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Analysis of the Effectiveness of Promotion Strategies of Social Platforms for the Elderly with Different Levels of Digital Literacy

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Abstract: This paper aimed to examine the effectiveness of social platform promotion strategies for the elderly with different digital literacy. Despite extensive research on the development of youth-oriented social platforms, research on the development of social platforms specifically targeting older adults with varying levels of digital literacy is lacking. The elderly population is divided into passive information receivers (PIRs) and active information seekers (AISs) according to their information seeking expertise, and an empirical study was conducted to assess the behavioral characteristics of PIRs and AISs. Grounded in innovation diffusion research and our empirical results, an agent-based model was developed, and the impact of the proportion of PIRs on the macro result of the social platform adoption (i.e., market penetration) and the impact of promotional strategies on market penetration under different proportions of PIRs were analyzed. The results demonstrate a direct negative effect of the proportion of PIRs on market penetration and a moderating effect on the effectiveness of various promotional strategies.

Keywords: senior social platform; innovation diffusion; digital literacy; agent-based model

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1. Introduction

Recently, social platforms have emerged to meet the social and entertainment needs of elderly individuals who have been exposed to social e-commerce. For example, OldKids, the first and by far the largest virtual platform for seniors in mainland China, provides online and offline computer training for seniors and a virtual space where seniors can interact [1]. Tangdou, another famous elderly social platform with RMB 100 million in financing gathers elderly square dance fans, provides square dance teaching services, and promotes interaction among platform members [2].

For an emerging elderly social platform, a certain number of users on the platform is a prerequisite for commercial returns, such as revenue from paid services, revenue from sponsors and advertising revenue, etc. [2–4]. Therefore, managers of social platforms use a variety of strategies to promote customer adoption and the participation of social platform, such as publishing promotional messages in mass media [5,6], frequently initiating high-quality interactive services with platform users [7–9] that cause users to spread word of mouth (WOM) spontaneously and cultivating opinion leaders to enhance the frequency and influence of their WOM [10,11].

Prior research has provided valuable insights into the effectiveness of social platform promotion strategies. For example, Lin (2007) [12] confirmed the impact of the quality of the online interactive services on the customer adoption of social platforms with users of successful virtual platforms (e.g., http://tw.club.yahoo.com, accessed on 28 July 2005) as samples. Turcotte et al. (2015) [13] confirmed the influential power of opinion leaders on consumer trust and adoption of social media platforms with undergraduate students as samples. However, the users of the social platforms studied by scholars are mainly young people, and studies that focus exclusively on the elderly are rare. There are significant differences in digital literacy levels within the elderly intergenerational group compared to the younger group. A major part of seniors are passive information receivers (PIRs), who are unskilled in searching for information online and neglect information from sources other than their personal relationships [14–16]. The remaining seniors are active information seekers (AISs), who are proficient in searching for information and thus utilize information from multiple digital sources to meet their needs [17]. In terms of the microprocess of senior social platform adoption, the effectiveness of promotional strategies may be closely related to the information seeking abilities and sources of information of the elderly. For example, the awareness of mass media messages is related to the information seeking ability of the target group [18]. The degree to which potential users perceive the service quality of online platform correlates with the amount of information they have [19]. Therefore, it is necessary to dissect the process of social platform adoption from a digital literacy perspective and to examine in depth the impact of the proportion of PIRs of the older population on the macro-outcomes of social platform adoption (market penetration) and how the impact of these strategies on market penetration varies in different proportions of PIRs.

The scarcity of data on senior platform operations creates challenges for research using empirical methods and the heterogeneity among individuals (the digital literacy divide of older adults) makes mathematical modeling inapplicable as well. Agent-based modeling is considered ideal for simulating complex phenomena resulting from the interaction of heterogeneous individuals driven by multiple factors and allowing researchers to overcome the limitations imposed by analytical tractability and lack of data [20,21]. The agent-based model developed in innovation diffusion research can be used as a reference because scholars consider online social platform adoption as the process of "accepting something emerging (i.e., joining an emerging platform)" spreading through the social network, i.e., the process of innovation diffusion [22,23]. Delre et al. (2016), (2010), (2007) and Van Eck et al. (2011) [19,24–26] used a utility threshold model that closely resembles the process of social platform adoption. The model clearly defines the process by which individuals are aware of emerging things through WOM and mass media, as well as the process by which they accept new things under informational influences (perceptions of service quality) and normative effects (the proportion of people around them who accept new things). However, the model fails to capture the various strategies managers use to engage platform users in spreading WOM, such as initiating interactions among members, and cultivating opinion leaders [7,27,28]. In addition, the model does not define the different behavioral characteristics of elderly people with different digital literacy when they interact with others and react to promotional strategies. Therefore, it is necessary to adapt the model to make it more consistent with the process of elderly social platform adoption.

To fill in the aforementioned gaps, this study aims to answer the following question: how does the digital literacy of the elderly population affect the effectiveness of platform promotional strategies? According to their information seeking expertise and the information sources they utilize to create meaning, we divide the elderly into PIRs and AISs. An empirical study was conducted to assess the behavioral characteristics of PIRs and AISs. With the assistance of our empirical results and research on innovation diffusion and platform promotion, we built an agent-based model to simulate the multistage process of social platform adoption among elderly people with different digital literacy levels. We used market penetration (that is, the proportion of older people joining the platform in the target population) to measure the macro results of social platform adoption. The impact of the proportion of PIRs on market penetration and the impact of each strategy on the market penetration of the social platform under different proportions of PIRs are analyzed. The results show that a high proportion of PIRs in the target population leads to the low market penetration of the platform. Improving service quality has a stronger effect on market penetration as the proportion of PIRs decreases. Strategies directly related to information diffusion, such as expanding the reach of mass media and increasing the number of seeds, are more effective when the proportion of PIRs is higher. In addition, cultivating opinion leaders is most effective when the proportion of PIRs is moderate. The effect of increased interaction time is marginal decreasing, regardless of the proportions of PIRs.

The rest of the article is organized as follows. Section 2 reviews the literature on digital literacy to classify the elderly on social platform and innovation diffusion. Section 3 describes the empirical study aiming to assess the behavioral characteristics of AISs and PIRs. Section 4 analyzes the differentiated behaviors of the elderly in the process of platform promotion to build an agent-based model. Section 5 explains the parameter setting of the model. Section 6 analyzes the results of simulation experiments. Section 7 discusses the study's main conclusions, contributions, implications and limitations.

2. Literature Review

2.1. Differentiated Elderly Population

Digital literacy refers to the ability to use the Internet and other digital resources to collect, evaluate, organize, and present information to meet needs [29]. Information seeking and use are digital activities that people undertake to create sense of the world (e.g., in coming to understandings, making decisions, and meeting their emotional needs) [30] and thus are the most commonly studied by scholars to measure digital literacy [31–33]. Existing research has emphasized the intergenerational digital gap in these two digital activities. The vast majority of young people actively engage in information seeking activities and do not exclude media information and use it as reference information for their own decisions [31,32]. Although there are also a small number of digital laggards among the younger generation, these young digital laggards have enough time, energy and physical condition to bridge the gap with their peers. In contrast, there are obvious intergenerational differences among the elderly. Quan-Haase et al. (2018) [15] found that 49% of elderly people never participate in information seeking activities since they lack knowledge of web searches and the capability to use web browsers and search tools. Magsamen-Conrad et al. (2019) [14] found that some seniors, although they participate in information seeking activities to a small extent, do not regard digital information as an ideal information source because they are not confident in their ability to evaluate and control large amounts of information online. In addition, those digital laggards are not willing to pay the cost of learning to improve their digital literacy unless they have a strong intrinsic need or external stimulus [34]. Therefore, an intergeneration digital divide is persistent in elderly generations.

Considering the prominent and persistent division within elderly generations, studies on the classification of the elderly have emerged. Some scholars classified the elderly according to their frequency of Internet access. For example, Quan-Haase et al. (2016) [34] classified the elderly as non-Internet users and Internet users. Neves and Barbosa (2015) [35] found that the elderly are mainly sporadic Internet users or non-Internet users. Another segment of scholars categorized older adults according to the digital activities they intend to engage in. For example, Nimrod (2013) [8] divided the elderly into "information swappers", "ageing-oriented" and "socializers". Vulpe (2020) [17] classified the elderly as "digitally immersed communicators", "asynchronous communicators" and "phone enjoyers". Since the effectiveness of promotion strategies on social platforms is closely related to the behavioral characteristics of older adults in searching for information and processing information, we tend to classify older adults according to their information seeking expertise and subsequent information processing methods. Therefore, similarly to the reports of Hu et al. (2019) and Zhao et al. (2018), we divided elderly individuals into active information seekers (AISs) and passive information receivers (PIRs) (see Figure 1). AISs are proficient in searching for information and thus utilize information from multiple digital sources to meet their needs. Therefore, they are autonomous in their digital actions. For example, when deciding whether to use a certain online service, they will collect relevant information independently and make rational decisions based on their needs. However, PIRs cannot or rarely search the Internet and rely on interpersonal relationships to obtain information. Due to their unskilled information seeking expertise, limited information and low self-efficacy, those PIRs are less autonomous in their digital actions and more susceptible to normal effects (e.g., group opinion). In addition, those PIRs tend to seek the opinions of the "opinion leaders" within their interpersonal network since "opinion leaders" can improve the knowledge level and self-efficacy of the audience through a knowledge transfer process [36].

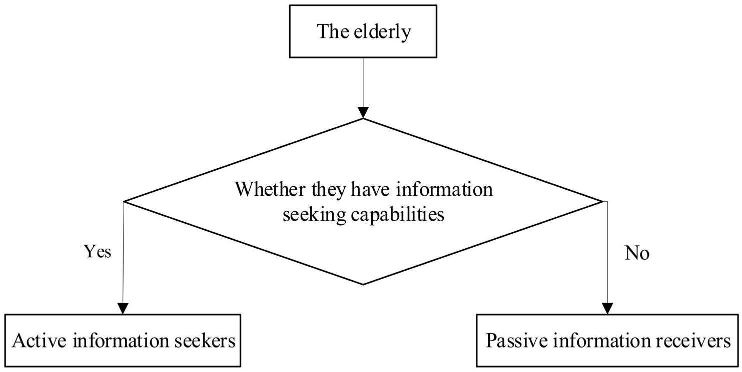

Figure 1. Classification of the elderly.

2.2. Social Platform Adoption

Social platform adoption is the process of "joining a social platform" that "spreads" through the network and leads to membership size growth and an increase in the market penetrations of the platform [23]. Scholars have tried to link social platform adoption to innovation diffusion theory, which studies the diffusion process of the act of "accepting emerging products or services" [22,23]. More recently, agent-based modeling has increasingly been adopted in the context of innovation diffusion because this bottom-up methodology can simulate how macrotrends dynamically emerge from aggregated individual behaviors and the interactions between agents [37,38]. For example, Stephen and Lehmann (2016) [39] used the agent-based Bass model to simulate the process by which individuals' recommendation behaviors aggregate to lead to a continuous increase in the market penetration of new products. Delre et al. (2016), (2010), (2007) and Van Eck et al. (2011) [19,24–26] used the utility threshold model to simulate the multistage development of individuals who heard of new services through WOM and mass media and then accepted new services and spread WOM. In the process of platform adoption, individuals also go through the stages of receiving information (i.e., WOM and mass media messages), joining the platform, and spreading WOM, so the agent-based model of innovation diffusion research is useful in describing the process of social platform adoption.

While agent-based models can serve as a suitable research paradigm to simulate how the microlevel interactions between heterogeneous individuals can lead to macrolevel outcomes in social platform adoption, which innovation diffusion research has provided valuable insights into, research aimed at developing an agent-based model specific to social platform adoption is lacking. Backstrom et al. (2006) [23] and Firth et al. (2006) [6] used mathematical models from innovation diffusion research to model social platform adoption, but this research paradigm tends to ignore interindividual heterogeneity. Chica and Rand (2017) [40] used an agent-based bass model to study how ordinary members of a gaming platform become senior members. However, this focus is different from our concern since we are interested in how to make nonmembers become members

2.3. Theoretical Gaps and Research Questions

We are interested in the impact of digital literacy on social platform adoption among the elderly and the effectiveness of platform promotional strategies. These studies on innovation diffusion have enhanced our understanding of social platform adoption; the agent-based model developed in innovation diffusion research is very informative as a reference. However, two aspects need to be considered carefully while drawing on innovation diffusion research to model aged social platform adoption.

First, the agent-based models derived from the innovation diffusion literature fail to carefully consider the various strategies that platform managers adopt to encourage customer adoption and participation of the platform. By reviewing the literature on social platforms, the main strategies of platform promotion address three aspects: strategies related to customers' hedonic value and relationship management (i.e., ensuring service quality and times of interactions), strategies directly related to information diffusion (i.e., increasing the strength of mass media messages, increasing the number of seeds) and strategies that encourage members to expand their influences (i.e., cultivating opinion leaders) [7,27,28]. Most campaign managers for general new products and services only use strategies that are directly related to information diffusion [39] and service quality [19,24–26] because consumers can hardly interact with others as social platform users and have fewer chances to develop into an opinion leader and exert their influences within or outside the social platform.

Additionally, previous literature did not mention individuals' differences in information activities due to their digital literacy in multistage platform adoption and their different behavioral responses to these strategies given their differences in digital literacy. As indicated in Table 1, previous innovation diffusion research has focused on groups such as social network users, game platform users, and cellphone consumers, but studies that focus exclusively on the elderly are rare. The existing innovation diffusion literature focuses on user characteristics such as interaction influences, demographics, and innovativeness—but not on digital literacy (see Table 1). We assume that the effect of promotion strategies is closely related to individual information seeking activities and the information sources they utilize. For example, the effect of mass media messages is related to individuals' information seeking capabilities [18]. The evaluation of service quality involves information seeking activities and the follow-up information processing process [41]. How and the probability that individuals become opinion leaders are also closely related to their information sources [19]. Considering the huge differences between PIRs and AISs in information seeking, information sources and information processing, the effect of promotional strategies on the target population with different proportions of PIRs and AISs may be different.

Table 1. Samples and their characteristics in innovation diffusion research.

Author (Year)	Samples	User Characteristics
Pescher et al. (2014) [42]	cellphone consumers	demographics
Chae et al. (2017) [43]	social network users,	interaction persuasiveness
Amini et al. (2012) [44]	consumers	/
Libai et al. (2013) [45]	social network users,	interaction persuasiveness
Nejad et al. (2015) [46]	social network users,	personal preferences
El Zarwi et al. (2017) [47]	vehicle users	innovativeness
Niamir et al. (2018) [48]	energy users	demographics
Chica and Rand (2017) [40]	game platform users	/
Barbuto et al. (2019) [49]	farmers	/
Stephen and Lehmann (2016) [39]	consumers	connectivity

Given the aforementioned two reasons, the rules of individual state transition and interaction between individuals in the process of platform adoption are different from those in general innovation diffusion processes. The corresponding agent-based model to describe the aggregated multistage individual behaviors and the interactions between individuals across the adoption process of elderly platforms should also be redesigned. Therefore, it is necessary to reconstruct the previous agent-based models to study the impact of the multistage behaviors of the elderly with different digital literacy on the macro results of platform adoption and how the effect of multiple strategies on platform adoption varies with different proportions of PIRs and AISs.

3. Empirical Study

To construct an agent-based model more in line with the actual situation, we conducted an empirical study to assess the behavioral characteristics of AISs and PIRs in the multiple-stage microprocess of platform adoption driven by multiple promotional strategies. The empirical results can be considered part of the underlying assumptions of the agent-based model in the following section and the basis of the model parameter setting.

In line with the previous literature [19,39], AISs and PIRs can be in three states: state 1, that is, have never heard of the platform; state 2, that is, have heard of the platform but are not the users of this platform; state 3, that is, are already users of this platform. We designed questionnaires to further understand PIRs' and AISs' information sources (WOMs or mass media) from state 1 to state 2, their information processing process and decision-making methods from state 2 to state 3, the timing of platform users (state 3) to conduct WOM activities, their roles in WOM activities (opinion leaders or not), and how they become opinion leaders.

We prepared 13 questions on multiple stages of platform adoption (see Table 2). Q1 and Q2 are designed to identify AISs and PIRs. The questions are designed according to the definitions of AISs and PIRs and are in line with previous literature [15,50]. Q3 is developed based on the work of Van Eck et al. (2011) [19] to identify the information sources of AISs and PIRs. The elaboration likelihood model proposed two routes of information processing [51]: central, which reflects the informational influences [52] corresponding to the personal judgments of the quality of the platform, and peripheral, which reflects the normal influences [53]. Therefore, Q4–Q6 are designed to assess the weight of informational influences and normal influences for AISs and PIRs when processing information. Q7 and Q8 are designed based on Deffuant et al. (2000) [54] to identify the differences in the degree of compromise when interacting with others. The following questions are only for individuals who have joined the platform. Q9 is designed according to Zheng et al. (2015) [7] to find the timing when platform users are most likely to promote the platform. Previous literature divided platform users into opinion leaders and nonleaders according to their opinion influences [55]. Q10 is refined from the opinion leadership scale developed by Sudman (1971) [56]. We define the 10% who score highest on the scale as opinion leaders (OLs) [57,58]. The other 90% of the platform users are nonleaders (NLs). Q11 are designed to assess the opinion influences of opinion leaders and nonleaders. Q12 is designed to assess the forwarding probability of the spread of WOM about the platform of opinion leaders and nonleaders. Q13 is designed to identify the necessary conditions to become an opinion leader for both AISs and PIRs.

We invited three academic experts in the field of innovation diffusion and social platforms to evaluate the face and content validity of each item. The results of this phase indicated that most items performed well in representing their respective constructs. We employed 97 seniors as respondents who were users of a social platform on which Tai Chi teaching and organizing services are provided online and offline. Their relatives and friends outside the platform were also employed as respondents. We obtained 235 respondents (141 males, 94 females) between 50 and 75 years of age. Platform users were required to answer all the questions, but nonusers were required to answer only Q1–Q8 in Table 2, since the remaining questions were designed for platform users. We found that 41.7% of the respondents were AISs, while 58.3% were PIRs.

Table 2. Questions.

Questions	Answers
Q1: You can use the internet to find information you need.	(a) Yes (b) No
Q2: Why can't you find the information you need? (skip if you answered yes in Q1)	(a) Unable to use web browsers and search tools. (b) Unable to judge the reliability of the information online (c) Other reasons
Q3: Where did you get information about these social platforms? (more answers possible)	(a) Friends (b) Relatives (c) Someone else (d) Mass media (advertisement or e-WOMs from strangers)
Q4: Your own judgments are important when you are active online. (10-point scale)	1–10 (from extremely not important to extremely important)
Q5: Other people's choices are important when you are acting online. (10-point scale)	1–10 (from extremely not important to extremely important)
Q6: You own judgments are important when you're active online once you have acquired necessary information from authoritative sources such as opinion leaders. (10-point scale) (skip if you are an AIS)	1–10 (from extremely not important to extremely important)
Q7: How likely do you sway your own judgment about service or product online when interacting with others holding different opinions?	1–10 (from extremely impossible to extremely possible)
Q8: If you have acquired necessary information from authoritative sources such as opinion leaders, how likely do you sway your own judgment about services or products online when interacting with others holding different opinions? (skip if you are an AIS)	1–10 (from extremely impossible to extremely possible)
Q9: When do you usually talk about the platform with others?	(a) After participating in platform interactions (receiving services, participating in platform tasks or topic discussions, etc.) (b) Other situations
Q10: How many friends have you told about the platform?	(a) 0 (b) 1 (c) 2 (d) 3 (e) 4 or more
Q11: It is easy for you to convince others of your point of view.	1–10 (from extremely agree to extremely disagree)
Q12: How often do you talk to people around you about the platform interactions you're involved in?	1–10 (from never to always)
Q13: In which ways do you think you can become an opinion leader?	(a) Being educated by an opinion leader (b) Learn by yourself (c) Others (d) Impossible

According to the data, we confirmed some critical assumptions in the model, which was in line with previous literature.

First, AISs can access more information sources than PIRs. According to the respondents' answers to Q3 in Table 2, AISs receive and utilize information through mass media (ads, e-WOM outside the local social network) when acting online, while PIRs do not (e.g., 33.09% of AISs received mass media messages compared with 0 PIRs, t = 1.6691, $p < 0.05$), while nearly all AISs and PIRs rely on WOM from interpersonal channels (friends and relatives).

Second, compared to AISs, PIRs rely more on social norms and lack confidence in their own judgment when engaging with the network unless they acquire enough information from authoritative channels in human relations. According to respondents' answers to Q4–Q6 in Table 2, AISs score high on normative influence (mean 7.80) and slightly lower on informational influence (mean 5.87). PIRs score high on normative influence (mean 8.77) but considerably lower on informational influence (mean 1.01). However, PIRs score higher on informational influence (mean 6.12) after acquiring necessary information from authoritative sources, such as opinion leaders. Combining both types of influence, ordinary

PIRs weight normative influence much higher (mean 0.90, $t = 31.5367$, $p < 0.001$) compared to AISs and PIRs who have acquired enough information from authoritative channels in human relations (AISs = mean 0.59, PIRs′ = mean 0.60, $t = 1.1294$, $p > 0.1$).

Third, compared to PIRs, AISs are more confident in their original views when interacting with others. According to respondents' answers to Q7 in Table 2, PIRs easily sway their original opinions before they believe they have adequate information, while some AISs are quite confident (Q7 Table 2: PIRs = mean 9.02, AISs = mean 5.41, $t = 20.5992$, $p < 0.001$), with 26.26% of AISs seldom or never change their mind after interacting with others. Additionally, PIRs become nearly as confident as PIRs if they acquire necessary information from authoritative sources such as opinion leaders (Q8 Table 2: mean 5.21, Q7 Table 2: AISs = mean 5.41, $t = 1.2462$, $p > 0.1$).

Fourth, platform users mainly talk about the platform after interaction with managers, service providers or other users of the platform. According to respondents' answers to Q9 in Table 2, 96.91% of users talk about the platform with nonusers after only these interactions, and only 4.95% may spread WOM in other situations.

Fifth, opinion leaders are effective in persuading others and improving the information amount and self-efficacy of others who have limited knowledge. According to respondents' answers to Q10 and Q11 in Table 2, opinion leaders are more persuasive (Q11 Table 2: OL = mean 8.90, NL = mean 5.03, $t = 9.7080$, $p < 0.001$), which might be the result of their higher notoriety and expertise.

Sixth, opinion leaders are particularly willing to spread WOM. According to respondents' answers to Q10 and Q12 in Table 2, opinion leaders are more involved in interactions and share the platform with more nonusers than nonleaders do (OL = mean 8.8, NL = mean 4.84, $t = 10.0366$, $p < 0.001$)

Seventh, PIRs cannot become new opinion leaders without the help of opinion leaders. According to the respondents' answers to Q13 in Table 2, nearly all of the PIRs completely denied the possibility of becoming opinion leaders without being educated, while 67.68% of AISs said that they were able to become opinion leaders by themselves ($t = 14.1443$, $p < 0.001$).

4. Descriptions of the Process of Platform Adoption and Model Design

In this section, we describe the process of social platform adoption through certain channels (mass media and interpersonal WOM) to encourage the target population to join the platform [6].

4.1. Different States for the Elderly

Figure 2 shows the different states for the elderly. Most of the target population was unaware of the social platform in the beginning (state 1), with the exception of a small number of seeds that initially became users of the platform (state 3). They became aware of the platform after receiving relevant information (state 2). Through a specific type of decision-making, some individuals decided to join the platform (state 3). Individuals who entered the platform received services and engaged in platform interaction, which influenced them to make WOM recommendations and contribute to the continued adoption process of the platform.

4.2. State Transition Rules for the Elderly

4.2.1. State 1 to State 2

The platform was promoted among the senior population through WOM and mass media. PIRs cannot receive or trust information other than from interpersonal sources such as mass media messages due to their low digital literacy and self-efficacy [59,60]. This group of seniors became aware of the platform (state 2) when they received WOM from interpersonal relationships. AISs have high information seeking and harnessing skills and are relatively rich in information sources. WOM and mass media campaigns allowed them to become aware of the platform and reach state 2.

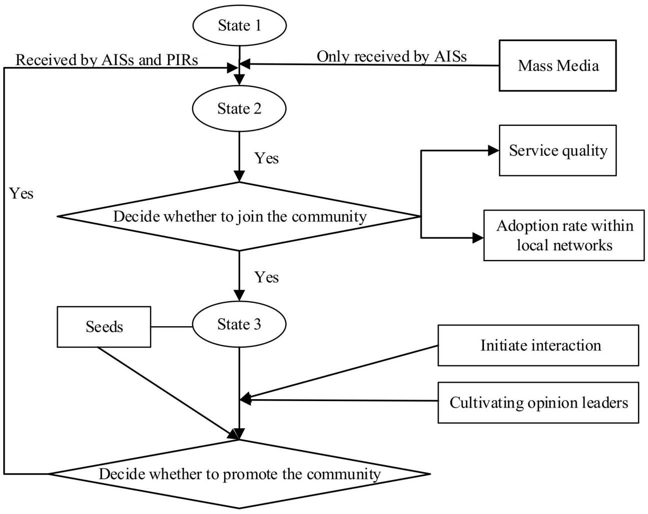

Figure 2. Different states for the elderly.

4.2.2. State 2 to State 3

Delre et al. (2016), (2010), (2007) and Van Eck et al. (2011) [19,24–26] used a utility threshold model to describe the decision-making process of rational agents. The model included both central and peripheral routes, corresponding to the personal judgments of service quality and perceived social norms. Unlike the original model, in our model, we did not include a threshold for these two parts but considered them as continuums: if individuals perceive high quality and attract more neighbors to join the platform, informational and normative influence in favor of the platform increases. The model is as follows:

$$U_{it} = (1-\beta)Q_i + \beta K_{it},\ with\ K_{it} = \sum\nolimits_{j\in N} a_{jt-1}/J \tag{1}$$

Q_i is the personal judgment of the service quality of the social platform and reflects informational influences. AISs make judgments based on the information searched from multiple resources; thus, their judgments are close to the real quality Q_0. However, PIRs can only utilize the information from WOM to make judgments [17] and have a random judgment. K_{it} reflects normative influence. Specifically, it refers to the proportion of all individuals who join the platform in the local social network of individual i, corresponding to the peripheral route of the information process. N indicates the number of individuals connected to the individual i. a_{jt-1} indicates whether individual j who is connected to the individual joins the platform at time $t-1$. If individual j has joined the platform, $a_{jt-1} = 1$; otherwise, $a_{jt-1} = 0$. β is the weight of K_{it}. Individual i decides to join the platform when the perceived utility (U_{it}) of individual i at time t exceeds the utility threshold R_i for this individual.

Given PIRs' low literacy to acquire multiple information resources and thus their disadvantage in conducting information diagnosis, they have less confidence in their personal judgments of service quality and view public action as a signal of service quality. As a result, PIRs rely more on peripheral routes (i.e., social norms) to reduce the probability of making terrible decisions [19], which is also validated by our empirical results. Therefore, we have:

$$\beta_{i,i\in PIR} > \beta_{i,i\in AIS} \tag{2}$$

4.2.3. Follow-Up Activities for the Elderly in State 3

After elderly people join the platform, the administrator and service providers of the platform will provide services and initiate high-frequency interactions between users to encourage them to participate in WOM activities [61,62]. According to our empirical results, the time when users and nonusers share information about the users is usually after interacting through the platform. We set IT as the interaction times of the platform within a certain period of adoption.

Platform users can be divided into opinion leaders and nonleaders based on the frequency and content of their WOM. Since opinion leaders transmit more concrete and precise information than nonleaders, they may have different information influences when communicating within and outside the platform [63]. We used Deffuant–Weisbuch model [54] to describe the information and opinion exchange process, where:

$$Q_{it} = Q_{it-1} + u_i * w_j * (Q_{jt-1} - Q_{it-1}) \quad (3)$$

Considering that all individuals are strongly connected, that opinions do not vary widely among AISs, and that PIRs are not confident in their original views, we assumed that all individuals can be somehow influenced by each other. Individual i refers to the person who receives information, and individual j is the person who transmits information. u_i is the coefficient of uncertainty of individual i, which reflects individual i's uncertainty in their original opinion. w_j is the influence coefficient of individual j, which shows the persuasive power of their opinion. $u_i * w_j$ reflects the coefficient of convergence of individual i when receiving information from individual j. The literature shows that opinion leaders are better at explaining their opinions than nonleaders [19]; thus, their WOMs are more persuasive, where:

$$w_{j,j \in OL} > w_{j,j \in NL} \quad (4)$$

Additionally, opinion leaders help PIRs make their judgments close to the real quality by offering enough information and thus improving their self-efficacy [19,64]. Therefore, PIRs who acquire enough information from opinion leaders can rely less on social norms and more on informational diagnosis after interacting with opinion leaders, which is also validated by our empirical results. We set $\beta\prime_{i,i \in PIR}$ as the weight of the normal influences of PIRs before being educated by OL, where:

$$\beta_{i,i \in PIR} > \beta'_{i,i \in PIR} \quad (5)$$

We set F_{OL} as the forwarding probability after each interaction and F_{NL} as the forwarding probability of nonleaders after each interaction. Our empirical results and the literature show that nonleaders may carry out WOM communication activities, while the probability that they spread WOM after each interaction is lower than that of opinion leaders [55], where:

$$F_{OL} > F_{NL} \quad (6)$$

We set the parameter P_{OL} as the proportion of opinion leaders among opinion leader candidates. According to the previous literature and our empirical results, only members who participate in interactions in depth and have high self-efficacy have the potential to become opinion leaders [55,64,65]. The cognitive level and self-efficacy of PIRs deprive them of the possibility of becoming opinion leaders unless they are educated by opinion leaders, which was also validated by our empirical study.

The WOM recommendation activities of both opinion leaders and other users enable the elderly in state 1 to be aware of the platform (state 2), triggering information cascades. Through this process, the number of platform users continuously grows.

5. Design of the Simulation Experiment

In this section, we investigate the adoption process of a social platform for elderly people with different digital literacy levels through agent-based model simulation experiments. We briefly set the parameters according to the related literature and data from the empirical study and design the simulation experiments.

The research suggests that many real-life social networks (e.g., WeChat, Microblog, Twitter, Facebook, LinkedIn and mobile social networks) are small-world networks [24]. Following Bampo et al. (2008) [66], we set the social network of the elderly to a small-world network and the rewiring probability to 0.1. Considering computer memory and time limitations, we used a network of size of 1000 to represent realistic (larger) elderly populations. Assuming that a time step represents 1 day, we set the stop condition of the model to 180 time steps to simulate a social platform adoption process of 6 months. The output index is the proportion of older people who join the platform (i.e., the market penetration). The model parameters were divided into variable and fixed parameters. In the simulation runs, fixed parameters of the model are theoretically driven and are not the object of analysis. We set the value of fixed parameters according to our underlying theoretical assumptions. Table 3 specifies the complete list of the parameters, their values and the underlying theoretical assumptions.

Table 3. Variable parameter setting.

Description	Parameter	Values	Assumption
Simulation runs	NA	100	To make our results more robust, the authors run 100 simulation runs per condition and calculate the average of the different runs
Time steps of the simulation run	NA	180	Assuming that each step represents 1 day, the promotion period is 180 days. In addition, according to the experimental results, the additional spread after 180 steps, although adding only a small number of consumers, greatly increases the number of steps
Proportion of PIRs	PP	30%;50%; 70% Default values: 50%	According to Quan-Haase et al. (2018) [15] and Vulpe and Crăciun (2020) [17]
Weight of the normal influences of AISs	$\beta_{i,i \in AISs}$	N (0.6, 0.1)	According to our empirical study
Weight of the normal influences of PIRs before being educated by OL	$\beta_{i,i \in PIRs}$	N (0.9, 0.01)	PIRs lack confidence in their personal judgment of service and rely more on social norms as a signal of service quality
Weight of the normal influences of PIRs before being educated by OL	$\beta\prime_{i,i \in PIRs}$	N (0.6, 0.1)	According to our empirical study, PIRs acquire confidence in their personal judgment of service and have a similar weight of normative influence as AISs
Individual's original judgment about the quality of service of AISs	$Q_{i,i \in AISs}$	N (Q0, 0.2) Max: 1 Min: 0	According to Van Eck et al. (2011) [19], individuals with adequate information from multiple sources are good at making judgments
Individual's original judgment about the quality of service of PIRs	$Q_{i,i \in PIRs}$	U (0, 1)	According to Van Eck et al. (2011) [19], individuals with limited information have a random judgment
Individuals' utility threshold	R_i	U (0, 1)	According to Delre et al. (2007) [24] and Van Eck et al. (2011) [19]
The influence weight of opinion leaders who transmit information	$w_{j,j \in OL}$	U (0.8, 1)	Opinion leaders transfer more concrete and precise information and are adept at persuading others [55]
The influence weight of nonleaders who transmit information	$w_{j,j \in NL}$	U (0, 1)	The influence of nonleaders is random and lower than that of opinion leaders
The coefficient of uncertainty of AISs when interacting with others	$u_{i,i \in AISs}$	U (0, 0.5)	According to Deffuant et al. (2000) [54]
The coefficient of uncertainty of -PIRs when interacting with others	$u_{i,i \in PIRs}$	1 or U (0, 0.5)	PIRs easily sway their original opinion before they acquire adequate information from authoritative sources
The forwarding probability of opinion leaders	F_{OL}	U (0.8, 1)	Opinion leaders are keen on sharing knowledge with others [19]
The forwarding probability of nonleaders	F_{NL}	U (0, 1)	The probability that nonleaders spread WOM after each interaction is random and lower than that of opinion leaders [55]
Service quality	Q_0	From 0.5 to 0.9 Default values 0.6	The service meets the needs of most people
Seed number	SN	From 2–20 Default values: 10	According to Delre et al. (2007) [19] and Van Eck et al. (2011) [19]

Table 3. *Cont.*

Description	Parameter	Values	Assumption
Reach of mass media	MM	From 0.0002 to 0.002 Default values: 0.001	The mass media campaign is not strong for an emerging platform. The authors determine its default value according to Delre et al. (2007) [19] and Van Eck et al. (2011) [19]
Interaction times	IT	From 20 to 180 Default values: 180	The interaction between social platforms is very intensive
Proportion of opinion leaders	P_{OL}	From 2%~20% Default values: 10%	According to Goldsmith (2004) [57] and Watts and Dodds (2007) [58]

The main strategies of platform promotion include promoting continuous value output (i.e., ensuring the service quality and times of interactions), expanding information diffusion (i.e., increasing the strength of mass media messages, increasing the number of seeds) and encouraging platform users to use their influences (i.e., cultivating opinion leaders) [7,27,67]. Accordingly, the input parameters a campaign manager can influence are service quality, the number of interactions, the reach of mass media, the number of seeds, and the proportion of opinion leaders. We set the proportion of PIRs and the five parameters related to promotional strategies at different levels to investigate the direct impact of the digital literacy of the target population on the market penetration of the platform after 6 months and the influences of promotional strategies on the market penetration of the platform in the target audience with different proportions of PIRs. The range of values of these variable parameters and their default values are also shown in Table 3.

6. Simulation Results

6.1. Model Validation

We used the macro verification method [68] to verify whether the process of spreading individuals' adoption of the social platform in our model is consistent with the diffusion phenomenon in the real environment.

The literature shows that the modified exponential curve, logistic curve, and Gompertz curve are the basic diffusion models of product growth [69]. However, previous literature such as Firth et al. (2006) [6], Kossinets and Watts (2006) [70] and Leskovec et al. (2007) [71] showed that the plots for diffusion in social network sites exhibit logarithmic curves, dominated by a "diminishing returns" property in which the curve continues increasing but more slowly over time [23]. We used SPSS to analyze the curve fitting of the platform adoption process plot with default parameter values. As indicated by Figure 3, the plot of the adoption process of a social platform resembles a logarithmic curve. As indicated by Table 4, the plot of our models has a significant fitting effect with each curve equation ($p < 0.001$), but it has the best fitting degree with logarithmic curves with the largest R square (0.948). Therefore, our model simulates the macro process of a social platform adoption well.

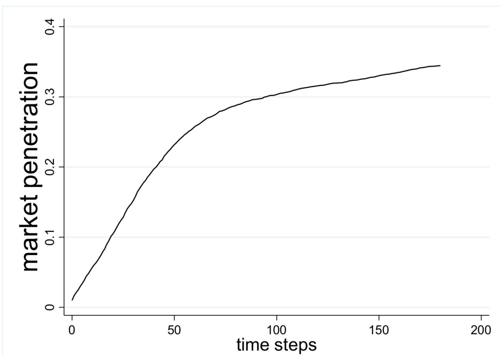

Figure 3. The adoption process of a social platform.

Table 4. Model summary and parameter estimates.

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Logarithmic	0.948	3273.083	1	178	0.000	−0.132	0.092
Compound	0.592	258.241	1	178	0.000	0.102	1.009
S	0.548	215.861	1	178	0.000	−1.318	−4.951
Growth	0.592	258.241	1	178	0.000	−2.282	0.009
Exponential	0.592	258.241	1	178	0.000	0.102	0.009
Logistic	0.592	258.241	1	178	0.000	9.800	0.991

Notes: The dependent variable is market penetration, and the independent variable is time step.

6.2. Sensitivity Tests

We conducted sensitivity tests to analyze the impact of the proportion of PIRs (PP) on platform adoption and on the effect of promotional strategies that platform managers may use. The input parameters a campaign manager can influence are service quality (Q_0), the reach of mass media (MM), the seed number (SN), interaction times (IT) and the proportion of opinion leaders (P_{OL}) [7,27,28] (see Table 3). We varied each of these parameters once at a time (while keeping all other parameters constant and in line with the default value) and simulated the process of social platform adoption. Output indexes included (i) market penetration in each step; and (ii) final market penetration within the promotion period.

6.2.1. Varying the Proportions of PIRs

Figure 4 shows the sensitivity of the market penetration (at each step) in varying the proportions of PIRs from 30% to 50% to 70% within 180 steps. In general, the change in market penetration in each step increases with the decrease in the proportion of PIRs, and we observe that the increase in the proportion of PIRs results in a decrease in final market penetration (from 43.17% to 36.17% to 25.18%). This suggests that higher proportions of PIRs will cause more obstacles to platform adoption.

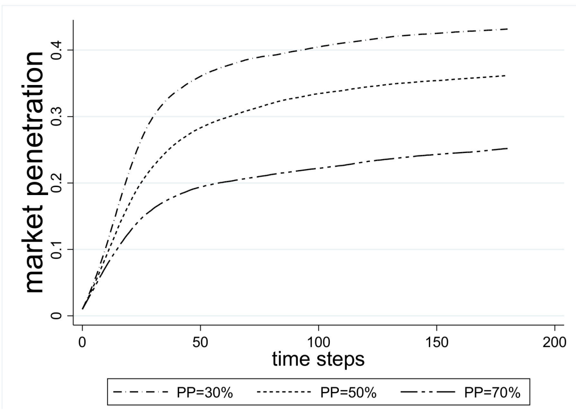

Figure 4. Market penetrations of the total target audience at each step.

6.2.2. Varying Strategy Indexes among Different Proportions of PIRs

1. Varying the index related to value output
   - Varying service quality

Figure 5 shows the sensitivity of the market penetration at each step to varying service quality from 0.5 to 0.9 with different proportions of PIRs. An increase in service quality contributes to the increase in market penetration, while the effect of enhancing service quality is more effective in the target audience with lower proportions of PIRs. To clearly analyze the moderating roles of the proportions of PIRs in the positive relationship between service quality and final market penetration (MP), we conducted an additional regression test. As indicated by Equation (7), the interactions of the proportion of PIRs with service quality have a significant negative impact on final market penetration; that is, the lower the proportion of PIRs is, the larger the impact of service quality. The results are reasonable since AISs are more adept at judging quality using multiple information sources and are more influenced by their personal judgments of the service quality of the social platform than PIRs.

$$MP = 0.746Q_0 - 0.651PP - 0.106Q_0 * PP \tag{7}$$

with:

$$\mathrm{R}^2 = 0.992,\ \mathrm{F} = 99999.00,\ \mathrm{t(PP)} = -492.95,\ \mathrm{t}(\mathrm{Q}_0) = -80.22,\ \mathrm{t}(\mathrm{Q}_0 * \mathrm{PP}) = 62.57$$

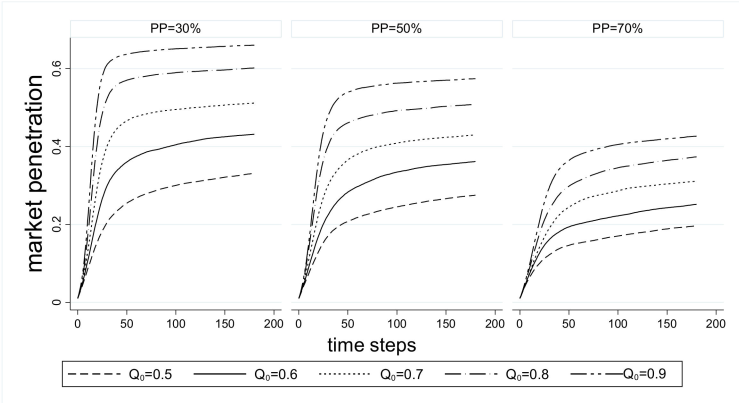

Figure 5. Market penetration at each step.

Since service quality influences individuals who have been aware of the platform, we conducted a sensitivity test of the adoption rate of people who are aware of the platform to varying service quality and found that the positive relationship between service quality and the adoption rate was stronger in lower proportions of PIRs (see Figure 6). Interestingly, we found that the marginal effects of service quality on the proportion are increasingly growing with the increase in time steps and that such marginal effects will peak at a certain step. The occurrence timing of the peak occurs more quickly in lower proportions of PIRs. We also observed that service quality has a larger effect on the final adoption rates when the proportions of PIRs of the elderly are lower.

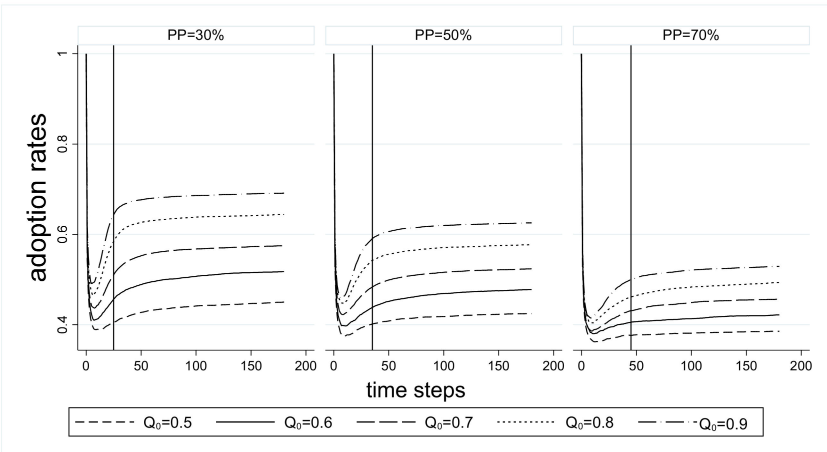

Figure 6. The adoption rate of people who are aware of the platform.

- Varying interaction times

Figure 7 show the sensitivity of the market penetration in each step to varying interaction times from 20 to 180 with different proportions of PIRs. We observe a positive relationship between interaction times and final market penetration within a certain range of interaction times, but this positive relationship disappears at a certain level of interaction times. This occurs because platform users have already made all the individuals in their personal social network aware of the platform in the WOM activities caused by the previous interaction, and the subsequent increase in interaction times does not contribute to information diffusion.

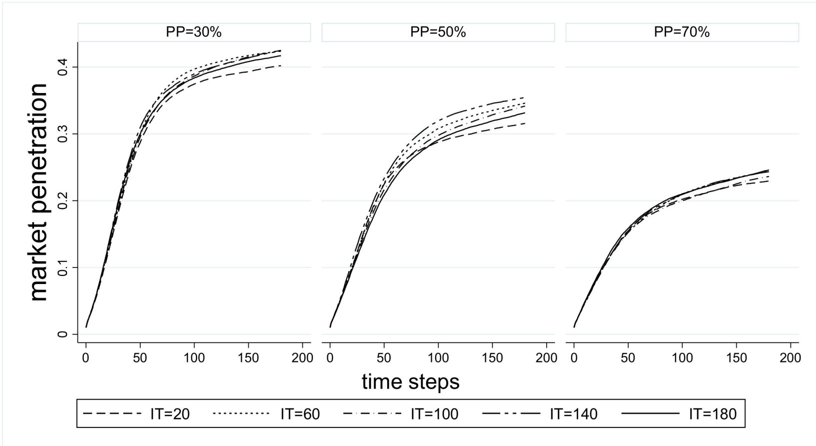

Figure 7. Market penetration at each step.

Since the marginal effect of interaction times is decreasing, we conducted the sensitivity of final market penetration to varying interaction times from 1 to 40 times to deeply test the relationship between interaction times and final market penetration. From Figure 8, we observe an apparently decreasing marginal effect of interaction times on final market penetration.

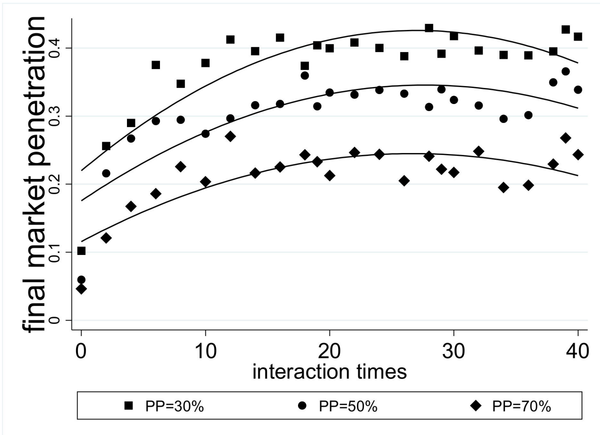

Figure 8. Final market penetration.

Combining the above results related to valuable output, we found that launching a small amount of interaction with high-quality content is a wiser option for platform managers compared with spending efforts and time launching multiple interactions with low-quality content. Additionally, improving service quality is more valuable when there are more AISs and fewer PIRs.

2. Varying indexes related to information diffusion
   - Varying seed number

Figure 9 shows the sensitivity of the market penetration in each step to varying the number of seeds from 2 to 20 with different proportions of PIRs (30%, 50%, 70%). An increase in the seed number contributes to an increase in market penetration. The effect of increasing the seed number is more effective with higher proportions of PIRs. The results are reasonable since more seeds contribute to more WOM that can be received directly by PIRs. As indicated by Equation (8), the interactions of the proportion of PIRs with the seed number have a significant positive impact on the final market penetration; that is, the higher the proportion of PIRs is, the greater the impact of seeds:

$$MP = 0.317SN - 0.933PP + 0.109SN * PP \tag{8}$$

with:

$$\mathrm{R}^2 = 0.984,\ \mathrm{F} = 99999.00,\ \mathrm{t(PP)} = -541.28,\ \mathrm{t(SN)} = 184.09,\ \mathrm{t(SN * PP)} = 62.57$$

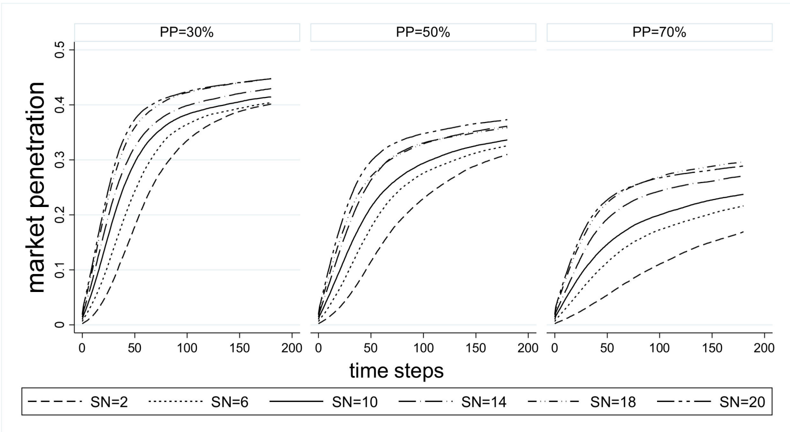

Figure 9. Market penetration at each step.

- Varying reach of mass media

Figure 10 shows the sensitivity of the market penetration in each step to varying the reach of mass media from 0.0002 to 0.002 with different proportions of PIRs. A stronger mass media campaign contributes to an increase in market penetration, while the effect of a mass media campaign is slightly greater in higher proportions of PIRs. This seems surprising since mass media campaigns only work for AISs. The results may occur because mass media campaigns result in more information diffusion and thus spread the act of "joining the platform" among AISs as well as PIRs indirectly since PIRs are more influenced by social norms. To clearly analyze the possible moderating roles of proportions of PIRs in the positive relationship between the mass media reach and final market penetration (MP), we conducted an additional regression test. As indicated by Equation (9), the interactions between the proportion of PIRs with mass media reach have a significant positive impact on the final market penetration; that is, the higher the proportion of PIRs is, the greater the impact of mass media campaigns:

$$MP = 0.299MM - 0.915PP + 0.019MM * PP \tag{9}$$

with:

$$\mathrm{R}^2 = 0.921,\ \mathrm{F} = 21029.29,\ \mathrm{t(PP)} = -239.51,\ \mathrm{t(MM)} = 75.48,\ \mathrm{t(MM * PP)} = 4.86$$

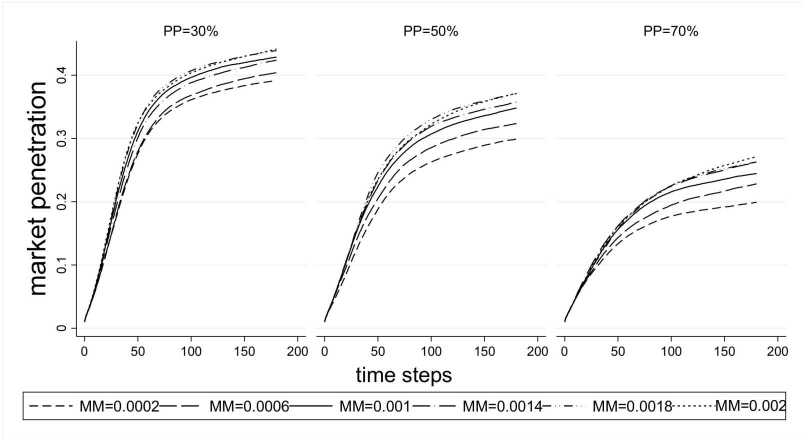

Figure 10. Market penetration at each step.

Since these two strategies are more effective when proportions of PIRs are higher, managers should strengthen these strategies related to information diffusion with an increase in PIRs.

3. Varying proportions of opinion leaders

Figure 11 shows the sensitivity of the market penetration at each step to varying proportions of opinion leaders from 0.02 to 0.2 with different proportions of PIRs. More opportunities to generate opinion leaders contribute to the increase in market penetration, while the effect of opinion leaders seems to increase at first and then decrease with the increase in proportions of PIRs. We used a regression test to further investigate the relationship between the positive impact of opinion leaders on final market penetration with different proportions of PIRs. To obtain a more precise analysis, we varied the proportions of PIRs from 30% to 70%, with a 10% increase each time.

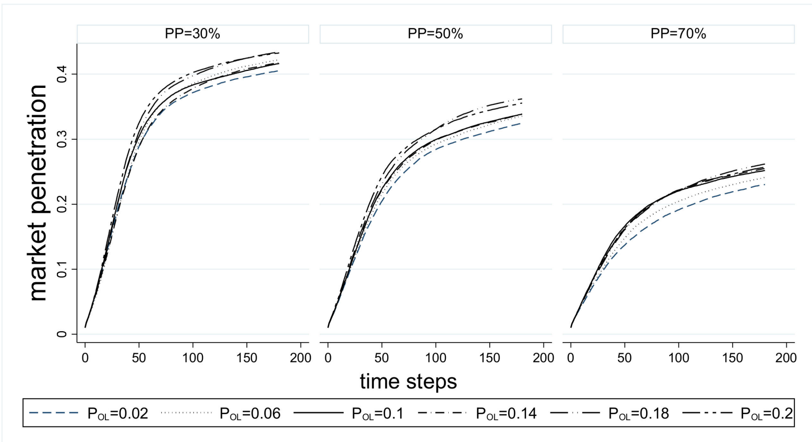

Figure 11. Market penetration at each step.

As indicated by Table 5, the effect of cultivating proportions of opinion leaders on final penetration increases when the proportions of PIRs increase from 30% to 50% and then stop increasing. These results may occur because cultivating opinion leaders contributes to higher self-efficacy and more precise personal judgments of service quality and then induces PIRs to join the platform before most of their friends join. Considering that such a mechanism works mainly on PIRs, it exerts a larger effect with the increase in proportions of PIRs to a certain degree. However, if the proportions of PIRs are too large, there are many PIRs who lack an opportunity to be educated by opinion leaders, thus diluting its effect.

Table 5. Regression results.

Parameters	Final Market Penetration
P_{OL}	0.058 ***
	(0.005)
PP = 30%(bn)	
PP = 40%	−0.043 ***
	(0.001)
PP = 50%	−0.084 ***
	(0.001)
PP = 60%	−0.124 ***
	(0.001)
PP = 70%	−0.174 ***
	(0.001)
PP = 30%* P_{OL} (bn)	
PP = 40%* P_{OL}	0.099 ***
	(0.007)
PP = 50%* P_{OL}	0.146 ***
	(0.007)
PP = 60%* P_{OL}	0.044 ***
	(0.006)
PP = 70%* P_{OL}	0.054 ***
	(0.006)
_cons	0.418 ***
	(0.000)
Obs.	10498
R-squared	0.990

Note: *** $p < 0.01$ (based on a Student's t (4999) distribution with two tails); * interactions of two parameters, e.g., PP = 30%* P_{OL} means interactions of PP = 30% with $P_{OL.;}$ bn, base number; the numbers in parentheses are standard errors.

7. Discussion

This study aimed to explore how the digital literacy of the elderly population affects the effectiveness of social platform promotional strategies. An empirical study was conducted to analyze the behavioral characteristics of AISs and PIRs at multiple stages of platform adoption. By referring to our empirical results and research on social platforms and innovation diffusion, we built an agent-based model to simulate the process of social platform adoption among the elderly. By changing the proportion of the target group of PIRs and the relevant parameters representing the promotional strategies of the platform, we analyzed the impact of the proportion of PIRs as well as the effect of each strategy under different proportions of PIRs on market penetration.

The digital literacy of the target group directly affects platform adoption. The fewer PIRs with information seeking capabilities there are in the target group, the greater the market penetration of social platforms will be. The high proportion of PIRs is a significant obstacle that hinders platform adoption.

The effect of some promotional strategies on market penetration is affected by the proportions of PIRs. Improving service quality is more effective for market penetration when the proportion of PIRs in the target group is lower. Strategies directly related to information diffusion, such as increasing the number of seeds and increasing the strength of mass media messages, have stronger effects on market penetration when the proportion of PIRs in the target group is higher. In addition, cultivating opinion leaders is most effective for market penetration with a moderate proportion of PIRs. Interestingly, regardless of the proportions of PIRs, the effect of increasing interacting times marginally decreases.

7.1. Theoretical Implications

This paper was the first to link the digital literacy of the target group to macro-outcomes of innovation diffusion and to draw a direct effect of the proportion of PIRs in the older population on diffusion outcomes, as well as a moderating effect on the effectiveness of various promotional strategies. The research has three contributions.

First, this study developed an agent-based model to simulate the process of the use of social platforms by the elderly. The innovation diffusion literature focuses on the diffusion of general products or services [39,40]. The agent-based model constructed by these scholars cannot reflect the impact of the characteristics of social platform and fails to consider various strategies that the managers of social platforms adopt to encourage platform adoption. In addition, previous innovation diffusion studies have failed to mention the behavioral differences that result from individuals' digital literacy. We combined research on the digital literacy of the elderly, the literature on innovation diffusion and empirical research on social platforms to build an agent-based model that is more appropriate for the adoption process of social platforms for the elderly.

Second, this study suggested that the digital literacy of the elderly who have been connected to the Internet has a direct impact on the market penetration of social platforms. Previous literature on the digital literacy of the elderly is often a statistical study of the manner and frequency of information activities in which the elderly participate [14,16,34,72]. We divided the elderly into PIRs and AISs according to whether they participated in information seeking and investigated the impact of proportions of PIRs on platform adoption, which enriched the research on the digital literacy of the elderly.

In addition, this study demonstrated that promotional strategies may have varying degrees of impact on platform adoption with different proportions of PIRs. Since research seldom links the effect of promotional strategies with the digital literacy of the target audience, our conclusions provide new insights into promotion campaigns.

7.2. Practical Implications

In determining the target group of the social platform for the elderly, it is not sufficient to consider only whether they have access to the Internet or use mobile phones, computers, etc. The information seeking ability of the elderly determines the information sources and information processing methods of the elderly and affects the results of platform adoption. The digital literacy of the elderly, especially the ability to search for information, should be fully investigated. Managers should choose to promote social platforms in areas or platforms in which the proportion of PIRs is as low as possible.

The results show that increasing the number of seeds, increasing the strength of mass media messages, improving service quality and cultivating opinion leaders are always beneficial to platform adoption. However, the strength of these strategies may be different under varying proportions of PIRs. Strategies that contribute to market penetration by influencing awareness rates are more effective with higher proportions of PIRs. However, service quality contributes to market penetration by encouraging individuals who are aware of the social platform to become users; this strategy is more effective among lower proportions of PIRs. Thus, managers can adjust their efforts on these three strategies based on the proportions of PIRs. The impact of service quality is minor at the beginning, gradually increases and peaks at some points; such points occur quicker with lower proportions of PIRs. Due to a lack of experience, it is difficult for managers to provide perfect emerging services at the beginning; therefore, managers can be dedicated to using stronger mass media campaigns and more seeds to improve awareness with a basically satisfying service in the beginning and then further refine the service later. It is necessary to flexibly grasp the timing of strategic adjustment according to the proportion of PIRs. The higher the proportion of PIRs, the later the adjustment.

Since interaction times have a decreasing marginal effect, managers may choose to control the number of interaction times within its most effective range and dedicate the rest of their efforts to improving the service quality of each interaction.

Cultivating opinion leaders always contributes to market penetration, but this strategy is most effective with a moderate proportion of PIRs (approximately 50%). Considering that the proportions of PIRs in the real world are close to 50%, managers should consciously urge the elderly to deeply participate in interactions and cultivate opinion leaders. In addition, managers should guide opinion leaders to identify PIRs in their personal social networks and invest time, energy and emotion in WOM communication activities with PIRs. In this way, PIRs can obtain richer information, improve their cognitive level and self-efficacy and thus lower their adoption threshold under “education” (knowledge transfer) from opinion leaders.

7.3. Limitations and Future Research

As social platforms for the elderly are currently emerging services and the degree of competition among platforms is very weak, the possible impact of market competition was not taken into account in our analysis. If there is intense competition between social platforms, the conclusions of this paper need to be reinterpreted. Second, we did not consider the withdrawal of the elderly who joined the social platform because we set the adoption period of the social platform to six months (short term) and because the elderly hesitate to accept an innovation but will be very loyal once they accept it [73,74]. Our conclusions are applicable only to the elderly social platform but not to the social platform of young people who are curious but only have a passing interest. In addition, we used the information seeking behavior, which was the variable most frequently mentioned in the literature on digital literacy [15,31–33], to classify elderly individuals. The differences in other information behaviors caused by digital literacy among the elderly may also have an impact on social platform adoption; this topic is worthy of further study.

8. Conclusions

This paper aimed to examine how the digital literacy of the elderly population affected the effectiveness of platform promotional strategies. The elderly population was divided into PIRs and AISs according to their information seeking expertise, and an empirical study was conducted to assess the behavioral characteristics of PIRs and AISs. Grounded in innovation diffusion research and our empirical results, an agent-based model was developed, and the impact of the proportion of PIRs on the macro result of social platform adoption (i.e., market penetration) and the impact of promotional strategies on market penetration under different proportions of PIRs were analyzed. The results show that as the proportion of PIRs in the target population increases, the market penetration of the platform will decrease. Improving service quality has a stronger effect on market penetration when the proportion of PIRs is lower. Strategies directly related to information diffusion, such as expanding the reach of mass media and increasing the number of seeds, are more effective when the proportion of PIRs is higher. In addition, cultivating opinion leaders is most effective when the proportion of PIRs is moderate. Interestingly, increasing interaction times may have a marginally decreasing effect regardless of the proportion of PIRs. Our study enriches the literature on innovation diffusion by focusing on the impact of digital literacy on the effectiveness of social platform promotional strategies among the elderly and provides valuable practical implications for managers.

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