510						
PS	0.816	0.660	0.780	0.728	0.595					
PI	0.555	0.563	0.507	0.549	0.829	0.551				
PC	0.634	0.610	0.580	0.545	0.834	0.601	0.767			
SS	0.636	0.641	0.580	0.565	0.801	0.599	0.734	0.837		
EB	0.779	0.647	0.678	0.512	0.616	0.724	0.534	0.610	0.608	

Notes: FM = Functional Mismatch; PI = Perceived Intrusiveness; PC = Perceived Control; ED = Expectation Disconfirmation; SM = Socio-emotional Mismatch; SS = Self-Stigma; PS = Public Stigma; TA = Technology Anxiety; AB = Avoidance Behavior; EB = Exit Behavior.

4.2. Structural Model

SmartPLS 3.32 was used to test the structural model. Bootstrapping was used, and the maximum number of iterations was 5000. The specific results are shown in Figure 2 and Table 8.

Table 8. Results of hypotheses testing.

Hypotheses	Path Coefficient	T Value	*p*-Value	Results
H1: PI -> FM	0.043	1.02	0.307	No support
H2: PC -> FM	0.363	7.842	<0.001	Support
H3: ED -> FM	0.275	6.071	<0.001	Support
H4: SS -> SM	0.154	4.441	<0.001	Support
H5: PS ->SM	0.549	12.610	<0.001	Support
H6: TA -> SM	0.162	3.544	0.001	Support
H7: FM -> AB	0.363	5.683	<0.001	Support
H8: FM -> EB	0.630	12.237	<0.001	Support
H9: SM -> AB	0.308	4.902	<0.001	Support
H10: SM -> EB	0.069	1.307	0.191	No support

Finally, we conducted a control variable test. The t-test results show that demographic characteristics (age, gender, education, and type of AI used) have no significant impact on the results of the analysis. The t-test results show that age, gender, education, and type of AI used have no significant impact on this research. The results show that demographic characteristics have no significant influence on the results of the analysis.

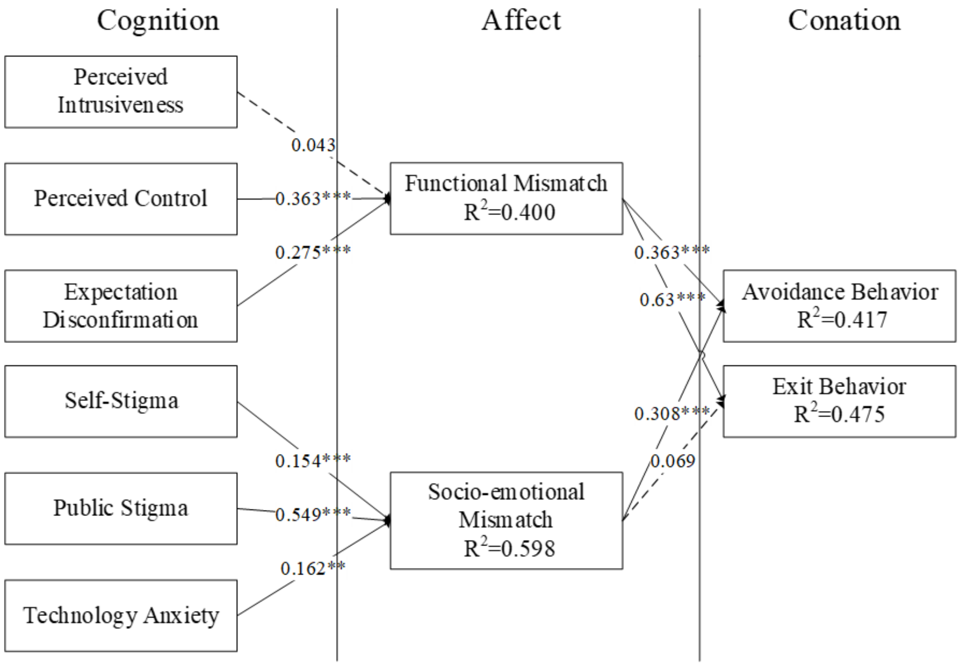

Figure 2. Model results. *** $p < 0.001$; ** $p < 0.01$.

In addition, to evaluate whether the proposed model has predictive ability, we evaluated whether Q^2 is greater than 0; a positive Q^2 value shows that the predictive error of the PLS results is less than that of using only the mean value [73]. In this model, Q^2 ranges from 0.204 to 0.550, all of which are greater than 0, indicating that the model has good predictability.

5. Discussion

5.1. Discussion

This study explored the causes of negative behaviors of older people toward AIPs from the perspectives of a socio-emotional mismatch and functional mismatch. We constructed a structural equation model, tested our hypotheses, and drew the following conclusions:

(1) The functional mismatch is affected by expectation disconfirmation (H3, β = 0.275, $p < 0.001$) and perceived control (H2, β = 0.363, $p < 0.001$); however, perceived intrusiveness does not share any relationship with it (H1, β = 0.043, $p = 0.303$). As suggested in previous research, the excessive reminders and suggestions of AIPs, as well as unrealistic advertisements by AIP sellers, result in the variables of perceived control and expectation disconfirmation, aggravating the functional mismatch [33]; this mismatch reflects older people's yearning for independence. The invalidity of H1 highlights the choice AIP users must make between privacy and functional needs. This is because AIPs must acquire the personal information and preferences of users to provide personalized service and realize their target functions [74]. That is, the more private information obtained by the AIPs, the more likely the AIPs will be able to meet the requirements of the users. The initial intention of older people to use AIPs affects their choice: they are more inclined to concede their privacy when the expected functions of the AIPs match their actual needs so as to acquire better effects. Essen's study reached the same conclusion, with older adults viewing a home care monitoring device as freeing and protecting their privacy, as the device enabled them to continue living in their own homes rather than moving to a nursing home [75]. This valuable finding shows that older people are willing to concede some privacy to acquire the expected functions of AIPs, reflecting older people's desire to satisfy their life needs and further proving H2 and H3;

(2) The socio-emotional mismatch is affected by public stigma, self-stigma, and technology anxiety. However, in terms of specific impact, public stigma has the greatest impact

(H4, β = 0.549, $p < 0.001$); second is technology anxiety (H6, β = 0.162, $p = 0.001$); and third is self-stigma (H5, β = 0.154, $p < 0.001$). We believe that the reason for H4 is that older people often experience social prejudices and stereotypes in the process of using AIPs, such as that older adults are weak, unhealthy, and technologically illiterate. In addition, the over-praise of older people when they do use AIPs is a potential stigmatization and likewise leads to negative perceptions of the social significance of AIPs among the users [76]. Older people often feel further stigmatized in the digital society since the level of digital social participation increases when they use AIPs. Therefore, public stigma has the greatest impact on the socio-emotional mismatch. In addition, older people are more likely to internalize the public stigma, causing fundamental damage to their self-image in regard to the digital age and making it difficult for them to integrate into digital society from a psychological level [15]. This valuable finding shows that social opinions and potential negative evaluations do serious harm to older people in the process of using AIPs;

(3) For older people, a significant difference exists in the impacts of the functional and socio-emotional mismatches on negative behaviors toward AIPs. On the one hand, both the functional mismatch (H7, β = 0.363, $p < 0.001$) and socio-emotional mismatch (H9, β = 0.308, $p < 0.001$) lead to avoidance behavior. This is consistent with previous research showing that older people have avoidance intentions toward AIPs, driven by their efforts to reduce their cognitive load, avoid the threat of stigma, and regulate their emotions [16], and helps to explain this negative behavior among older adults. On the other hand, while the functional mismatch significantly affects the exit behavior of older people (H8, β = 0.63, $p < 0.001$), the socio-emotional mismatch does not share any relationship with the exit behavior (H10, β = 0.069, $p = 0.2$). We believe that the reason for this is that functional satisfaction and perceived usefulness are the main requirements for products for older people [77]. Therefore, if a functional mismatch occurs with AIPs, older people turn to an alternative, useful product and abandon the AIP. The same is not true of a socio-emotional mismatch. Although a socio-emotional mismatch may cause a series of negative effects, such as depression, anxiety, and injury to the user's self-esteem [15], older users are conservative and often reluctant to give up a product once they become expert at using it. Accordingly, it is unlikely that older people will abandon AIPs completely when they can use the AIPs effectively and the AIP functions satisfy user requirements. This valuable finding suggests that designers should focus on the suitability of AIP functions to the needs of older adults.

5.2. Implications for Research

The present study has outlined three contributions to the theory and the literature.

(1) In this study, the mismatch between products and requirements/expectations is divided into a functional mismatch and a socio-emotional mismatch, and the mechanism of each mismatch's influence on negative behavior toward AIPs is systematically analyzed. The results show significant differences between the two kinds of mismatch in the avoidance and exit behaviors of older adults. Our study comprehensively considers the functions of AIPs and the socio-emotions they evoke in order to solve the problem of adoption by older adults, which provides new empirical evidence for the systematic relationship between the functional mismatch and the socio-emotional mismatch. It fills the gap in research on the influence of these two factors on the behavior toward AIPs of older people. In addition, the application of the CAC framework to study the interaction between older people and AIPs fully explains why AIPs are not popular among older people and proves the value of applying the CAC framework in the field of information system behavior and artificial intelligence;

(2) This study analyses the causes of the functional mismatch in AIPs, and the results show that perceived control and expectation disconfirmation have a significant impact on the functional mismatch, which provides new empirical evidence for the design theory of AIPs. However, perceived intrusiveness does not share any relationship with the functional mismatch. This finding indicates that seeking an effective balance point between privacy

concerns and intelligent services for older adults is an issue for future research and provides new insights for theories of privacy protection among older users. On the flip side, this study explores the reasons for the socio-emotional mismatch, and the results show that public stigma is the most important source. This finding contributes to the development of theories about stigma in the digital society, increases the ways of bridging the digital divide, enriches the research on the psychological integration of older adults in digital society, and improves the theory of social integration;

(3) The last valuable theoretical contribution of this study is about "Technologies in Service of Humanity". According to Kotler, digital technology, especially AI technology, should serve human beings [78]. In this study, our findings reveal, from a theoretical perspective, why older groups are reluctant to use the new generation of information technology products based on AI technology. Because AIPs have both emotional and functional properties, people's perception of them is more complex than other types of products. The results of this study show the important impact of functionality and social emotion of AIPs on the elderly, providing a valuable research perspective from the aspects of social opinion, product design, user behavior, etc., and providing new empirical evidence for the expansion of relevant theoretical research in a friendly digital society.

5.3. Practical Implications

This study has three practical contributions.

(1) The results show that both the functional mismatch and socio-emotional mismatch have a significant impact on negative behavior toward AIPs among older people and confirm that the functional mismatch is a key factor in older adults' exit behavior. This shows that current AIPs are not able to achieve the goal of "Technologies in Service of Humanity". Based on this, we propose that designers should focus on the functional development of AIPs and then design products that are close to users' actual requirements. In addition, the large language model should be applied to improve existing AIPs, especially the friendliness and efficiency of human–computer interaction. This will help AIPs better adapt to the requirements of older people and help older people bridge the digital divide and integrate into digital society;

(2) The findings reflect the significant influence of perceived control on the functional mismatch, which conversely demonstrates the desire of older people for independent living and the importance to older people of maintaining their independence and autonomy with the help of AIPs. Therefore, families and organizations need to safeguard the independence of older people. Families are encouraged to solve the problem of AIP accessibility and support older people in using AIPs from informational, emotional, and other aspects. The government should provide policy and financial support to improve the digital literacy of older adults. In addition, nongovernmental organizations such as senior universities and community centers need to play an active role in guiding and communicating with older people in the process of using AIPs to better promote the use of AIPs by older people;

(3) The results emphasize that public stigma is the most important factor of the socio-emotional mismatch. Older people's lives are losing significance in the digital age due to stigma, marginalization, and a lack of belonging and security. It is difficult for AIPs to satisfy the social and self-identification needs of older people due to algorithmic bias and age discrimination. To alleviate the negative impact of stigma on older people, designers of AIPs can help older adults better use them through embedding large language models to improve AI algorithms, improve older people's desire to explore the digital society, maintain the positive image of older adults consciously and change the prejudice and discrimination against them. The mainstream media can shape a positive image of older people and bridge the inter-generational digital gap.

5.4. Limitations and Future Research Directions

The study has three limitations. First, data in this paper came from AIP users in Hefei, Anhui Province, China. Due to regional, cultural, and economic differences, the results of this study may not extend to other countries with different cultural systems. Future studies should further examine the influence of cultural differences on the relationship between different older groups (country, ethnicity, and region) and AIPs. Second, the study did not consider the role of family members in helping older people. As an important influencing factor for the elderly to use AIPs, family members and experts can help the elderly better accept and use AIPs [79,80]. Therefore, in future studies, we will further explore the influence of family members on the use behavior of AIPs in the elderly. Finally, due to the heterogeneity of different elderly groups' needs, cognitive abilities, and other characteristics, the research results in this paper cannot effectively reflect such differences. Therefore, in future studies, we will consider this difference, collect data on elderly people with different characteristics, and use multi-group comparative analysis for further research.

6. Conclusions

Although AI and its applications have penetrated every corner of society, most AIPs face the reality of being shelved or abandoned after short-term usage by older people. Existing research has shown that the mismatch between the requirements of older people for the products they use and the AIPs' actual functions, along with the mismatch between their expectations and the socio-emotions the AIPs evoke, explain this phenomenon. Hence, this study explored the causes of avoidance and exit behaviors from both a functional mismatch and socio-emotional mismatch perspective. The results have shown that (1) the functional mismatch is influenced by expectation disconfirmation and perceived control; (2) public stigma has the greatest impact on the socio-emotional mismatch; and (3) both the functional mismatch and socio-emotional mismatch lead to avoidance behavior, while only the functional mismatch affects the exit behavior of older adults. Based on these findings, we propose that all organizations should work together to help older people maintain their independence and mitigate the negative effects of stigma. In addition, our study offers theoretical implications of the CAC framework, product design, privacy protection, and social integration, as well as practical implications for designing, developing, and promoting AIPs. These implications can help improve the adaptation of AIPs to older users and promote the active use of AIPs by older people for integration into digital society. These implications can help improve the adaptation of AIPs to older users and promote the active use of AIPs by older people for integration into a digital society, contributing to "Technologies in Service of Humanity".

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