What influences users’ continuance intention of internet wealth management services? A perspective from network externalities and herding

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Accepted: 14 June 2022
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Abstract
In recent years, more and more wealth management platforms have adopted Internet wealth management (IWM) services to attract users. Due to the intensive competition and low switching costs, it is essential for platforms to enhance users’ willingness to continue using IWM services. Comprehensively considering the role of network externalities and herding, this study identified the factors affecting users’ continuous intention of IWM service. The research model was tested using survey data collected from 637 respondents concerning their perceptions of IWM services. The results indicate that network externalities (network size, perceived complementarity, network strength) have significant impact on herding and perceived value, thus affecting continuance intention. Furthermore, herding and perceived value have a greater impact on continuance intention of users with low financial literacy than that of users with high financial literacy. This study could benefit wealth management platforms and researchers seeking to improve the retention rates of IWM users.

Keywords Network externalities · Herding · Perceived value · Continuance intention · Internet wealth management services · Financial technology

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Published online: 16 July 2022
1 Introduction

With the rapid development of emerging technologies such as the Internet, big data, and artificial intelligence, financial innovation has become necessary [1]. The COVID-19 pandemic has further accelerated the transformation of the financial industry, especially the innovation of “contactless” digital services in traditional financial enterprises [2]. Financial technology (fintech), which is a combination of financial services and technology, has emerged in response to this trend [3]. Fintech innovates business models, applications, and processes by improving transparency and accuracy, reducing costs, and enabling users to engage with a variety of innovative financial services such as payment technology, wealth management, and crowdfunding [1, 3]. As a critical part of fintech services, Internet wealth management (IWM) services have witnessed considerable technological innovations in recent years [4]. These innovations include the intellectualization and automation of financial products and services through emerging technologies [5, 6].

IWM services refer to the decision support and value-added services provided by digital or intelligent means for users’ financial management behaviors [4, 7]. Compared to traditional wealth management, IWM can automatically generate investment suggestions and portfolio allocation for users according to their investment preferences and characteristics, providing diversified services of investment financial products [5]. This greatly reduces the cost of user information search and improves the convenience and versatility of financial services [8]. These advantages make IWM become the mainstream of wealth management. In 2020, the number of IWM users in China reached 610 million [9]. With its huge commercial value, IWM has become increasingly attractive in the financial industry. Global IWM investment totaled $47.2 billion in 2020 [10]. At present, WealthFront, SigFig, Ant Fortune, and other well-known wealth platforms have launched IWM services. However, due to intensive market competition and low switching costs, users can easily switch IWM services providers, which makes it an important goal for wealth platforms to compete for users. Thus, effectively enhancing users’ willingness to continue using offered IWM services is not only a necessary condition to build users’ loyalty to wealth platforms, but also a necessary condition to ensure that platform enterprises can obtain the return on their IWM investment [7].

The existing literature has mainly examined customers’ adoption and use of IWM services based on the general technology adoption models and theories, including the technology acceptance model (TAM), the theory of reasoned action (TRA), and the innovation diffusion theory (IDT). A central assumption of these studies is that adoption and use of IWM services are primarily driven by general instrumental factors, such as perceived usefulness, perceived ease of use, and based on that individuals have the necessary information and expertise to judge and evaluate the effectiveness and security of IWM services [7, 11–13]. However, compared with traditional wealth management, IWM involves more uncertainties and risks, such as performance, transaction process, and social risks [14, 15].
many cases, users are constrained by bounded rationality [16, 17]. Specifically, due to the limitations of information asymmetry, professional knowledge, time, and other factors, most users cannot have a thoughtful and rational understanding of IWM services [16]. In this case, imitating others’ behavior seems to be a convenient way for users to overcome uncertainty and avoid costs or losses [18]. In other words, herd behavior may occur when users are uncertain about their next action.

Herding refers to the phenomenon that people often weaken or even do not use their own information but imitate others in decision-making activities [19]. According to the definition, it may be reasonable for an individual to observe the behavior of others and learn from the signals of others if there is no clear plan to follow [20]. This phenomenon is especially important and influential in the Internet era [21, 22]. Due to the platform, users can easily observe others’ decisions and evaluations about using IWM services. Therefore, it is crucial to understand the impact of herd behavior in the context of IWM. On the one hand, it may have a positive impact by accelerating users’ continuance of IWM. Previous studies have shown that herding has a positive effect on users’ continuous intention of IT [18, 21]. On the other hand, herding may also produce unrealistic expectations and distortion of facts [18]. In particular, when users find that the new service does not meet their needs, they will feel disappointed and may give up the service [17]. Although previous studies have proved that herding plays an important role in people’s decision-making under different backgrounds [23, 24], in the context of IWM, we know little about the influence of herding on users’ continuous use behavior.

In addition, different people, based on their unique characteristics, exhibit different degrees of herding behavior [18]. Past studies have shown that financial literacy is an important user attribute related to decision-making behavior in both traditional and electronic finance [25, 26]. Users with high financial literacy tend to choose complex or high-risk financial products by themselves, while users with low financial literacy tend to rely too much on others’ advice when making investment decisions [27]. Therefore, in the context of IWM, when users face an uncertain environment and complex IWM services, we believe that financial literacy may be an important factor affecting the development of herding.

Previous studies found that network externalities are important determinants of users’ continuous use behavior [28–31]. Network externalities (NE) refer to “the value or effect that users obtain from a product or service will bring about more value to consumers with the increase of users, complementary products, or services”[32]. In essence, the IWM platform has the characteristics of NE [3]. According to the “Matthew Effect”, wealth management platforms with a larger number of users are more likely to attract new users. When more users join the same platform, it means that users have more opportunities to acquire knowledge and experiences about IWM services from others, and thus have more possibilities to determine the products or services they want. With the increase in the number of users, the externalities of these wealth management platforms improve the utility perception of users and attract more users to visit regularly and interact frequently. Therefore, users may prefer to continue using IWM services on wealth management platforms that provide them with NE. At present, most scholars focus on the impact of NE on
the perception of technical attributes, such as perceived value [28, 29] and perceived usefulness [11, 30]. In addition, a few scholars focus on the impact of NE on the perception of social attributes, such as trusting beliefs and interaction [33]. Due to the uncertainty and multi-dimensional risks of IWM, when the size of platform users expands (the dimension of NE), it may cause individuals to perceive other social attributes, such as herding. Studies on online shopping, innovative crowdfunding, and peer-to-peer lending show that NE is a significant predictor of herding [22, 34]. However, the literature of IWM rarely focuses on the impact of NE on herding.

Broadly, this study seeks to address the above-mentioned research gaps in the literature. Specifically, we focus on the impact of NE on herding and perceived value that influence users’ continuance intention of IWM services. Furthermore, we also examine the moderating role of users’ financial literacy. Ultimately, this study mainly answers the following research questions:

**RQ1.** How do network externalities impact herding and perceived value in the context of IWM?

**RQ2.** What is the effect of herding on the facilitation of users’ continuance intention in the context of IWM?

**RQ3.** Does financial literacy moderate the relationship between herding and users’ continuance intention?

### 2 Theoretical background and literature review

#### 2.1 Internet wealth management (IWM)

IWM mainly includes online transactions and intelligent recommendations of financial products and services [4]. Specifically, through IWM, financial platforms can accurately recommend financial products to users, provide personalized investment advice, and improve users’ investment experience and efficiency. IWM has been proposed as an important solution to the electronic financial market [35]. Currently, IWM services are growing popular not only with digital natives (millennials and Generation Z) but also with older and wealthier users [7].

Existing literature mainly examined the impact factors of user adoption and use behavior in IWM. Some researchers have investigated the influence of user factors. For example, Ryu [36] discussed the impact of perceived benefits and perceived risks on the continuous use of IWM services from the perspective of users. Similarly, Xie et al. [37] clarified the relationship between perceived value and fintech adoption intention. In addition, some scholars have examined the impact of information technology (IT) factors on user behavior. For example, Hwang et al. [38] explored the impact of uncertainty and IT quality on users’ continuance intention. The results show that service quality is the most important quality factor to control uncertainty and encourage continuance intention. Based on the information system success model, Zhou [39] proved that IT quality promotes users’ continuance intention by positively affecting trust, flow, and satisfaction. Wang et al. [35] examined the impact of system quality on users’ continuous use behavior. Overall, a central assumption of these studies is that the adoption and use of IWM services are mainly
driven by general instrumental factors, such as perceived usefulness, perceived ease of use, and based on that individuals have sufficient personal information and expertise to judge and evaluate the effectiveness and security of IWM services [7, 11, 40]. However, compared with traditional wealth management, IWM involves more uncertainty and risks [15]. In many cases, due to the limitation of information asymmetry or professional knowledge, users may not make a thoughtful and rational cognition of IWM services, that is, it may produce herding.

However, few studies have considered both the antecedents and consequences of herding in IWM. In addition, there is little research pay attention to the impact of NE on user behavior. Therefore, the purpose of this study is to link NE and herding in the IWM context to investigate how NE affect users’ continuance intention of IWM services.

2.2 Network externalities (NE)

At present, NE have been widely used in the study of e-commerce [28, 30], software applications [41], financial services [42, 43], and other fields. They are important features of the information and communication technology industry. Table 1 summarizes the dimensions of NE used in research on user pre-adoption/post-adoption of the IS technology.

NE can be classified into direct network externality and indirect network externality [44]. Direct network externality is measured by network size [31]. Specifically, direct network externality is related to the number of users in the network. As more and more users purchase and use network products, existing users are likely to obtain greater benefits, including utilitarian benefits related to the practical value of network products and hedonic benefits related to the pleasant experience of using network products [31, 45]. For example, the increase in the number of users joining the IWM platform will strengthen the interaction between users, and generate a large number of data related to their investment experience, financial product recommendation, and comments on the platform. These data will help the platform improve IWM services. Therefore, existing financial users will benefit from these improvements, while new users will be attracted by the platform.

Indirect network externality is measured by perceived complementarity [46, 47]. Specifically, indirect network externality represents the value brought to users by the increase in the number of compatible complementarities of a product or service when the user scale of the product or service expands. For example, IWM platforms will integrate with third-party tools, such as social media and e-commerce sites to improve users’ financial management experience. On the IWM platform, users can share their investment portfolio and investment experience with friends at any time, and users can quickly switch between financial management and online shopping, which will further enhance their interaction with the platform and continuous use of financial services.

In short, direct network externality comes from the demand side of the network, while indirect network externality comes from the supply side [32], both of which reflect the network coverage built by the platform and users, that is, the breadth of
| Source                  | Research Context                                      | Dimensions of NE                                                                 |
|------------------------|-------------------------------------------------------|----------------------------------------------------------------------------------|
| Cen and Li [28]        | Loyalty to online B2B platforms                       | Perceived network size; Perceived external prestige; Perceived compatibility; Perceived complementarity |
| Chiu et al. [46]       | Loyalty to social networking sites (SNSs)             | Perceived compatibility; Perceived complementarity; Perceived external prestige; Perceived network size |
| Hong et al. [55]       | Satisfaction with mobile social apps                  | Number of peers; Perceived complementarity                                          |
| Hsu and Lin [29]       | Adoption of the Internet of Things services           | Number of IoT services; Perceived critical mass; Perceived compatibility; Perceived complementarity |
| Lee and Kim [75]       | Adoption and continuance intentions toward Internet-only banks | Number of services; Critical mass                                                  |
| Li et al. [41]         | Persist in completing MOOCs                           | Network size; Perceived complementarity                                              |
| Lu and Lin [30]        | Continue use intention of SNSs                        | Number of members; Number of peers; Perceived complementarity                       |
| Lin and Bhattacherjee [45] | IM technology adoption                             | Network size; Perceived complementarity                                              |
| Lin et al. [57]        | IM technology adoption                                | Overall installed base; Perceived compatibility; Perceived critical mass            |
| Xiao et al. [33]       | Repurchase intention on O2O platforms                 | Number of members; Number of peers; Perceived complementarity                       |
| Yong Chun and Hahn [48] | Future usage of Internet services                    | Total network size; Local network size; Network strength                          |
| Zhang et al. [31]      | Continuance intention of WeChat                      | Network size; Number of Peers; Compatibility; Complementarity                      |
| Zhao and Lu [58]       | Continuance intention of microblogging services       | Perceived complementarity; Perceived network size                                  |
| Zhou and Lu [47]       | Loyalty of mobile instant messaging                   | Referent network size; Perceived complementarity                                  |
the network. From Table 1, it can be seen that most people believe that network size and perceived complementarity are the main components of NE. However, in many such studies, the influence of users’ interaction intensity on the network has been ignored. Network strength is also an important part of NE because it deals with the depth of interactions that users make in a network [48]. Network strength reflects the quality of the interaction that users participate in Internet services network. If a user spends more time in the network interacting with other members, the network strength of the Internet service is greater for that user and may promote continuance usage of the service [48].

We suggest that network strength is another key factor of NE that influences the continuous use of IWM services. In this study, network strength is defined as the total amount of interaction between users and the wealth management platform in a certain period. It reflects the relationship between users and the wealth management platform, including the relationship between users of the platform, and the relationship between users and platform services. Granovetter [49] pointed out that interpersonal relationship strength could be measured from four aspects: the amount of time, and the reciprocal services, the emotional intensity, and intimacy. Hansen [50] measured the strength of interaction between organizations in terms of frequency and closeness. Yong Chun and Hahn [48] measured the network strength between users and online services by the total time that users stay in a network. Based on the above research and in combination with the background of IWM, this study measured network strength by frequency of contact, closeness, and diversity. Specifically, the frequency of contact between users and the IWM platform is measured by the number of times to log in to the IWM platform. Closeness is measured by the length of time that users stay on the platform. Diversity is measured by the use of wealth management platform service types. Therefore, we will measure NE from three dimensions: network size, perceived complementarity, and network strength, and investigate how they affect users’ continuous intention through herding.

2.3 Herding

Herding is mainly composed of two aspects: discounting one’s own information and imitating others [18]. Among them, discounting own information shows that users are less sensitive to their own information and opinions, and tend to believe what most people believe, and think that other people have more information than they do [51]. Imitating others describes the degree to which people consciously make the same product choices as others when buying products [17]. That is, they observe the actions of others and then make the same decision as the majority of people.

Herding can occur in a variety of scenarios, for example, imitating the like sharing of other users on social media [52], following the choice of other supporters of crowdfunding [34], imitating the purchase decisions of other consumers on social commerce platforms [23], and imitating other user behaviors on technology adoption [18]. Prior studies have shown that herding plays an important role in people’s decision-making. In the financial market, when investors are uncertain about financial products, they tend to infer their own utility by observing the prior decisions.
of others [53]. Compared with traditional offline financial institutions, IWM platforms contain a large amount of information, such as comments and experiences of investment users, which may lead to information overload and make the environment uncertain. In an uncertain environment, people often use external information to improve their decision-making [54]. In addition, prior research has confirmed that online trading provides an opportunity for people who have not experienced it to imitate others [22]. Therefore, we strongly assume that herding may play an important role in users’ continuance intention of IWM services on the platform that has a wide range of financial products and massive social information.

3 Research model and hypotheses

Figure 1 presents the research model that we intend to examine. The model considers NE, herding, and perceived value which are key factors affecting users’ continuance intention. In the model, NE are decomposed into three dimensions, namely, network size, perceived complementarity, and network strength, while the constructs of herding are composed of imitating others and discounting own information. Moreover, we consider users’ financial literacy will moderate the relationship between herding and continuance intention, and between perceived value and continuance intention. We also add a series of control variables into the model, including age, gender, income, and education.

3.1 Network externalities and herding

In the research on IT adoption, online shopping, the P2P market, and so on, results show that online user behavior has an obvious herding effect [17, 18]. The main reason for herding in the IT industry is NE [53, 55]. As an important feature of the IT industry, NE is the main factor to measure the value of information.
products and services [42]. In a network environment, as more people use a particular product or technology, the additional utility gained by users increases [47]. In our study, the network size can be viewed as the number of users using IWM services on wealth platforms. When the network size is large, the platform will contain a huge amount of feedback from other users on platform products or services, which may reduce the effective information available to individual users, and make users lose too much information when users use IWM services [3]. In this case, users may ignore their own acquired information and imitate the behavior of other users [52]. Accordingly, we propose that:

**H1a** Network size has a positive impact on imitating others.

**H2a** Network size has a positive impact on discounting own information.

In addition, when the user scale of the IWM platform expands, enterprises tend to provide more compatible services by integrating a wide range of third-party tools (e-commerce websites, social media, etc.) to improve user stickiness. For example, on the IWM platform, users can quickly switch between financial services and online shopping; In the platform community, users can share their experience through text, pictures, videos, and other means. When users perceive that the complementary degree of IWM services increases, due to curiosity, they will try and use the functions of relevant compatible services. In this process, they will improve their familiarity with IWM services and products, gradually strengthening their self-awareness and reducing herd behavior [35]. Therefore, we propose that:

**H1b** Perceived complementarity has a negative impact on imitating others.

**H2b** Perceived complementarity has a negative impact on discounting own information.

With the increase in frequency and time for users to communicate and interact on the IWM platform and the deepening of their understanding of financial services and related products, their financial awareness and experience will be improved [56]. Moreover, when users interact through the IWM platform community using texts, comments, and reviews to spread their experience of using financial technology to other investors, such information-sharing reduces the information asymmetry of IWM to a certain extent [22], thus strengthening users’ judgment ability and inhibiting the herding effect. Therefore, the network strength of interaction between users and the IWM platform will weaken the occurrence of herding. Thus, we hypothesize:

**H1c** Network strength has a negative impact on imitating others.

**H2c** Network strength has a negative impact on discounting own information.
3.2 Network externalities and perceived value

NE affect users’ perceived value [30, 57]. The perceived values are produced from the increasing number of users and the complementary products and services in the network [31, 58]. Perceived value reflects the comprehensive cognition of users in the process of using technical services, that is, the cognitive level of users on the expected performance and implementation risk of technical services [56]. In this study, perceived value refers to the comprehensive trade-off between perceived gains and perceived losses of users using IWM services on wealth management platforms. Research has shown that an online community with more members is more likely to promote positive interaction and communication experiences [47]. According to the theory of reference groups, individual behavior is influenced by group membership [31]. People will try to keep up with other members. For example, with more and more users on the platform using IWM services, the increasing size of the network facilitates communication and sharing among users, making it more attractive for non-users to use IWM services.

The complementarity of IWM services is important to users’ experience [35]. Prior research has confirmed that perceived complementarity is an important factor to enhance users’ perceived value [46, 47, 57]. At present, most IWM platforms not only provide personalized financial product recommendations and intelligent investment advisory services, but also support users to seamlessly switch between wealth management and online shopping, and make real-time shopping of financial income, which improves the user experience to a certain extent. In addition, in the process of users interacting with the IWM platform, as the network strength increases, users will get higher utility from the network, and these users will be motivated to stay in the network. Therefore, it is reasonable to argue that NE have a positive impact on perceived value. We put forward the following hypotheses:

H3a Network size has a positive impact on perceived value.

H3b Perceived complementarity has a positive impact on perceived value.

H3c Network strength has a positive impact on perceived value.

3.3 Herding and continuance intention

When people face uncertain information, they may imitate the behavior of others because they expect others to have more comprehensive information than they do [19]. When users discount their own information, they rely less on their own initial information and opinions than they do on the insights gained from observing the actions of others. Logically, the more a user weakens his own information, the more likely he is to imitate the behavior of others [17]. In the uncertain Internet environment, because the user is at a high level of uncertainty, he can only rely more on external information and complete his decision through the signals provided by
What influences users’ continuance intention of internet…

...behavior. Therefore, discounting own information will increase the possibility of users imitating others’ behavior [16]. Accordingly, we propose that:

H4 Discounting own information has a positive impact on imitating others.

The impact of herding on financial investment and technology adoption has been frequently examined in previous literature [18, 35]. Sun [18] finds that herding is positively correlated with users’ continuous use, as users may adjust their beliefs to justify their herding behavior. On the IWM platform, it is uncertain whether IWM services can bring wealth appreciation to users. If many people choose to use IWM services, users may think that other people have more comprehensive financial information, and then imitate the behavior of most people. For example, Duan et al. [53] found that a large number of positive reviews of applications encourage users’ further adoption. Literature in the context of existing IT technology shows that imitating others is usually robust and resilient [18]. We can argue that users’ imitating intention may affect their willingness to continue using the services. Therefore, we propose that:

H5a Imitating others has a positive impact on continuance intention.

In addition, according to the definition, discounting own information means less reliance on one’s own beliefs when making decisions [18]. Therefore, it is reasonable to believe that the fewer attention users attach to their own information, the lower the importance of personal beliefs in decision-making, indicating that the anchoring effect of beliefs is weak [17]. When the level of uncertainty is too high, it may lead to paralysis in the process of users judging the value of emerging technologies based on their own information [22]. As a result, after adopting new technology, many users may quickly reconsider the use of the technology when it is found to be inconsistent with the needs and environment. Therefore, we propose that:

H5b Discounting own information has a negative impact on continuance intention.

3.4 Perceived value and continuance intention

Previous studies have confirmed the positive influence of perceived value on behavioral intention and actual behavior [59, 60]. In the field of financial services, Yen and Wu [43] find that perceived value is an important antecedent of users’ continuous use of mobile financial services. In this study, continuous use refers to the extent to which a user believes that he/she will reuse IWM services. Rationally, users will only use the IWM service when they find it useful for their wealth management. When the IWM services provide users with more convenient and reliable asset allocation solutions to meet their personalized needs, it may enhance the user’s service experience and promote their willingness to continue to use. Thus, we hypothesize that:
H6 Perceived value has a positive impact on continuance intention.

3.5 The moderating effect of financial literacy

Financial literacy is the synthesis of financial knowledge, behavior, and skills that an individual has [61]. It measures the financial knowledge reserve and the ability to use financial knowledge to solve practical financial problems [62]. Investors with high financial literacy prefer complex or high-yield financial products, such as stock trusts or futures [25]. However, investors with low financial literacy tend to rely too much on the advice of relatives and friends rather than their own judgment before making financial decisions. More importantly, they will not even invest in complex financial products like stocks [27].

As financial markets become internet-based, their complexity increases, making users’ financial literacy more and more important. At present, more responsibility for financial decision-making, such as investment and savings, has been transferred from financial institutions to users, so the users are required to have sufficient financial literacy. The improvement of financial literacy is conducive to promoting individuals to minimize the possibility of being misled and making wise financial decisions [62]. In the context of IWM, users with high financial literacy can identify and judge the financial products and asset allocation provided by IWM services through their own financial knowledge and technology, improving the security of investment to a certain extent [25]. Users with low financial literacy will rely more on products and services recommended by IWM services and are more influenced by the decisions of other users. At the same time, they are more likely to continue to use services based on their perceived experience [61]. Accordingly, we propose that:

H7a Financial literacy negatively moderates the relationship between imitating others and continuance intention.

H7b Financial literacy negatively moderates the relationship between discounting own information and continuance intention.

H7c Financial literacy negatively moderates the relationship between perceived value and continuance intention.

3.6 The mediating roles of herding and perceived value

In this study, the mediating effect of herding is investigated to explore the influence mechanism of NE on users’ continuance intention. In the context of online shopping, innovative crowdfunding, and P2P lending, research shows that NE are important predictors of herding [22, 23, 34]. The expansion and growth of technology networks not only bring positive externalities to users, such as increasing users’ social interaction and service experience [22], but it may also bring potential negative externalities. Strader et al. [63] pointed out that the expansion of network scale may bring security and transaction risks to network members. In the context of
IWM, with the expansion of network size, the platform will contain a large number of reviews and comments about service products and evaluations, and the effective information available to individual users will be relatively reduced [3]. In this uncertain environment, users may ignore their own opinions and imitate others for continuous use of the service. Based on the above theoretical demonstration, we propose that:

**H8** Imitating others mediates the impacts of (a) network size, (b) perceived complementarity, and (c) network strength on continuance intention.

**H9** Discounting own information mediates the impacts of (a) network size, (b) perceived complementarity, and (c) network strength on continuance intention.

As for the research on how NE affect users’ application of technology through individual perception, scholars mainly focus on the impact of NE on the perception of technology attributes, such as users’ perceived value [28]. Regarding different Internet services such as social media [22], and massive online open courses (MOOCS) [41], research shows that NE will promote users’ continuance intention and loyalty by bringing more perceived benefits to users. Specifically, for a certain product or service, the expansion of user size and the increase of complementary services will improve the possibility of contact and communication between users, and keep users in the service network by creating additional network benefits [28]. Therefore, we hypothesize that:

**H10** Perceived value mediates the impacts of (a) network size, (b) perceived complementarity, and (c) network strength on continuance intention.

### 4 Research design

#### 4.1 Research instrument development

A survey was conducted to test the proposed theoretical model empirically. The scales of each construct are mostly adapted from mature scales in previous studies to ensure content validity. Appendix 1 lists the measurement items for each construct. The measurement of imitating others and discounting own information was evaluated by using the four-item scale and three-item scale of Sun [18]. Perceived value was evaluated by adopting the four-item scale of Karjaluoto et al. [59]. The network size and perceived complementarity were measured using three scales by Zhang et al. [31] and Zhou and Lu [47] respectively. Continuance intention was measured with a four-item adapted from Bhattacharjee [64]. The measurement of financial literacy was based on the three-item scales of Nguyen et al. [65]. In addition, the above seven variables (network size, perceived complementarity, imitating others, discounting own information, perceived value, financial literacy, and continuance...
intention) were measured on a five-point Likert-type scale, from “strongly disagree” (1) to “strongly agree” (5).

However, the measurement of network strength is different from the above seven variables. Previous studies have shown that the network strength of individual interaction with the platform can be measured by the length of time that users stay on the platform each login time and the number of login times per week [48]. According to the actual situation of IWM users, this study selected the following three elements and give them weights to evaluate the network strength of interaction between online financial users and the platform: the average number of times to log in to the wealth management platform app (or website) every week, the average length of time to stay on the wealth management platform app (or website), the average weekly use of wealth management platform app (or website) service types. That is, network strength is a formative construct. To facilitate the later statistical analysis, we need to process the survey data, score each data index, and present the data with a 1–5 point scale (see Table 2 for details). Finally, several demographic variables (gender, age, education, income) were added to the model as control variables.

Since the survey was conducted in China, we followed Chen et al.’s [66] guidance to translate the scales into Chinese, and the translation process strictly followed a popular back-translation procedure. Moreover, to ensure the validity of the scale, a small-scale pre-test and personal interview were conducted. 11 group members (including 3 professors from the information system department, 3 professors from the finance department, and 5 doctoral students with IWM services experience) were interviewed. Some ambiguous items in the questionnaire were further modified, and a pilot test was conducted on the questionnaire. This step aims to ensure the content validity of research tools, the completeness of suggestions, and the accuracy of expression.

### 4.2 Data collection

This study chooses two major IWM platforms as the sample research context, including Ant Fortune and JD Finance. There are mainly two reasons. The first one is that

| Table 2 | Network strength index scoring system |
|---------|---------------------------------------|
| Scores  | 1 | 2 | 3 | 4 | 5 |
| Network strength                                      |
| Average number of visits over the last week           | Twice or less | 3–4 times | 5–6 times | 7–8 times | 9 times or above |
| Average usage time per day over the last week         | Below 10 min | 10–30 min | 30–60 min | 1–2 h | 2 h above |
| The number of functions of IWM platform app (or website) used in the last week | 1–2 | 3–4 | 5–6 | 7–8 | 9 or above |

*The functions of the IWM platform include but are not limited to list categories: payment, shopping, and entertainment, financial information push, user consultation and communication, consultation appointment, investment analysis, acquisition of trading strategy, and user feedback.*
these platforms have a large user base and their wealth management communities are enthusiastic. This would ensure that the sample data that we obtain are representative. The second reason is that China’s IWM market is at a nascent stage. Ant Fortune and JD Finance, the pioneers of China’s IWM industry, began to launch IWM services in 2015. Therefore, it would be a good context to identify the criteria for the continued use of IWM services.

The survey subjects were users who had experience with IWM services. We posted a questionnaire on Sojump (www.sojump.com), a large third-party online survey platform in China with more than 2.6 million registered members. The generated uniform resource location (URL) of the questionnaires were randomly distributed by Sojump to potential IWM users through multiple channels, including (1) group emails to panel members of Sojump who matched the sample requirements; (2) posting to the official Ant Fortune and JD Finance communities; (3) posting on QQ, WeChat, Sina Weibo, Facebook, and other popular social platforms. In this way, the randomness of our sampling is guaranteed. Through multi-channels, the opinions of IWM users were widely obtained to improve the overall coverage of the survey. To encourage participation, we paid 6 CNY (the US $1) to respondents who completed the survey. Moreover, we strictly monitored and scrutinized each respondent’s IP address to ensure that each respondent participated only once in the survey.

A total of 1100 questionnaires were released, among which 762 target users accepted the questionnaire of this study. After strict screening and inspection procedures, 125 participants who did not pass the attention test questions or gave incomplete answers, or did not pass the reverse test were excluded. After eliminating invalid data, 637 valid samples were obtained, with a sampling efficiency of 57.9%. Table 3 showed the demographic information of the samples.

### 4.3 Common method bias

As this study was based on the self-report of cross-sectional design for data collection which comes from a questionnaire survey, its source was relatively single. This might lead to common method bias (CMB). We employed the following two tests to examine CMB. First, we applied Harman’s single-factor test [67]. The results indicated that six constructs with eigenvalues were greater than 1.0, but only 23.58% of the variance was accounted for by the first factor. Thus, CMB was unlikely a serious issue in our study. Second, we adopted the unmeasured latent method construct technique to refine the CMB test [68]. As shown in Appendix 2, the average substantive variance explained was 72% which was far higher than the average method-based variance of the indicators (1%). The results again indicated that CMB was not a severe problem in our research.
Data analysis and results

5.1 The estimation strategy

To verify the research model and hypothesis, we followed a three-step estimation strategy. For the first step, Partial Least Squares (PLS), a variance-based structural equation modeling (SEM) method, was employed for examining the measurement model in this study. PLS-SEM is suitable for estimating a composite research model that contains a formative construct as in our research model (i.e. network strength).
Moreover, to better investigate the whole-model fit statistics and avoid generating inflated pairwise correlations between constructs [70], we choose to use hierarchical regression for hypothesis testing. Therefore, we first evaluated both reflective construct and formative construct convergent validity and discriminant validity to test the measurement model. Additionally, we obtained the composite variable scores of a formative construct by item weights. Second, we conducted hierarchical regression to test the hypotheses. In this step, we used the composite variable scores obtained in the first step of the PLS estimation. In the third step, we used SPSS 26.0 and its macro (PROCESS) to check for the robustness of the proposed research model.

5.2 Measurement model assessment

To test the measurement model, we evaluated the convergent validity and discriminant validity. Convergent validity was tested by the item factor loading, Cronbach’s alpha (α), the composite reliability (CR), and the average variance extracted (AVE) [71]. Convergent validity is supported if AVE exceeds 0.5, the factor loading of CR, and α above 0.7. As shown in Table 4, the factor loadings of all items exceeded 0.7, all values of α were higher than 0.7, the CR values were above 0.8, and AVEs for each construct surpassed 0.5, which demonstrates sufficient convergent validity.

Discriminant validity was supported when the correlations among constructs were smaller than the square root of the AVE of those constructs [71]. Table 5 shows that the constructs had acceptable discriminant validity.

Due to network strength is a formative construct, we also examine the multicollinearity problem. Based on the scoring system, the number of times that users log on the wealth management platform APP (or website) every week, the length of time they stay on the platform and the number of functional types that users use the wealth management platform APP (or website) every week were scored as the formation quantity of network strength. Table 6 lists the weight of formative indicators and variance inflation factors (VIF). The different weights of each dimension for network strength are obtained, indicating that they play different roles. Importantly, all VIF values were less than the threshold of 5. This indicated that multicollinearity is not a problem in our study. We confirm that network strength can be conceptualized as the number of times that users log on to the platform app (or website) every week, the length of time that they stay on the platform every week, and the number of functional types of using the platform app (or website) every week. Moreover, according to the weights and specific scores of the three items of network strength, and through weighted summation, we calculated the composite scores of network strength to be included in the regression analysis in the next section.

5.3 Hypotheses testing

Hierarchical regression was employed to test the hypotheses. Before the regression analysis, we first conduct data centralized processing (mean = 0) on independent variables and moderator variables to minimize the influence of
### Table 4  Reliability and Convergent Validity of Constructs

| Construct                  | Item | Standard loadingα | Cronbach’s α | CR  | AVE  |
|----------------------------|------|-------------------|--------------|-----|------|
| Network size(NES)          | NES1 | 0.832             | 0.825        | 0.894 | 0.738 |
|                            | NES2 | 0.846             |              |      |      |
|                            | NES3 | 0.898             |              |      |      |
| Perceived complementarity(PC)| PC1  | 0.886             | 0.827        | 0.896 | 0.742 |
|                            | PC2  | 0.841             |              |      |      |
|                            | PC3  | 0.856             |              |      |      |
| Imitating others(IO)       | IO1  | 0.751             | 0.809        | 0.875 | 0.637 |
|                            | IO2  | 0.784             |              |      |      |
|                            | IO3  | 0.858             |              |      |      |
|                            | IO4  | 0.795             |              |      |      |
| Discounting own information(DOI)| DOI1 | 0.881             | 0.807        | 0.886 | 0.721 |
|                             | DOI2 | 0.882             |              |      |      |
|                             | DOI3 | 0.781             |              |      |      |
| Perceived value(PV)        | PV1  | 0.778             | 0.828        | 0.887 | 0.661 |
|                             | PV2  | 0.872             |              |      |      |
|                             | PV3  | 0.744             |              |      |      |
|                             | PV4  | 0.851             |              |      |      |
| Financial literacy(FL)     | Fl1  | 0.869             | 0.857        | 0.913 | 0.779 |
|                             | Fl2  | 0.914             |              |      |      |
|                             | Fl3  | 0.864             |              |      |      |
| Continuance intention(CI)  | CI1  | 0.706             | 0.713        | 0.823 | 0.538 |
|                             | CI2  | 0.722             |              |      |      |
|                             | CI3  | 0.776             |              |      |      |
|                             | CI4  | 0.728             |              |      |      |

α: All standard loadings are significant at $p < 0.001$

### Table 5  Discriminant Validity of the Constructs

| Construct     | CI   | DOI | FL   | IO   | NS  | PC  | PV   | NES  |
|---------------|------|-----|------|------|-----|-----|------|------|
| CI            | 0.733|     |      |      |     |     |      |      |
| DOI           | −0.528| 0.849|      |      |     |     |      |      |
| FL            | 0.104| −0.253| 0.882|      |     |     |      |      |
| IO            | −0.321| 0.641| 0.012| 0.798|     |     |      |      |
| NS            | 0.426| −0.523| 0.098| −0.428|     |     |      |      |
| PC            | 0.289| −0.185| 0.176| −0.159| 0.181| 0.861|      |      |
| PV            | 0.604| −0.592| 0.249| −0.543| 0.654| 0.491| 0.813|      |
| NES           | 0.181| −0.037| 0.133| −0.024| 0.258| 0.335| 0.403| 0.859|

CI: Continuance Intention; DOI: Discounting Own Information; FL: Financial Literacy; IO: Imitating Others; NS: Network Strength; PC: Perceived Complementarity; PV: Perceived Value; NES: Network Size

The numbers (bold) in the diagonal row are square roots of the AVE
multicollinearity among variables constituting interaction terms [72]. Moreover, we examined the VIF of each predictor in our regression model. All values were less than 10 (from 1.02 to 3.66), indicating that multicollinearity is not a problem in this study.

Table 7 presents the hierarchical regression results. Model 4 indicated that network size ($\beta = 0.112, p < 0.01$), perceived complementarity ($\beta = -0.126, p < 0.001$) and network strength ($\beta = -0.404, p < 0.001$) were significantly related to imitating others, supporting H1a, H1b and H1c. Model 2 indicated that the effects of network size ($\beta = 0.118, p < 0.001$), perceived complementarity ($\beta = -0.128, p < 0.001$) and network strength ($\beta = -0.485, p < 0.001$) on discounting own information were significant, supporting H2a, H2b and H2c. Model 7 showed that network size ($\beta = 0.163, p < 0.001$), perceived complementarity ($\beta = 0.338, p < 0.001$) and network strength ($\beta = 0.540, p < 0.001$) were significantly correlated with perceived value. As such, H3a, H3b, and H3c were supported. In addition, the introduction of discounting own information as an independent variable also significantly increased the $R^2$ of Model 5. Discounting own information ($\beta = 0.563, p < 0.001$) positively affected imitating others, thereby confirming H4. Four regression models (Model 8, 9, 10, 11) were estimated with continuance intention as the dependent variables. Model 8 indicated that all of the control variables (i.e. gender, age, education, income) had no significant effect on continuance intention. In Model 10, continuance intention was influenced by imitating others ($\beta = 0.171, p < 0.001$), discounting own information ($\beta = -0.341, p < 0.001$), and perceived value ($\beta = 0.459, p < 0.001$). Therefore, H5a, H5b, and H6 were supported.

The interaction terms were entered in Models 11. The interaction effect between financial literacy and imitating others did not affect continuance intention ($\beta = -0.038, n.s.$). The interaction effect between financial literacy and discounting own information has a negative effect on continuance intention ($\beta = -0.159, p < 0.001$). And the interaction effect between financial literacy and perceived value has a negative effect on continuance intention ($\beta = -0.254, p < 0.001$). Furthermore, we plotted Figs. 2 and 3 to illustrate the moderating effects and performed a simple slope test based on a standard deviation above and below the average of financial literacy (Toothaker and Larry 1994). The figures show that financial literacy negatively moderates the relationship between discounting own information and continuance intention and the relationship between perceived value and continuance intention. Thus, H7b and H7c were supported while H7a was not.

Table 6  Formative Indicator Weights and VIFs

| Formative Indicator | VIFs | Weights |
|---------------------|------|---------|
| NS1                 | 2.451 | 0.385*** |
| NS2                 | 2.575 | 0.389*** |
| NS3                 | 1.775 | 0.361*** |

VIFs: variance inflation factors; ***$p < 0.001$
### Table 7: Hierarchical regression results

| Variables       | Discounting Own Information (DOI) | Imitating Others (IO) | Perceived Value (PV) | Continuance Intention (CI) |
|-----------------|-----------------------------------|-----------------------|----------------------|--------------------------|
|                 | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 | Model 11 |
| Gender          | 0.011   | 0.011   | 0.026   | 0.029   | 0.023   | -0.009  | -0.018  | 0.001   | -0.007  | 0.001   | 0.017   |
| Age             | 0.014   | 0.028   | 0.027   | 0.039   | 0.023   | 0.019   | 0.007   | 0.015   | 0.005   | 0.005   | 0.003   |
| Education       | 0.022   | 0.003   | 0.031   | 0.016   | 0.014   | -0.038  | -0.016  | -0.016  | 0.001   | 0.005   | 0.005   |
| Income          | -0.051  | -0.075  | -0.034  | -0.054  | -0.012  | -0.012  | 0.007   | 0.007   | 0.022   | 0.002   | 0.008   |
| NES             | 0.118***| 0.112***| 0.112   | 0.045   | 0.163***| 0.023   | -0.029  | -0.031  |
| PC              | -0.128***| -0.126***| -0.054  | 0.338***| 0.215***| 0.041   | 0.038   |
| NS              | -0.485***| -0.404***| -0.131***| 0.540***| 0.390***| 0.047   | 0.073   |
| DOI             | 0.563***|          |         |         |         | -0.341***| -0.321***|         |
| IO              |         |         |         |         |         |         | 0.171***| 0.116***|
| PV              |         |         |         |         |         |         | 0.459***| 0.406***|
| FL              |         |         |         |         |         |         | -0.019  | -0.017  |
| FL*IO           |         |         |         |         |         |         |         | -0.038  |
| FL*DOI          |         |         |         |         |         |         |         | -0.159***|
| FL*PV           |         |         |         |         |         |         |         | -0.254***|
| $R^2$           | 0.003   | 0.254   | 0.003   | 0.182   | 0.419   | 0.002   | 0.568   | 0.001   | 0.234   | 0.426   | 0.462   |
| $\Delta R^2$   | 0.003   | 0.251   | 0.003   | 0.180   | 0.237   | 0.002   | 0.566   | 0.001   | 0.233   | 0.192   | 0.036   |
What influences users' continuance intention of internet…

5.4 Mediation analysis

Following the methods advocated by Hew et al. [73], this study analyzes the mediating effects of herding and perceived value in the impact mechanism of NE on the IWM continue intention. Through bootstrapping program, 5000 samples were generated from the original data set (n = 637) by random sampling, and the indirect impact of each sample was calculated. The specific results are shown in Table 8. It can be seen that herding (discounting own information and imitating others) mediates the impact of NE (network size, perceived complementarity, and network strength) on continuance intention. Therefore, H8(a,b,c) and H9(a,b,c) were supported. Perceived value completely mediates the impact of NE (network size, perceived complementarity, and network strength) on continuance intention, thereby confirming H10(a,b,c). In addition, discounting own information completely mediates the influence of network size and perceived complementarity on imitating others; And discounting own information partly mediates the role of network strength in imitating others in a complementary…
way. Moreover, all the impacts discussed above are significant, which again shows that perceived value and herding have multiple mediating effects.

### 5.5 Test of robustness

To enhance the persuasiveness of the research conclusion, we used SPSS 26.0 and its macro (PROCESS) to check for the robustness of the proposed research model. The results are shown in Table 9. Based on the process proposed by Edwards and Lambert [74], we tested the moderated mediating effect of the model. As shown in the left part of Table 9, whether users with high financial literacy or with low financial literacy, NE (network size, perceived complementarity, and network strength) affect the indirect effect of continuance intention through perceived value, imitating others, and discounting own information, and the corresponding 95% confidence interval does not contain zero. This also confirmed the mediating role of herding (discounting own information and imitating others) and perceived value in the impact mechanism of NE on users’ continuance intention. The right part of Table 9 reports the judgment index obtained according to the PROCESS operation to judge whether there is a moderated mediating effect. The results showed that financial literacy has a moderating effect on the indirect effects of NE (network size, perceived complementarity, and network strength) on perceived value and discounting own information, and the corresponding 95% confidence interval does not contain zero. Therefore, these three moderated mediating effects are significant. The above results fully proved the reliability and robustness of the hypotheses tested in this study.

### Table 8 Multiple mediation analysis

| Paths          | Specific indirect effect | Direct effect | Total effect | Types of Mediation |
|----------------|--------------------------|---------------|--------------|-------------------|
| NES→DOI→CI    | −0.051***                | −0.031        | 0.103*       | Full mediation    |
| PC→DOI→CI     | 0.048***                 | 0.021         | 0.198***     | Full mediation    |
| NS→DOI→CI     | 0.186***                 | 0.012         | 0.381***     | Full mediation    |
| NES→PV→CI     | 0.073***                 | −0.031        | 0.103*       | Full mediation    |
| PC→PV→CI      | 0.171***                 | 0.021         | 0.198***     | Full mediation    |
| NS→PV→CI      | 0.278***                 | 0.012         | 0.381***     | Full mediation    |
| NES→DOI→IO    | 0.083***                 | 0.043         | 0.135***     | Full mediation    |
| PC→DOI→IO     | −0.077***                | −0.045        | −0.119***    | Full mediation    |
| NS→DOI→IO     | −0.301***                | −0.132*       | 0.125**      | Complementary partial mediation |
| NES→DOI→IO→CI | 0.015**                  | −0.031        | 0.103*       | Full mediation    |
| PC→DOI→IO→CI  | −0.014**                 | 0.021         | 0.198***     | Full mediation    |
| NS→DOI→IO→CI  | −0.055***                | 0.012         | 0.381***     | Full mediation    |

*p < 0.05, ** p < 0.01, *** p < 0.001
6 Discussion and implications

The purpose of this study is to examine individuals’ continuance intention of IWM services. Drawing on relevant literature of the NE, herding, perceived value, and financial literacy, we theoretically develop and empirically test a model that explains and predicts users’ continuance intention of IWM services.

Table 9 Test of robustness

| Paths                  | Conditional Indirect Effect | Moderated Mediating Effect |
|------------------------|-----------------------------|----------------------------|
|                        | Moderator                   | Bootstrap (Percentile 95%)  | INDEX | SE   | LLCI  | ULCI  |
|                        | variable                    | Effect                     | SE    | LLCI | ULCI  | LLCLL | ULCI  | ULCI  |
| NES → DOI → CI         | Low  FL                     | −0.05                      | 0.03  | −0.1472 | −0.0523 | 0.02  | 0.01  | 0.0034 | 0.0463 |
| High FL                | −0.03                      | 0.02                       | −0.0644 | −0.0005 |          |          |        |        |        |
| NES → PV → CI          | Low  FL                     | 0.16                       | 0.02  | 0.1103 | 0.2044 | −0.06 | 0.01  | −0.089 | −0.0346 |
| High FL                | 0.06                       | 0.02                       | 0.0259 | 0.0932  |          |          |        |        |        |
| NES → IO → CI          | Low  FL                     | −0.02                      | 0.01  | −0.1158 | −0.0418 | 0.02  | 0.01  | −0.0002 | 0.0448 |
| High FL                | −0.01                      | 0.01                       | −0.0666 | −0.0026 |          |          |        |        |        |
| PC → DOI → CI          | Low  FL                     | 0.02                       | 0.01  | 0.0052 | 0.0376 | 0.02  | 0.01  | 0.0068 | 0.0365 |
| High FL                | 0.05                       | 0.02                       | 0.0245 | 0.0807  |          |          |        |        |        |
| PC → PV → CI           | Low  FL                     | 0.21                       | 0.03  | 0.1441 | 0.2518 | −0.08 | 0.02  | −0.1152 | −0.0455 |
| High FL                | 0.07                       | 0.02                       | 0.24  | 0.1143  |          |          |        |        |        |
| PC → IO → CI           | Low  FL                     | −0.02                      | 0.01  | −0.0278 | −0.0025 | 0.0036 | 0.01  | −0.0068 | 0.014  |
| High FL                | −0.01                      | 0.01                       | −0.023 | 0.0028  |          |          |        |        |        |
| NS → DOI → CI          | Low  FL                     | 0.05                       | 0.02  | 0.0104 | 0.0781 | 0.05  | 0.0142 | 0.0222 | 0.0786 |
| High FL                | 0.13                       | 0.02                       | 0.0934 | 0.1578  |          |          |        |        |        |
| NS → PV → CI           | Low  FL                     | 0.22                       | 0.03  | 0.1671 | 0.2691 | −0.095 | 0.02  | −0.1308 | −0.0568 |
| High FL                | 0.07                       | 0.02                       | 0.016 | 0.1147  |          |          |        |        |        |
| NS → IO → CI           | Low  FL                     | −0.03                      | 0.01  | −0.0576 | −0.0068 | 0.0095 | 0.01  | −0.0127 | 0.308  |
| High FL                | −0.02                      | 0.01                       | −0.0423 | 0.0068  |          |          |        |        |        |
6.1 Discussion of findings

NE (i.e. network size, perceived complementarity, and network strength) have varying degrees of influence on herding. Specifically, in the context of IWM, network size has a significant positive influence on herding. The results confirm that when facing the uncertainty of technology/service, people might think that others will have more complete information to assess technology than they are, ignoring their views about the technology and imitating others’ behavior. Our results are consistent with previous findings [59]. Perceived complementarity has a significant negative impact on herding. This means that in the process of using value-added services of the platform provided, users will improve their familiarity with financial services and products, gradually enhancing their self-awareness and reducing discounting their own information, and then reducing irrational imitation behavior [75]. In addition, network strength has a significant negative impact on herding, indicating that in the process of wealth management, a high degree of network information interaction between users and the platform will enhance users’ understanding of IWM services, strengthen their self-information, and reduce the imitation behavior of adoption of technical services.

This study explores the impact of NE on users’ perceived value. Specifically, we confirm the key role of network strength in users’ perceived value, and thus affects users’ continuance intention. With the increase in users’ understanding of the IWM services of the platform, users will obtain higher utility from the network and will be motivated to stay in the network. Similarly, we confirm that network size and perceived complementarity positively affect perceived value. If more users on the platform use IWM services, the increasing size of the network facilitates communication and sharing among users, making it more attractive for non-users to use these services. Meanwhile, with increased complimentary services of IWM, the users’ wealth management experience will be improved to a certain extent. The results are consistent with prior literature that the perceived value of IT services comes not only from the demand side (i.e., the number of users) but also from the supply side (i.e., service providers) by providing complementary services and products [57].

This study presents that herding directly affects users’ continuance intention. We argue that in the highly uncertain Internet environment, the tendency to imitate others influences users’ decisions (e.g., using IWM services). On the IWM platform, when individuals lack understanding of the applicability of IWM services due to time, knowledge, and other constraints, a reasonable alternative strategy is to imitate the behavior of others [24]. This approach assumes that the group has gone through the search and evaluation process and has determined that the adoption of the service is a reasonable decision. Discounting own information occurs when a group’s perception about a service is inconsistent with the individual’s previous beliefs. That is, users tend to downplay the importance of personal information, focus on group information, and imitate most decisions [17]. It is consistent with the view of the social identity model of deindividuation effects [76], which shows that when users are in groups or lack individual cues, deindividuation facilitates the transformation of users from personal identity to social identity, so as to increase the cognitive
significance of identity, and finally make individuals behave following the rules of the group.

It is worth noting that perceived value has the most significant impact on users’ continuance intention, and its coefficient is much higher than other factors. This means that to effectively promote the use of IWM services, it is very important to help users improve their perceived value of IWM services. If users experience higher management efficiency, more personalized services, and better wealth management performance during the use of IWM services, then it is reasonable for users to continue to use them for wealth management.

Additionally, this study demonstrates that users’ financial literacy negatively moderates the impact of discounting own information and perceived value on continuance intentions. Due to differences in financial knowledge and skills, users with low financial literacy pay more attention to the evaluation and feelings of other users on IWM services and are more likely to complete corresponding financial tasks by using IWM services. In contrast, users with high financial literacy pay more attention to whether IWM services match their wealth management performance needs, and will more rationally view the utility brought by services.

Finally, we find that in the context of IWM, all dimensions of NE can indirectly affect users’ continuance intention through herding and perceived value. As the provider of IWM services, the IWM platform based on the services network ultimately affects continuance intention by promoting users’ perception of social attributes and technical service attributes.

6.2 Implications for theory

First, this study contributes to the literature on user behavior for IWM services by investigating the effect of herding on users’ continuance intention of IWM services. We distinguish two aspects of herding: imitation others and discounting own information, and confirm that these two aspects have a significant impact on the continuous use of IWM services. Therefore, this study challenges the widely-held assumption in IWM services user behavior literature that users have the necessary personal information and expertise to judge and evaluate the effectiveness and security of IWM services [11, 13, 40]. We extend herding to IWM services and verify that herding provides a mechanism for NE to affect users’ continuous intention. Previous studies have well demonstrated the impact of network externalities on users’ behavior through perceived value [29, 47], but no study has discussed the mediating role of herding between network externalities and users’ continuous intention. Our results are helpful to understand which dimensions of network externalities will promote herding and affect users’ continuous use intention. Therefore, our study can provide a useful reference for future research on IWM service users’ behavior.

Second, this study provides novel insights into the impact of NE on users’ continuance intention in the context of IWM. We extend the previous work and verify the important influence mechanism of NE on users’ continuous intention through perceived value and herding in the context of IWM. In addition, we comprehensively evaluate the three dimensions of NE: network size, perceived complementarity, and technical service attributes.
network strength. Most previous studies believe that network size and perceived complementarity are the main dimensions of NE [47, 55]. However, this study effectively measures the network strength of users’ interaction with the IWM platform and finds its important role in users’ continuance intention through empirical research. This helps to supplement the measurement of network strength [48] and promotes the development of network externality theory in the field of IWM.

Third, this study identifies the role of financial literacy on users’ behavior in the context of IWM. Previous research on users’ financial behavior emphasizes the differences in financial literacy [25, 62]. In the context of IWM, how financial literacy plays a role in the impact of herding and perceived value on user behavior is still unknown. This study extends the research on the impacts of users’ financial literacy on herding behavior and perceived value and puts forward that the impact of herding and perceived value on users’ continuance intention depends on users’ financial literacy. This study enriches the understanding of the differences in financial literacy in IWM and provides a direction for future research on the users’ behavior toward IWM services.

6.3 Implications for practice

Our study has provided some potentially important insights for wealth management platform companies. First of all, we believe that perceived value in wealth management is the key to users’ continuance intention of IWM services. Therefore, for the wealth management platform, it is necessary to improve IWM services, including the personalized recommendation of products and generation of investment strategies, to promote the user experience. Enterprise managers should invest more resources in promoting users’ perceived value, such as providing personalized financial products and services, and a reasonable asset allocation portfolio. In addition, managers should pay attention to users’ experience in using the IWM platform, including simplifying the transaction process, improving the practicability and fluency of the platform’s services, strengthening users’ interaction and sharing, and improving the attractiveness of the platform.

Secondly, this study emphasizes that herding is an important factor affecting users’ continuance intention. Therefore, wealth management companies and financial institutions need to consider social factors and take advantage of social influence. To facilitate herding, wealth management platforms can establish online communities, so that the number of users and the decisions and activities of active users can be seen. In addition, the platform should also encourage users to generate self-generated content about their use of financial products and services to reduce users’ information asymmetry and enhance users’ trust, thus generating greater sustainable willingness. In addition, it is suggested that wealth management platforms integrate social network services to obtain users’ social connections. Users’ sense of belonging can be improved by displaying information, such as their friends actively using IWM services on the platform. Through this strategy, the wealth management platform can ultimately retain users of IWM services.
Finally, considering the differences in users’ continuance intention with different levels of financial literacy, the wealth management platform should subdivide the users according to their financial literacy levels, to design separate IWM services for the subdivided groups and provide diversified customized financial plans. For users with high financial literacy, the platform should regularly track and record their feelings about the use of IWM services, analyze their wealth management performance, recommend products and services personalized based on the results because users with high financial literacy pay more attention to the matching between IWM services and wealth management results. For users with low financial literacy, the platform should focus on providing wealth management knowledge and product and service information, and at the same time improving users’ confidence in IWM services and further guiding users to continue to use them. For example, the platform should design the interactive interface according to the user’s habit of using traditional financial services and other systems and technologies, to reduce the user’s uncertainty.

6.4 Limitations and future directions

Several limitations of this study can be addressed in future research. Firstly, the sample of our study was mainly based on the wealth management platform in China, which may limit the generality of our research findings. Therefore, future research should consider collecting data in other cultural contexts.

Secondly, the only moderating variable considered in our study is the user’s financial literacy. In the IWM context, there may be other factors that moderate the impact of herding and perceived value on continuance intentions, including platform characteristics, service quality, and the users’ motivation. Future research can incorporate these factors to more comprehensively understand the impact differences when users use IWM services.

Finally, our study adopted a static self-report questionnaire survey, and the cross-sectional data obtained may limit our follow-up investigation, so the actual behavior of IWM services by users is not included in this study. Future research should introduce longitudinal research and field research to investigate users’ actual use behavior and dynamic changes of IWM.
## Appendix 1: Constructs and measurement items

| Constructs                  | Measurement Item                                                                 | Reference                                      |
|-----------------------------|----------------------------------------------------------------------------------|------------------------------------------------|
| **Network Size (NES)**      | **NES1** I think that many people use IWM services on the wealth management platform | Zhang et al. [31], Zhou and Lu [47]            |
|                             | **NES2** I think that most people use IWM services on the wealth management platform |                                                |
|                             | **NES3** In the future, I believe that many people will continue to use IWM services on the wealth management platform |                                                |
| **Perceived Complementarity (PC)** | **PC1** A wide range of applications is available on the wealth management platform | Zhang et al. [31], Zhou and Lu [47]            |
|                             | **PC2** A wide range of supporting tools is available on the wealth management platform (e.g., photo sharing, message sharing, video sharing) |                                                |
|                             | **PC3** A wide range of news and information I can subscribe to on the wealth management platform |                                                |
| **Imitating Others (IMI)**  | **IMI1** It seems that IWM services are widely used, therefore I would like to use them too | Sun [18]                                       |
|                             | **IMI2** I follow others in deciding to use IWM services                           |                                                |
|                             | **IMI3** I would use IWM services because it is widely introduced by wealth management platforms |                                                |
|                             | **IMI4** I would choose to use IWM services because many others are already using them |                                                |
| **Discounting Own Information (DOI)** | **DOI1** I don’t fully trust my own thinking about how IWM services could work for me | Sun [18]                                       |
|                             | **DOI2** I would not necessarily follow my own thoughts about IWM services’ features |                                                |
|                             | **DOI3** I would not rely only on my own information about how IWM services work  |                                                |
| Constructs                  | Measurement Item                                                                 | Reference             |
|-----------------------------|----------------------------------------------------------------------------------|-----------------------|
| Perceived Value (PV)        | PV1 Using IWM services enhances my effectiveness in managing personal finances   | Karjaluoto et al. [59]|
|                             | PV2 Using IWM services increases my experience in managing personal finances     |                       |
|                             | PV3 Using IWM services has many advantages                                        |                       |
|                             | PV4 Using IWM services yields a superior outcome quality than traditional financial services |                       |
| Financial Literacy (FL)     | FL1 My knowledge of finance is profound                                            | Nguyen et al. [65]    |
|                             | FL2 I feel confident in my ability to invest                                       |                       |
|                             | FL3 I am qualified for the task of making personal investments and financial planning |                       |
| Continuance Intention (CI)  | CI1 I intend to continue investing using IWM services                               | Bhattacherjee [64]    |
|                             | CI2 I plan to continue investing using IWM services                                 |                       |
|                             | CI3 I would prefer IWM services                                                    |                       |
|                             | CI4 I will continue investing using IWM services in the future                     |                       |

**Appendix 2: Common Method Bias Analysis**

| Construct                  | Indicator | Substantive Factor Loading (R1) | R1² | Method Factor Loading (R2) | R2² |
|----------------------------|-----------|---------------------------------|-----|---------------------------|-----|
| Continuance Intention      | CI1       | 0.574                           | 0.329 | 0.142 | 0.020 |
|                            | CI2       | 0.779                           | 0.607 | −0.070 | 0.005 |
|                            | CI3       | 0.846                           | 0.716 | −0.079 | 0.006 |
|                            | CI4       | 0.723                           | 0.523 | 0.020 | 0.000 |
| Discounting Own Information| DOI1      | 0.916                           | 0.839 | 0.154 | 0.024 |
|                            | DOI2      | 0.813                           | 0.661 | −0.080 | 0.006 |
|                            | DOI3      | 0.833                           | 0.694 | −0.054 | 0.003 |
| Imitating Others           | IO1       | 0.754                           | 0.569 | −0.009 | 0.000 |
|                            | IO2       | 0.879                           | 0.773 | 0.124 | 0.015 |
|                            | IO3       | 0.815                           | 0.664 | −0.053 | 0.003 |
|                            | IO4       | 0.745                           | 0.555 | −0.057 | 0.003 |
| Construct          | Indicator | Substantive Factor Loading (R1) | R1²  | Method Factor Loading (R2) | R2²  |
|--------------------|-----------|---------------------------------|------|----------------------------|------|
| Network Strength   | NS1       | 0.848                           | 0.719| 0.069                      | 0.005|
|                    | NS2       | 0.839                           | 0.704| 0.095                      | 0.009|
|                    | NS3       | 0.972                           | 0.945| −0.192                     | 0.037|
| Perceived Complementarity | PC1      | 0.853                           | 0.728| −0.017                     | 0.000|
|                    | PC2       | 0.894                           | 0.799| −0.068                     | 0.005|
|                    | PC3       | 0.872                           | 0.760| −0.002                     | 0.000|
| Perceived Value    | PV1       | 0.876                           | 0.767| 0.029                      | 0.001|
|                    | PV2       | 0.870                           | 0.757| 0.003                      | 0.000|
|                    | PV3       | 0.984                           | 0.968| −0.259*                    | 0.067|
|                    | PV4       | 0.990                           | 0.980| −0.143                     | 0.020|
| Network Size       | NES1      | 0.892                           | 0.796| −0.078                     | 0.006|
|                    | NES2      | 0.836                           | 0.699| −0.005                     | 0.000|
|                    | NES3      | 0.856                           | 0.733| 0.080                      | 0.006|
| Average            |           | 0.844                           | 0.720| −0.019                     | 0.010|

**Acknowledgements** We acknowledge the financial support from the National Natural Science Foundation of China (Grant number: 72110107002, 71974021), the National Social Science Foundation of China (Grant number: 21BGL246) and the Fundamental Research Funds for the Central Universities of Chongqing University (Project No. 2019 CDJSK 02 XK 12).

**Declarations**

**Conflict of interest** none

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