A Quantitative Study on the Influencing Factors of AI-Powered Elderly E-commerce Consumption

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Abstract

By 2035, my country's population aged 60 and over is projected to exceed 400 million, marking the beginning of a period of advanced aging. This trend is accompanied by the rapid development of new productivity, exemplified by Artificial Intelligence (AI), creating new opportunities for silver e-commerce. E-commerce platforms not only improve shopping and payment efficiency for elderly consumers but also become a crucial channel for unlocking their consumption potential and expanding the silver market. Based on the Technology Acceptance Model, this study constructs a theoretical model of how AI influences e-commerce consumption behavior among the elderly. Data were collected through a questionnaire survey and empirically tested using structural equation modeling (SEM). The study focuses on the mechanisms by which internal and external variables, such as perceived usefulness, perceived ease of use, digital literacy, and social support, influence consumer intention. It aims to provide empirical evidence and strategic recommendations for the AI-enabled aging economy, enhance the quality of life for the elderly, and promote the development of "elderly well-being and prosperity".

Keywords AI-powered; Elderly E-commerce; Influencing Factors; Elderly Consumption

1 Introduction

With the rapid development and in-depth application of AI technology, as a core driver of new productivity, it is profoundly reshaping the e-commerce ecosystem [1]. AI-enabled applications, including recommendation algorithms, intelligent customer service, and supply chain optimization, have substantially enhanced the operational efficiency and user experience of e-commerce platforms. These advancements have driven changes in consumer behavior and progressively established a new paradigm of intelligent consumption, where products seamlessly reach consumers automatically, without the need for active searching or visibility [2]. Against this macro-technological backdrop, a niche market with both enormous potential and unique challenges, the silver e-commerce consumer market is rapidly emerging, making it an excellent example and a key area for exploring how AI-enabled e-commerce consumption can be driven [3].

1.1 Profound Demographic Shifts Provide a Vast Market Foundation for Silver E-commerce

China's aging population continues to accelerate. According to forecasts, during the 14th Five-Year Plan period, the number of people aged 60 and over will exceed 300 million, accounting for over 20% of the total population. By 2050, the size of the silver consumer market is projected to reach nearly 50 trillion yuan, accounting for 12.5% of GDP. Its enormous consumption potential cannot be ignored [4]. This indicates that e-commerce consumption has become a crucial bridge for the elderly to connect with and integrate into the digital society, and the industry is about to enter a new era centered on the elderly [5].

1.2 The Dual Benefits of Policy and Technology have Created a Favorable Development Environment for AI-enabled Silver E-commerce

At the national strategic level, the General Office of the State Council issued the "Opinions on Developing the Aging Economy and Improving the Well-being of the Elderly" in January 2024 [6]. This clearly defined and strongly advocated the development of the "silver economy," noting its "broad scope, long industrial chain, diverse business models, and enormous potential," sending a clear policy signal for industry development. At the technological level, new productivity, exemplified by AI, is propelling profound industrial transformation and upgrading through revolutionary technological breakthroughs. China, with its status as the country with the largest internet user base and extensive data resources, ranking second globally in data volume, then establishes a strong foundation for AI technological innovation [7]. The integration of AI technology with e-commerce has spawned new intelligent and personalized business models, enabling targeted outreach and services for the elderly [8].

1.3 The Upgrading of the Elderly's Own Consumption Capacity and Digital Habits Constitutes An Internal Driving Force

By December 2023, the number of internet users in my country aged 50 and above will have reached 350 million, accounting for 32.5% of the total internet population. This is particularly true for the younger generation, who were born after 1960, who have relatively high levels of education and have gradually developed digital consumption habits such as online shopping and online payments, demonstrating significant spending power. Quest Mobile data shows that by September 2024, the elderly population will have exceeded 329 million monthly active users, with a significant share of time spent in short videos and e-commerce, demonstrating their strong online vitality [9].

1.4 While AI Empowers Silver E-commerce and Stimulates the Enormous Demand Potential of the Silver Market, It Also Faces Significant Challenges and Numerous Uncertainties

On the one hand, the "digital divide" remains significant. The barriers to the adoption of intelligent technologies and the increasing cyber risks hinder the deep participation of some of the elderly [10]. On the other hand, the development of silver e-commerce faces regional imbalances. Constrained by the distribution of computing power and economic development levels, the effectiveness of AI-enabled e-commerce varies significantly across regions and between urban and rural areas [11]. More importantly, current product and service offerings still struggle to fully meet the diverse, personalized, and high-quality needs of the senior population. Front-end user experience, transaction processes, and after-sales service all require higher standards of age-friendliness.

Thus, against this backdrop, this study aims to integrate macroeconomic policies, demographic trends, and technological change, focusing on the specific area of "silver e-commerce" and conducting a systematic empirical analysis of the key factors influencing e-commerce consumption driven by AI. Exploring how AI can effectively bridge the digital divide, optimize service experience, and stimulate consumer potential not only actively supports the national strategy of developing the aging economy and new-quality productivity, but also has important theoretical and practical implications for promoting high-quality development of the e-commerce industry and achieving socially inclusive growth [12].

2 Literature Review

Most studies have generally concluded that artificial intelligence technology, by reshaping every aspect of the e-commerce industry, provides unprecedented opportunities for the development of the elderly market. The enabling role of AI is mainly reflected in three aspects: precise marketing, experience optimization, and bridging the gap.

A recommendation system based on machine learning can overcome the coarseness of traditional marketing and provide highly personalized product and service information for the highly heterogeneous elderly group, thereby significantly improving the marketing conversion rate [13]. This aligns closely with the policy direction advocated by the Chinese government, which emphasizes "strengthening the supply of elderly products and services". Alibaba's "elderly mode" integrates voice search and personalized human customer service, aiming to reduce operational barriers and enhance accessibility for elderly users [14]. These applications enhance the confidence and willingness of elderly consumers to

shop online by providing a more friendly and convenient human-computer interaction method. AI is regarded as a potential "technical bridge". Wang et al., in their research on digital inclusion in China, proposed that elderly-adapted AI tools, such as simplified interfaces and voice control, can effectively help elderly people with low technological literacy overcome the fear of using technology [15], promoting their more equal integration into the digital society and enjoying the convenience brought by the digital economy.

2.1 Perceived Ease of Use

Perceived Ease of Use refers to the degree of effort users believe is required to use a particular technological system. For the elderly, this is the primary barrier to entry when deciding whether to try AI e-commerce tools.

Numerous studies have confirmed that due to declining cognitive abilities and physical functions, such as vision and finger dexterity, as well as learning anxiety about new technologies, older users have much higher usefulness requirements for technology than younger users [16]. If AI e-commerce applications are perceived as difficult to learn and operate (e.g., complex navigation menus and cumbersome payment processes), they will directly resist and abandon their use. Therefore, platform-friendly design, such as larger fonts, simpler interfaces, clear voice prompts, and one-click ordering, is key to improving perceived usefulness. Zeng and Li found that for older Chinese netizens, perceived usefulness even outweighed perceived usefulness in their initial trust in and adoption of mobile shopping platforms [17]. This suggests that getting older users to "use" a platform first is far more important than simply telling them it's useful.

2.2 Perceived Usefulness

Perceived usefulness refers to the degree to which users believe that using a particular technology will improve their lives or behaviors. Once older users overcome the initial usability threshold, perceived usefulness becomes a key driver of continued use and loyalty. The usefulness of AI-enabled services manifests itself in multiple ways: saving shopping time, making it easier to discover affordable or desirable products, and obtaining health management advice. For example, if AI-based personalized recommendations accurately match the health needs of older adults, such as low-sugar foods and elderly-friendly devices, they will truly perceive the value of the technology [18]. Research shows that when older adults truly experience the convenience and enjoyment that AI e-commerce tools bring to their lives, their willingness to use them increases significantly, and they are more likely to share and spread the word [19]. In other words, perceived usefulness is key to transforming a one-time trial into a long-term habit. Perceived ease of use also indirectly influences usage intention by influencing perceived usefulness. A system that is easy to use is inherently perceived as more useful [20]. In the context of silver e-commerce, an easy-to-use interface itself makes the elderly feel that "this shopping method is very friendly and practical for me".

2.3 Digital Literacy

Digital literacy refers to the knowledge, skills, and attitudes required for individuals to confidently, critically, and creatively use information technology in digital environments to acquire, manage, understand, integrate, communicate, evaluate, and create information [21]. For the elderly, digital literacy goes far beyond simply being able to operate a mobile phone; it encompasses a comprehensive set of operational, cognitive, and social capabilities. High levels of digital literacy can directly enhance older adults' confidence and ability to use AI-powered e-commerce features, such as searching for products, using coupons, making online payments, and interacting with intelligent customer service, thereby reducing their perceived difficulty and improving perceived ease of use [22]. Recent research found that elderly Chinese e-commerce users found that digital literacy not only directly and positively impacted their willingness to shop online, but also indirectly impacted their willingness by significantly reducing their "technological anxiety" and improving their "perceived security" [23]. Their research suggests that simply providing an age-friendly app interface is insufficient; it must be supplemented with digital skills development to fundamentally enhance elderly adoption willingness. Similarly, Shin and Lee (2024), in their study of elderly use of AI services in South Korea, noted that digital literacy is key to distinguishing between "passive users" and "active beneficiaries".

2.4 Social Support

In the context of AI-enabled silver e-commerce, social support primarily refers to instrumental and emotional support, which comes from the elderly's family, friends, community, and even official organizations, which are intended to help them learn and use digital technologies [24]. Corbett et al clearly pointed out that within the family, "technical support" provided by children is one of the strongest predictors of whether parents can successfully use digital services [25]. In the Chinese cultural context, Wang found that for elderly people with low digital literacy, the impact of social support on their willingness to use e-commerce even exceeds their own perception of ability [26]. Gao et al. further expanded the sources of support to the community, who found that digital training courses organized by the community can also significantly enhance the elderly's sense of digital efficacy, thereby promoting their participation in digital consumption [27].

3 Methods

In the operational phase, this study used scales or questionnaires to assess variables related to all hypotheses. These scales have strong reliability and validity and are widely used in research.

3.1 Conceptual Framework

Based on the original model, this study expanded and refined the model based on the physical and mental characteristics of the senior population, factors influencing e-commerce spending, and the context of the development of e-commerce among the elderly in my country analyzed above. Two external factors, digital literacy and social support, were added as variables. Furthermore, considering the inevitable risks inherent in the internet and digital age, the model was introduced to observe whether perceived risk moderating effects on consumer willingness were observed. The conceptual framework and hypotheses are as follows:

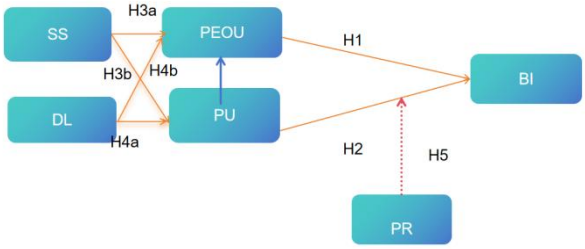

Fig. 1. Conceptual framework of study

Note:
Perceived Ease of Use (PEOU) -> Perceived Usefulness (PU) (Path: H1)
Perceived Ease of Use (PEOU) -> Behavioral Intention (BI) (Path: H2a)
Perceived Usefulness (PU) -> Behavioral Intention (BI) (Path: H2b)
Digital Literacy (DL) -> Perceived Ease of Use (PEOU) (Path: H3a)
Digital Literacy (DL) -> Perceived Usefulness (PU) (Path: H3b)
Social Support (SS) -> Perceived Ease of Use (PEOU) (Path: H4a)
Social Support (SS) -> Perceived Risk (PR) (Path: H4b)
Perceived Risk (PR) -> Behavioral Intention (BI) (Path: H5)

3.2 Research Design

Data were collected online using a structured questionnaire on the Wenjuanxing platform, using a 5-point Likert scale. The survey consisted of 37 questions, six validated scales, and three introductory questions for screening. The questionnaire included 34 questions covering six variables. The reliability and validity of the instrument were confirmed by expert review before distribution. The collected data underwent descriptive analysis to summarize sample characteristics, reliability testing to ensure internal consistency, and normality assessment to verify data distribution. Demographic information was also analyzed to understand respondent characteristics. The sample size was 308.

3.3 Reliability and Validity Analysis

This study verified the quality of the data through reliability and validity analyses. Regarding reliability, Cronbach's alpha coefficients for all dimensions were greater than 0.85, indicating high internal consistency [28]. Regarding validity, exploratory factor analysis (EFA) was first conducted. The KMO value was 0.902, and Bartlett's test of sphericity was significant (*p* < .001), indicating that the data were suitable for factor analysis [29]. Principal component analysis extracted six factors, with a cumulative variance explanation of 67.447%. Each item loading on its corresponding factor was greater than 0.4, indicating good construct validity [30]. Furthermore, Harman's one-way test showed that the first factor explained 27.739%, which did not exceed 50%, indicating the absence of significant common method bias [31].

3.4 Multiple Linear Regression

Regression analysis is introduced to study the relationship between independent and dependent variables in order to further investigate causal relationships. It aims to establish a mathematical model that uses known values of independent variables to predict or explain changes in dependent variables.

Table 1. PEOU, PU, and regression analysis

	Non-standardized coefficient		Standardization factor	t	p	collinearity diagnostics	
	B	standard error	Beta			VIF	tolerance
constant	1.861	0.207	-	8.991	0.000**	-	-
Perceived ease of use	0.290	0.055	0.290	5.313	0.000**	1.067	0.937
Perceiving usefulness	0.206	0.049	0.228	4.182	0.000**	1.067	0.937
R 2	0.170						
Adjust *R* 2	0.164						
F	F (2,297)=30.328,p=0.000						
D-W value	0.240						

Note: The dependent variable is behavioral intention

As shown in the table above, when using perceived ease of use and perceived usefulness as independent variables for linear regression analysis with behavioral intention as the dependent variable, the model equation is: Behavioral Intention =1.861 + 0.290* Perceived Ease of Use + 0.206* Perceived Usefulness. The R^2 value of 0.170 indicates that perceived ease of use and perceived usefulness account for 17.0% of the variance in behavioral intention. The F-test results ($F=30.328$, $p<0.05$) confirm the model's validity, indicating that at least one of these two factors influences behavioral intention. Specifically, the regression coefficient for perceived ease of use is 0.290 ($t=5.313$, $p<0.01$), demonstrating a significant positive relationship with behavioral intention. Similarly, the coefficient for perceived usefulness is 0.206 ($t=4.182$, $p<0.01$), also showing a significant positive correlation. The analysis confirms that both perceived ease of use and perceived usefulness significantly positively influence behavioral intention, thereby validating Hypotheses H1 and H2.

Table 2. SS, DL, and PU regression analysis of BI

	Non-standardized coefficient		Standardization factor	t	p	collinearity diagnostics	
	B	standard error	Beta			VIF	tolerance
constant	1.188	0.225	-	5.277	0.000**	-	-
social support	0.278	0.053	0.283	5.211	0.000**	1.100	0.909
Digital literacy	0.290	0.058	0.272	4.997	0.000**	1.100	0.909
R 2	0.201						
Adjust *R* 2	0.195						
F	F (2,297)=37.287,p=0.000						
D-W value	0.834						

Note: The dependent variable = perceived usefulness

As shown in the table above, when conducting linear regression analysis with social support and digital literacy as independent variables and perceived usefulness as the dependent variable, the model equation is: Perceived usefulness =1.188+0.278 × social support+0.290 × digital literacy. The R^2 value of 0.201 indicates that social support and digital literacy collectively explain 20.1% of the variance in perceived usefulness. The F-test results (F=37.287, p=0.000 <0.05) confirm the model's validity, indicating that at least one of these two factors influences perceived usefulness. Specifically, social support has a significant positive correlation with perceived usefulness, with a coefficient of 0.278 (t=5.211, p=0.000 <0.01). Digital literacy similarly demonstrates a significant positive impact, showing a coefficient of 0.290 (t=4.997, p=0.000 <0.01). The comprehensive analysis confirms that both social support and digital literacy exert substantial positive effects on perceived usefulness, thereby supporting Hypothesis H3.

3.5 Analysis of Mediation Effects

The mediation analysis results indicate that social support has a significant positive impact on behavioral intention (total effect=0.304, p <0.01). Perceived ease of use and perceived usefulness each play a significant partial mediating role in this relationship. The mediating effect of perceived ease of use is 0.083 (p=0.001,95%CI= [0.044,0.147]), while that of perceived usefulness is 0.057 (p=0.012,95%CI= [0.020,0.110]). Both paths demonstrate significant direct effects (c'= 0.164), indicating that social support not only indirectly enhances behavioral intention by improving individuals' perceived ease of use and perceived usefulness, but also exerts a direct positive influence. This demonstrates a typical partial mediation structure, confirming hypotheses H3a and H3b.

Mediation analysis reveals that digital literacy influences behavioral intention through two mediating variables: perceived ease of use and perceived usefulness. The path "digital literacy→perceived ease of use → behavioral intention" demonstrates significant mediation (a × b=0.080, p< 0.001, 95%CI= [0.044,0.130]), while the path "digital literacy→perceived usefulness→behavioral intention" also shows significant mediation (a × b=0.067, p=0.004, 95%CI=[0.025,0.117]). Digital literacy enhances individuals' perception of ease of use and usefulness, thereby strengthening their behavioral intention—thus confirming hypotheses H4a and H4b.

3.6 Moderating Variable Effect

Regression analysis revealed that perceived usefulness significantly positively predicted behavioral intention (B=0.272, p<0.001), while perceived risk itself showed no significant effect (p=0.304). The introduction of the interaction term revealed a significant "perceived usefulness × perceived risk" interaction (B=-0.106, p=0.048), indicating that perceived risk exerts negative moderation in the "perceived usefulness→behavioral intention" relationship. When individuals experience higher perceived risks, the positive impact of perceived usefulness on behavioral intention is diminished. The inclusion of

the moderating variable increased model explanatory power from R^2 =0.091 to 0.106 ($\triangle R^2$ =0.012), achieving statistical significance and supporting the validity of the moderating effect (Hypothesis H5).

4 Conclusion

This study aims to explore the key factors influencing the elderly' acceptance of AI-enabled e-commerce consumption, thereby providing theoretical support and practical guidance for boosting the potential of the senior e-commerce market and optimizing the shopping experience for the elderly.

4.1 The Core Role of Perceived Ease of Use and Perceived Usefulness

Both perceived ease of use (H1) and perceived usefulness (H2) have a significant positive impact on the elderly' behavioral intention. This suggests that when the elderly perceive AI tools (such as intelligent customer service and voice assistants) as simple to use and understand (high perceived ease of use) and effective in helping them make shopping decisions, save effort, or discover more deals (high perceived usefulness), their willingness to use them increases significantly. This conclusion is highly consistent with the core insights of the classic technology acceptance model [32].

4.2 The Key Driving Role of Social Support and Digital Literacy

Social support (H3) not only directly enhances behavioral intention but also indirectly influences it through enhanced perceived ease of use and perceived usefulness, playing a partial mediating role. This suggests that technical support and emotional encouragement from family, friends, or the community are important external forces that help older adults overcome initial fears of technology and develop positive perceptions of it [33]. Furthermore, digital literacy (H4) indirectly influences behavioral intention by enhancing perceived ease of use and usefulness, suggesting that individuals' abilities to operate devices and discern information are inherent foundations for effective use of AI technology.

4.3 The Moderating Effect of Perceived Risk

Perceived risk (H5) negatively moderates the path from perceived usefulness to behavioral intention. Specifically, when older adults harbor significant concerns about the privacy, financial security, or decision-making reliability of AI applications, their willingness to adopt them is significantly weakened, even if they believe the technology is useful. This highlights the crucial importance of building a safe and trustworthy consumer environment for the elderly in the AI-enabled process [34].

4.4 Implications and Recommendations

Based on the research findings, this study proposes the following recommendations to promote AI technology empowering e-commerce consumption among the elderly:

First, optimize AI interaction design to enhance usability and usefulness. E-commerce platforms should develop age-friendly AI interfaces, integrate voice input, simplify operational processes, and highlight practical features such as price comparison, authenticity verification, and personalized recommendations to enhance the perceived usability and usefulness of senior users.

Second, build a social support system and strengthen digital literacy training. Family members should be encouraged to provide "digital feedback", and organizations such as communities and senior universities should be supported to conduct specialized training to help the elderly master the necessary digital skills, thereby increasing their acceptance and willingness to use AI tools.

Third, establish a trust and security mechanism. Platforms should transparently disclose the boundaries of AI technology use and data protection policies, introduce authoritative certification, and provide a risk-free experience environment to effectively reduce the perceived risk among senior users.

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Conflicts of Interest

The authors declare no conflicts of interest.

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AI賦能銀髮電商消費的影響因素研究

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摘要：據中國國家衛生健委預測，我國60歲及以上的老年人口預計在2035年超過4億，這標誌著進入重度老齡化階段。這一趨勢伴隨著新質生產力的迅速發展，以人工智能為例，為銀髮電商創造了新的機遇。電商平臺不僅提高了老年消費者的購物和支付效率，而且成為釋放他們的消費潛力和擴大銀髮市場的重要渠道。基於技術接受模型，本研究構建了一個關於人工智能如何影響老年人電子商務消費行為的理論模型。通過問卷調查收集數據，並使用結構方程模型（SEM）進行實證檢驗。本研究關注內部和外部變量（如感知有用性、感知易用性、數字素養和社會支持）如何影響消費者意向的機制。本研究旨在為人工智能驅動的銀髮經濟提供實證證據和戰略建議，提高老年人的生活質量，並促進「老年人富強協同效應」的發展。

關鍵詞：AI賦能；銀髮電商；影響因素；銀髮消費

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