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Understanding Digital Hoarding Behaviors of Social Media Users from a Stress Coping Perspective

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Completed Research Paper

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Abstract

Despite the information value brought by social media, the abundance of information on social media also contributes to digital hoarding. However, the underlying mechanisms about how digital hoarding behaviors in the social media context are formed has not been well studied. Thus, capturing the unique features of social media, this study tries to explore the impacts of information characteristics on digital hoarding from a stress coping perspective. Specifically, we identify three key information characteristics of social media namely information narrowing, information redundancy and information overload, and proposes that these information characteristics affect digital hoarding through two key cognitive appraisals namely perceived value uncertainty and cognitive load. Further, individuals' information-seeking self-efficacy is proposed to moderate the relationship between cognitive appraisals and digital hoarding. A survey was administered to examine the proposed research model. The theoretical and practical implications are thoroughly examined and discussed finally.

Keywords: digital hoarding, social media, stress coping theory, cognitive load

Introduction

While the widespread utilization of social media provides convenience for users to obtain information, huge volume of information emerging on social media creates obstacles for users to conduct effective information management. Based on the 2022 Data Never Stop report, it was found that Twitter users generate 347,000 tweets every minute, while YouTube users upload 500 hours of video content within the same time frame (DOMO, 2022). Given the overwhelming volume of information available, users encounter difficulties in evaluating the value of information and making informed choices amidst a mixed information environment. In this situation, users may get excessive information, no matter whether the information is valid or invalid, as a coping strategy for potential future use of the information. This behavior is called as digital hoarding (Sedera & Lokuge, 2018).

Digital hoarding may cause lots of negative effects, such as no use for personal information management (Hulber, 2020). In the long run, a lot of messy digital information can cause psychological stress to users and thus cause anxiety (Swar et al., 2017). Recently, social media has emerged as the primary platform through which people obtain information in our daily life. Therefore, digital hoarding can lead to problems such as digital clutter, which leads to users' negative emotions (Sedera et al., 2022). Thus, to circumvent meaningless digital hoarding behaviors, it's necessary to explore the reasons behind the behaviors. Particularly, the formation mechanism of digital hoarding behaviors should not be neglected, especially its psychological motivation and contributing factors. Although digital hoarding behaviors have attracted research attention in prior studies, there are still some research gaps.

First of all, the existing studies mainly focus on the measurement of digital hoarding behaviors (Bozacı & Gökdeniz, 2020; Neave et al., 2019) but pay less attention to the underlying mechanisms about how these behaviors are formed. In the limited research on the antecedents of digital hoarding, prior studies may develop conceptual models to articulate the motivations of digital hoarding such as future use, as evidence, laziness, emotional value, a sense of possession and so on (Sweeten et al., 2018). Moreover, Thorpe et al. (2019) and Luxon et al. (2019) explored the relationship among digital hoarding, obsessive-compulsive disorder (OCD) and physical hoarding through empirical studies, but these studies provide no empirical evidence to validate the propositions and clarify the internal mechanism of the behaviors. Thus, with this objective, the study tries to formulate a research model that elucidates the antecedents of digital hoarding and examines it through empirical testing.

Second, prior studies mostly focus on the digital hoarding of emails in the workplace environment (McKellar et al., 2020; Sweeten et al., 2018).Given that the convenience of social media has elevated it to a primary avenue for seeking information, whether the findings in the traditional workplace contexts can applied within the realm of social media is an issue. Specifically, the digital hoarding behaviors exhibited within the social media context differ from those observed in the workplace environment in several aspects. Compared with the email information in the working environment, the information on social media is shared and flowing, with a larger information volume and a wider range of information value. It is because that recommendation algorithm technology on social media platforms makes recommended information more fixed and overlapped according to users interest. Therefore, even if the same antecedents based on the future utility, it still has apparent discrepancy on the formation of hoarding behaviors. Digital hoarding behaviors on social media are more complex, involving influences of characteristics of the information itself, such as information narrowing, information redundancy, and information overload. Previous studies fail to clarify this point.

Third, prior research on digital hoarding assumes that all individuals deal with excessive information in a same way, ignoring the potential individuals' differences. They only elaborate underlying motivations from the perspective of behaviors (Sweeten et al., 2018), whether the mechanisms vary across individuals' needs to be further explored. Specifically, individuals' self-efficacy is different in the process of information-seeking, users with high level of information-seeking self-efficacy may have better ability to deal with perceived uncertainty (You & Cho, 2020), at the same time, self-efficacy is one of the drivers of individuals' information-seeking, which will affect their mental state of individuals while processing excessive information (Bandura et al., 2003) . Thus, this study will explore how the underlying mechanisms vary across the levels of individuals' information-seeking self-efficacy.

In order to address the aforementioned research gaps, this study adopts the stressor-appraisal-coping (SAC) framework proposed by Lazarus and Folkman (1984). Drawing upon this framework and recognizing the distinctive characteristics of social media, a research model is formulated to investigate the factors that contribute to digital hoarding within the social media context, unravelling the underlying mechanisms, and identifying the boundary conditions. According to the SAC framework, the potential for stress to arise from stressors primarily hinges on two crucial processes: cognitive appraisal and coping mechanisms. Prior research has demonstrated the efficacy of the stressor-appraisal-coping (SAC) framework in effectively elucidating stress-related factors and their impacts within the domain of technology utilization. Therefore, leveraging the SAC framework in the analysis of digital hoarding behaviors on social media is anticipated to yield a more profound and accurate understanding of the behaviors. The framework emphasizes the interactions between individuals and the environment and has gained widespread usage in the field of information systems, enabling researchers to examine users' responses and behaviors in relation to stressors. Within our research, excessive information on the social media platforms serves as stressors and digital hoarding behaviors act as the behaviors to cope with the stress induced by these stressors. Therefore, the SAC framework is deemed appropriate for our research as it can effectively elucidate the underlying mechanisms behind the development of digital hoarding behaviors among social media users.

This study makes several noteworthy contributions to the existing literature. Firstly, beyond the prior conceptual or measurement research on digital hoarding, we empirically investigate the formation mechanism of digital hoarding behaviors through a quantitative study. Secondly, we extend the research context of digital hoarding from the workplace environment to the social media context by capturing the unique information characteristics of social media (McKellar et al., 2020). Thirdly, we recognize the individuals' differences during the formation process of digital hoarding, and examine how the underlying mechanism varies across individuals with different information-seeking self-efficacy (Sweeten et al., 2018).

Literature review

Digital hoarding

The earliest definition of digital hoarding in academia was formally proposed by Bennekom et al. (2015) in a paper in the field of spiritual science, which described a new subtype of digital hoarding as a hoarding obstacle. It is characterized by the excessive accumulation of digital files to the extent of losing perspective, eventually leading to stress and chaos. Sedera and Lokuge (2018) proposed that digital hoarding refers to "the accumulation of digital content caused by obtaining without consideration of use and failing to discard or effectively manage digital content" (p. 2). The existing definition perspectives of digital hoarding behaviors have developed from pathology to psychology, and research field has also extended to information sciences. This study considers that digital hoarding refers to behaviors of the excessive access to data and that users cannot delete useless data. On social media, those useless or old data means the information forgotten by users in individual favorites and no longer being utilized. It is an extreme form of digital information possession (Hulber, 2020). Thorpe et al. (2019) investigated the similarities in emotional attachment between physical hoarding and digital hoarding by employing the cognitive behavior model of physical hoarding and further explored the possible connection between digital hoarding behaviors and obsessive-compulsive disorder (OCD). Based on the online survey, the researchers found that digital hoarding is positively related to physical hoarding, obsessive-compulsive disorder and indecisive emotions.

Measurement and evaluation of digital hoarding

Neave et al. (2019) developed DBQ (Digital Behaviors Questionnaire) for digital hoarding behaviors, and evaluated digital hoarding behavior from DHQ (The Digital Hoarding Questionnaire) and DBWQ (Digital Behaviors at Work Questionnaire) respectively, in which DHQ is for continuous data accumulation and data deletion difficulties; DBWQ serves as an assessment tool for capturing the digital hoarding behaviors of subjects in workplace, such as storing data files, deleting behaviors and cognition of the consequences of digital hoarding on itself and organization.

Thorpe et al. (2019) developed an instrument of digital hoarding behaviors and investigated the possible link between digital hoarding behaviors and obsessive-compulsive disorder (OCD) through questionnaires. The measurement is composed of five scales: Digital Saving Cognitions Inventory (DSCI), Compulsive Acquisition Scale (CAS), Hospital Anxiety and Depression Scale (HADS), Indecisiveness Scale, and Obsessive–Compulsive Inventory Revised (OCI-R).

Bozaci et al. (2020) developed the DPHS (Digital Photo Hoarding Scale) based on undergraduate groups to determine five dimensions of digital photo hoarding: uncontrolled acquisition, clutter, uncontrolled clutter, failure to handle photos and resulting problems, and uncontrolled photography accompanied by constant desire.

Sedera et al. (2022) argued that Signs of digital hoarding are evident through various characteristics, including challenges in discarding digital content, the presence of digital clutter, and a tendency to excessively acquire digital materials on a frequent basis. They measured the behaviors from these three aspects. The items of digital hoarding and anxiety aimed to confirm the behaviors and its association to anxiety. Through the implementation of a survey and a multigroup analysis, the researchers presented corroborative evidence on the existence of digital hoarding and its correlation with anxiety. It marked the pioneering introduction of this novel concept to the field of information systems research.

The motivation and negative effects of digital hoarding

The potential motivation and negative consequences of digital hoarding behaviors were studied from a psychological perspective for the first time by Sweeten et al. (2018). Early digital hoarding studies were more focused on their pathology, and as the research deepened, scholars began to shift their focus to interdisciplinary research such as psychology.

The existing literature are mainly about the motivation of digital hoarding behaviors, while they mostly explore the antecedents from perspective of qualitative analysis rather than from the quantitative empirical perspective. For example, after compiling DBQ, Neave et al.(2020) further proposed four types of digital hoarding: "collector", "accidental hoarder", "instruction" hoarding" and "anxious hoarder", but they ignored other motives other than emotional motivation. Sweeten et al. (2018) identified various intrinsic motivations related to this behavior such as for future use, as evidence, laziness, emotional value, and sense of possession. Furthermore, Hulber (2020) figured out five main motivations for respondents to accumulate large amounts of data. Moreover, Gormley (2012) believes that "information hoarders are not always information sharers" (p. 91), and they may enjoy the sense of power and control brought by hoarding resources. In addition, he also suggested that digital hoarding will have negative impacts on individuals, organizations and the environment.

In conclusion, relevant scholars have studied antecedents and consequences of digital hoarding behaviors. On the one hand, most of studies are exploratory research. On the other hand, the research background needs to be extended. And with technology developed, the behavioral environment has also changed, which is not limited to the work environment of email hoarding, but various forms of digital hoarding on social media. The differences between environments also make the antecedents of digital hoarding behaviors different to a certain extent. In addition, the existing literature fails to focus on the individuals' differences and related mechanism constraints, so this study tries to introduce the stress-appraisal-coping theory to confirmatory analysis to explore the formation mechanism of digital hoarding behaviors, which will fill the literature gap.

Information characteristics of social media

In social network era, the most obvious characteristics of the platforms are the widely use of recommendation algorithm. Personalized recommendations use tags, ratings, comments, and explicit people relationships to constantly update the content recommended to users. As social media platforms' volumes of content keep growing and recommendation algorithm develops fast, the information quality on social media has become uncertain. Considering the direct influence of information characteristics on users' perceived value of information and cognitive load during the use of social media, we should find key factors which could represent information characteristics.

With personalized recommendation algorithm more and more detailed, the phenomena of echo chamber and information cocoons have emerged. Three constructs namely information narrowing, information redundancy, and information overload are proposed to capture the information characteristics in this research context. Specifically, information narrowing signifies a decrease in content diversity, where the range and variety of information become progressively limited (Huang et al., 2020). information redundancy denotes the absence of information novelty (Liang & Fu, 2017), and information overload denotes the situation when the amount of information provided is beyond users' abilities to process information (Apuke et al., 2022).

Stressor-appraisal-coping framework

The Stressor-Appraisal-Coping (SAC) framework, proposed by Lazarus and Folkman (1984), comprises three key components. The stressor component encompasses external stimuli or objective events that individuals construe as challenges or difficulties. Cognitive appraisal denotes the cognitive process which encompasses individuals' assessment of how the situation affects them personally. This includes identification of stressors, engagement in thinking and expectations, and the assessment of one's personal coping abilities. Perception, thinking, reasoning, and decision-making are the primary psychological activities within this process. Coping pertains to the utilization of behavioral or cognitive strategies to meet the demands of both the environment and the individual. It involves resolving conflicts, assessing stress, exerting control or making changes to stressors in the environment, thereby addressing difficulties and resolving emotional issues triggered by stress.

The theory emphasizes Stress arises from the dynamic interplay between individuals and their environment. When individuals perceive that the stimuli from both the internal and external environment surpass their coping resources and abilities, they experience stress. The extent to which stressors can induce stress in an individual primarily relies on two critical processes: cognitive appraisal and coping. Due to its ability to elucidate the relationship among environmental stimuli, individual responses, and resulting outcomes through a stress perspective, the SAC framework has found extensive application in Information Systems (IS) field. For instance, drawing on the SAC framework, researchers identified both direct and indirect effects of emotions on the utilization of information technology (Beaudry & Pinsonneault, 2010). Recent studies employed SAC to examine the interaction between users' coping strategies and the use of information technology (Salo et al., 2020). Thus, SAC is an appropriate framework to explore the negative influence of stress that recommendation algorithm technology brings. While, studies have found that discontinuation behaviors on social media platforms are associated with stressors such as information overload and the irrelevance of information, which can impact individuals' psychological process of cognitive appraisal (Guo et al., 2020). Based on this, it is necessary and feasible to study the mechanism of the formation of digital hoarding behaviors through regarding information characteristics as stressors.

On the background of social media, information characteristics such as information narrowing, information redundancy, and information overload may act as stressors since they interfere with the user's perceived value judgment of the information and the cognitive load level during browsing the information. Finally, these information characteristics may in turn induces psychological process, that is to say, they may affect cognitive appraisal, thus indirectly affect the formation of digital hoarding behaviors. Building upon this foundation, we have adopted the SAC framework as the theoretical underpinning to explain the formation mechanism of digital hoarding behaviors from a stress perspective. In the social media context, information characteristics serve as stressors, thereby prompting cognitive appraisal. When individuals feel stimuli of stressors, they will run the cognitive function to understand information, and judge the value of information, and decide whether to adopt information. Finally digital hoarding behaviors as coping formed.

Research model and hypotheses

The formation of digital hoarding of user groups on social media can be explained through the stressor-appraisal-coping (SAC) framework, which examines mechanism of digital hoarding behaviors between stressors and coping outcomes. Social media platforms driven by recommendation algorithm enable information with certain characteristics. As argued above, information narrowing, information redundancy and information overload can affect users' cognitive appraisal. That is to say, these three features of information will exert pressure on users (Ma et al., 2021). Thus, at stressor level, the selection of these three variables is meaningful. Moreover, people's psychological activities of cognitive appraisal include perception, thinking, reasoning, and decision-making. Perceived value uncertainty and cognitive load are exactly the benefits and costs users feel when browsing and seeking information on social media. Benefit-cost theory is the basic logic of decision analysis (Vessey, 1994), so these two variables are reasonable as cognitive appraisal dimension. In our study, we developed a research model that examines the determinants of users' digital hoarding behaviors on social media based on the information-related stressors, the impact of stressors on users' perceived value uncertainty and cognitive load, and in turn the coping measures of hoarding. In addition, we add the demographic information as control variables. As shown in Figure 1, the stressors dimension is composed by three variables, information narrowing, information redundancy, and information overload, while appraisal dimension consists of two variables, information perceived value uncertainty, cognitive load and digital hoarding behaviors is outcome on coping dimension. Besides, information-seeking self-efficacy was selected as a moderating variable to track individuals' differences in the digital hoarding process. From the perspective of stress and coping under the background of social media, we investigated user' influencing factors of digital hoarding behaviors.

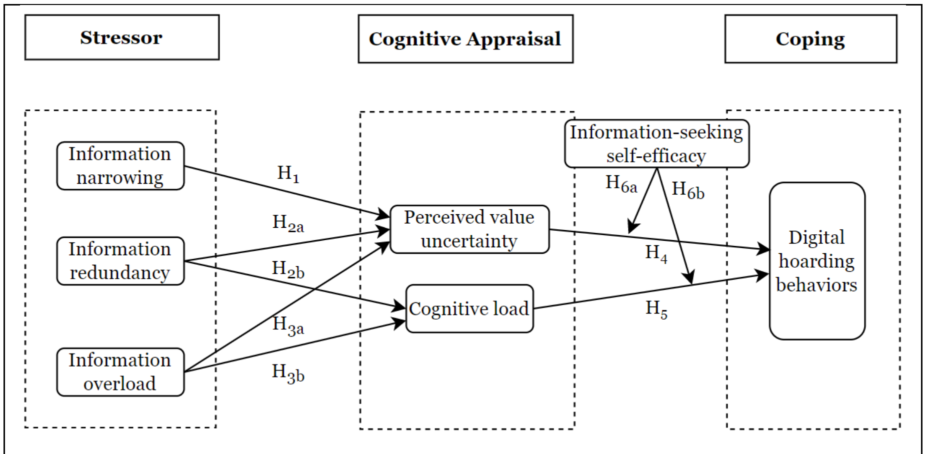

Figure 1. The research model on the SAC framework

Information characteristics and cognitive appraisal

Information narrowing refers to a phenomenon that users' exposure to excluded information progressively diminishes, as determined by recommendation algorithm. As a result, the diversity and depth of the information they receive decline over time (Huang et al., 2020). With the rapid development of information technology, personalized recommendation algorithm not only brings convenience to users, but also generates a series of problems, resulting in "information cocoon room", "filter bubbles"," echo chamber effect " and other network phenomena. In terms of information filtering mechanism, the personalized recommendation algorithm will filter information based on the user's browsing records, search records and user tags , thus causing the users to be surrounded by relatively fixed topic information (Pariser, 2011b). When individuals are in the information cocoon for a long time, the homogenized information world will increase the individuals' perceived value uncertainty of information (Blom et al., 2011). As it is uncertain whether information has future utility, individuals tend to continuously acquire information (Sweeten et al., 2018), leading to digital hoarding behaviors. Therefore, we put forward that:

H1: Information narrowing is positively related to individuals' perceived value uncertainty of information.

Information redundancy refers to the problem of information duplication (Zhang et al., 2002) in a series of information exposed to users. Information redundancy is a phenomenon caused by the recommendation algorithm, which weakens the performance of the recommendation (Zhu et al., 2017). As one of the derivative problems of information cocoon room, information redundancy puts individuals in the homogeneous information environment, and thus it enhances users' perceived value uncertainty of information. When the user is surrounded by a large amount of similar information, processing these similar information will make the individuals feel the time cost (Zhang et al., 2016), improving the individuals' cognitive load level . Individuals' uncertainty of the perceived value of information works with cognitive load to promote digital hoarding behaviors. Thus, we propose that:

H2a: Information redundancy is positively related to individuals' perceived value uncertainty of information.

H2b: Information redundancy is positively related to individuals' level of cognitive load.

Information overload refers to users' limited ability to handle the large amount of information (Zhu et al., 2017) they receive on social networks. Information overload can have many negative effects on users' emotions, information decisions and behaviors (Bawden & Robinson, 2008). It will increase the cognitive burden of users (Bawden & Robinson, 2008). Users who encounter information overload are more susceptible to experiencing pressure and feeling overwhelmed by the constant flow of information (Lee et al., 2016). Also, in terms of information processing and behaviors, information overload will make it easier for users to misinterpret information and reduce the accuracy of decision (Eppler & Mengis, 2004). As a result, information overload will lead to higher perceived value uncertainty of information, and enhance the cognitive load level of individuals when processing information (Wheeler et al., 2007). It makes users more inclined to hoard data in the information world with unequal supply and demand. Therefore, we put forward that:

H3a: Information overload is positively related to individuals' perceived value uncertainty of information.

H3b: Information overload is positively related to individuals' cognitive load level

Cognitive appraisal and digital hoarding

Perceived value uncertainty pertains to the degree of uncertainty of an individual's value judgment on information. In big data era, the surge of data brought many problems such as the unevenness of information quality and low quality homogeneity information (Agarwal & Yiliyasi, 2010). In addition, algorithm technology according to the personal interest of selective contact makes users in the information cocoon room caused by information narrowing, information redundancy, information overload (Pariser, 2011a). Thus, it leads to the result that individuals will spend a lot of energy and time in the process of discrimination information (Gil-Gómez de Liaño et al., 2016), and then in the process of obtaining information, the judgment uncertainty of information value becomes higher (Wheaton, 2016). Therefore, when users cannot accurately grasp the value of data and find data matching their own needs, individuals tend to continuously accumulate data to avoid future uncertainty based on uncertainty factors, such as data scarcity and future utility (Sedera & Lokuge, 2018). Moreover, the endowment effect indicates that individuals show a tendency to overestimate their value after having digital files (Cushing, 2011). When an individual is in a state of strong endowment, the perceived value uncertainty of the data becomes higher, and giving up something will produce a loss-aversion effect (Walasek et al., 2018). At this point, the user's digital hoarding is manifested in the difficulty of data deletion. Hence, we proposed that:

H4: Individuals' perceived value uncertainty of information is positively related to digital hoarding behaviors.

Cognitive load is the amount of information (Apuke et al., 2022) that individual memory function can process during a given period. Studies have shown that humans have limited memory capacity, so when users face an excessive amount of information on social media, cognition may occur (Sweller, 2011). Therefore, the human brain has a limited capacity to process a small amount of information simultaneously, and an overwhelming influx of information can impede learning and knowledge acquisition (Sweller, 2011). Problems such as information redundancy and information overload on social media will cause too complex cognitive circuits of individuals, and then cause cognitive load (Islam et al., 2020). In the face of massive information on the Internet, when the cognitive load level of users is too high, it will cause users' burnout (Whelan et al., 2020). However, once the burnout, the ability of individuals to identify information will decrease (Laato et al., 2020), and the accuracy of decision-making will be reduced, leading to users' digital hoarding behaviors. On this basis, we propose that:

H5: Individuals' cognitive load is positively related to digital hoarding behaviors.

Moderating effects of information-seeking self-efficacy

Information-seeking self-efficacy refers to the individual' s cognition and judgment on himself about the ability to locate relevant information through information retrieval (Ren, 2000). In the age of big data, the information landscape is evolving into a highly intricate ecosystem, and the problems such as information cocoon, information anxiety and information overload have brought new challenges to individuals' acquisition and utilization of information.

First, users who have higher self-efficacy deal with complex search tasks more actively and strive to overcome the challenges encountered in the information-seeking process (Hong, 2006). They are more confident about their ability to decide and judge (Tang et al., 2022). Therefore, in the face of massive information on social media, individuals with high level of self-efficacy can judge the value of the information based on their own needs more accurately. That is to say, their ability to distinguish and perceive useful information is higher, which is manifested as low perceived value uncertainty of information. In turn, it negatively affects digital hoarding behaviors. Based on this, we propose that:

H6a: Individuals' information-seeking self-efficacy weakens the relationship between perceived value uncertainty and digital hoarding behaviors.

Second, if users' information-seeking self-efficacy is higher, they tend to be more active during the process and respond actively to possible negative effects (Hilaire, 2016). When individuals encounter difficulties and obstacles, self-efficacy will affect their emotional repair ability and reduce anxiety, making them effectively relieve negative emotions and experience more positive emotions (Mustafa et al., 2010). Therefore, when facing huge volume of information, individuals with high self-efficacy have stronger psychological control ability rather than anxiety. Hence, their cognitive load is at low level, which negatively affects digital hoarding behaviors. Thus, we posit that:

H6b: Individuals' information-seeking self-efficacy weakens the relationship between cognitive load and digital hoarding behaviors.

Methodology

Research setting

To validate our research model and test the proposed hypotheses, we obtained data through an online survey of college students who use social media platforms, including Sina Weibo, RED, Bilibili, Douyin, Jinri Toutiao. These social media platforms are propelled by technology of recommendation algorithm and have garnered immense popularity in China, boasting an impressive user base of over 500 million active users. Most of the users are young and middle-aged groups, which makes them a suitable context for the investigation.

Instrument development

The constructs in this study were measured using previously validated instruments, with necessary adaptations made to suit our specific context. A five-point Likert scale, ranging from "strongly disagree" to "strongly agree," was employed to capture participants' responses to the survey items. Specially, the section on information narrowing perception measurement of users on social media platforms , which had three items, was adapted from Huang et al. (2020). Information redundancy consisting of three items was adapted from Ma et al. (2021). And the items assessing information overload were adapted from Lee et al. (2016). The items measuring users' perceived value uncertainty of information were adapted from Dimoka et al. (2012), concluding four items. Users' cognitive load level was measured with three items adapted from Hu et al. (2017). The measurement of information-seeking self-efficacy consisted of a five-item scale adapted from Tang et al. (2022). Digital hoarding behaviors was adapted from Neave et al. (2019), containing ten items with two dimensions of deletion difficulty and continuous accumulation. In addition, deletion difficulty and continuous accumulation were processed as first-order variables, while digital hoarding was second-order formative observed variable in data analysis. To ensure linguistic accuracy, all items were translated into Chinese using a back-translation approach, considering our sample of native Chinese speakers. Detailed explanations of the constructs and measures can be found in the Appendix section.

Data collection

Our data was collected using the prominent online questionnaire distribution and collection platform in China, wjx.cn. Our aim was to recruit individuals who had prior experience with social media platforms using the snowball sampling method. We initially reached out to participants online and offered a 2 RMB incentive as a voluntary participation incentive. Participants were encouraged to distribute the survey URL to their acquaintances as part of the incentive program. It's worth noting that all participants received an equal reward for their participation. To ensure the inclusion of social media platform users, a screening question was incorporated, asking respondents to indicate their perceptions of their most frequently utilized social media platform. Responses indicating "never use" were deemed invalid and excluded from the analysis. Besides, to facilitate comprehension of digital hoarding behaviors on social media platforms, a concise overview of digital hoarding behaviors was provided at the outset of the questionnaire. It is pertinent to mention that participants were restricted to a single response, and their engagement was voluntary, guaranteeing anonymity in data processing. The survey lasted for ten days from November 5th 2022 to November 15th 2022. Finally, a total of 231 questionnaires were received.

We eliminated participants who did not use social media, provided inconsistent responses, or gave routine answers, and submissions under two minutes, resulting in a final sample of 218 responses for analysis.

In this study, 218 valid questionnaires were obtained, and the proportion of valid respondents was evenly distributed, including 96 men, accounting for 44.04% and 122 women, or 55.96%. In terms of educational level (study), undergraduates were the main body of the survey, with junior college students accounting for 7.8%, 84.4%, undergraduates for 5.5%, and 2.29%. Moreover, the majors of respondents were as follows. Engineering accounted for the largest proportion at 29.36%. Science and Management accounted for 14.68% and 14.22% respectively. Economics, Literature and Law were relatively small. Others accounted for 19.72%.

Data analysis results

Partial Least Squares (PLS) technique was utilized for data analysis, chosen for its various advantages. It is an advanced structural equation modeling (SEM) method. The analysis encompassed two key components: the assessment of measurement models, which examined the relationship between indicators and constructs, and the evaluation of structural models, which investigated the connections between different constructs (Fornell & Bookstein, 1982). Furthermore, we used SPSS to conduct the Kolmogorov-Smirnov test (with Lilliefors correction) (Mooi & Sarstedt, 2011). The data showed a deviation from normal distribution, as indicated by the result ($p<0.05$). Given the non-normal distribution of our data, PLS was deemed more suitable for our study compared to a covariance-based SEM approach, as it imposes fewer assumptions on data distribution. To analyze the data, we employed a two-stage analytical procedure. Firstly, we evaluated the measurement model by analyzing the associations between indicators and constructs. Subsequently, we examined the proposed hypotheses within the structural model, exploring the relationships between constructs.

Measurement model

In the examination of the measuring model, we scrutinized the constructs for their reliability, convergent validity, and discriminant validity to gauge the soundness. Moreover, we calculated each variable's mean and standard deviation through SPSS. In the field of social sciences, Cronbach's α, composite reliability (CR), and average variance extracted (AVE) serve as significant metrics for evaluating the reliability and consistency of the measurement content. The results demonstrated that each variable had a Cronbach's α exceeding 0.70, a composite reliability (CR) surpassing 0.70, and an average variance extracted (AVE) exceeding 0.50, as is shown in Table 1 (Fornell & Larcker, 1981) So it can be inferred that the constructs designed in this study had good reliability and consistency, and the reliability test met the requirements.

Construct	Mean	SD	α	CR	AVE	IN	IR	IO	PVU	CL	ISSE	DD	CA
IN	3.68	.81	.82	.89	.74	**.86**							
IR	4.14	.63	.89	.93	.82	.41	**.91**						
IO	3.71	.75	.74	.86	.67	.46	.45	**.82**					
PVU	3.86	.72	.88	.92	.74	.47	.57	.52	**.86**				
CL	3.38	.93	.88	.93	.82	.23	.19	.37	.36	**.91**			
ISSE	3.37	.75	.87	.91	.66	.06	.16	.15	.19	.37	**.81**		
DD	3.27	.94	.88	.92	.69	.29	.13	.35	.20	.37	.33	**.83**	
CA	3.79	.71	.82	.88	.66	.34	.41	.36	.48	.28	.23	.46	**.81**

Table 1. Construct reliability & Construct correlations

Note: SD=Standard Deviation; IN=Information narrowing; IR=Information redundancy; IO=Information overload; PVU=Perceived value uncertainty; CL=Cognitive load; ISSE=Information-seeking self-efficacy; DD=Deletion difficulty; CA=Continuous accumulation; The diagonal data in bold represent the square root values of AVEs.

	IN	IR	IO	PVU	CL	ISSE	DD	CA
IN1	**.84**	.41	.36	.39	.21	.06	.25	.26
IN2	**.90**	.36	.40	.37	.17	-.01	.26	.26
IN3	**.83**	.30	.42	.44	.21	.10	.25	.34
IR1	.38	**.92**	.40	.54	.21	.17	.18	.42
IR2	.37	**.91**	.41	.50	.15	.12	.13	.36
IR3	.37	**.89**	.40	.51	.15	.13	.06	.34
IO1	.37	.39	**.84**	.43	.27	.11	.28	.34
IO2	.48	.39	**.85**	.44	.33	.12	.30	.27
IO3	.27	.31	**.76**	.40	.30	.14	.29	.27
PVU1	.47	.55	.49	**.85**	.30	.17	.22	.43
PVU2	.39	.47	.46	**.85**	.30	.13	.19	.40
PVU3	.41	.47	.39	**.88**	.32	.16	.12	.42
PVU4	.33	.47	.44	**.85**	.32	.18	.14	.41
CL1	.21	.22	.33	.32	**.89**	.31	.30	.26
CL2	.22	.13	.30	.32	**.92**	.34	.35	.22
CL3	.20	.17	.36	.33	**.90**	.35	.35	.27
ISSE1	-.01	.12	.10	.08	.29	**.80**	.31	.18
ISSE2	.09	.16	.17	.22	.31	**.83**	.32	.22
ISSE3	.01	.06	.08	.17	.31	**.82**	.22	.21
ISSE4	.08	.13	.13	.19	.25	**.80**	.19	.11
ISSE5	.08	.16	.13	.12	.31	**.81**	.26	.17
DD1	.29	.13	.32	.22	.24	.17	**.79**	.41
DD2	.32	.18	.27	.19	.22	.19	**.76**	.44
DD3	.22	.20	.28	.18	.25	.36	**.81**	.35
DD4	.21	.05	.29	.13	.38	.33	**.88**	.35
DD5	.23	.04	.33	.13	.37	.26	**.91**	.33
CA1	.24	.35	.26	.36	.28	.31	.47	**.84**
CA2	.23	.32	.27	.36	.15	.18	.39	**.78**
CA3	.30	.35	.34	.46	.22	.10	.26	**.81**
CA4	.32	.30	.29	.38	.24	.16	.32	**.82**

Table 2. Cross-loadings

Note: IN=Information narrowing; IR=Information redundancy; IO=Information overload; PVU=Perceived value uncertainty; CL=Cognitive load; ISSE=Information-seeking self-efficacy; DD=Deletion difficulty; CA=Continuous accumulation; The highlighted data represents the loadings of items on their respective constructs.

In the process of scale validity analysis, because the scale designed and the items addressing issues in this study were sourced from pre-existing scale system, so the content validity of the scale can be guaranteed. That is to say, the structural validity of the scale, including convergent validity and discriminant validity needs to be tested. Within the realm of disciplines about humanities and social sciences, the item loadings on the expected constructs are the observation index of the convergent validity of the scale, and the squared average variance extracted value serves as an indicator of the discriminant validity of the scale. Table 2 demonstrates that all measurement items exhibit item loadings exceeding 0.70, indicating favorable convergent validity for the scale's structure. To assess discriminant validity, two methods were employed in this study. Firstly, we conducted a comparison between the squared Average Variance Extracted (AVE) of each construct and its corresponding correlation coefficients. Secondly, we examined the item loadings on their designated constructs and compared them to the cross-loadings. As evidenced by Table 1 and Table 2, the squared AVE for each construct exceeded its correlation coefficient, and all item loadings for each construct surpassed the cross-loadings. These findings confirm that all constructs demonstrate robust convergent and discriminant validity, meeting the validity test requirements.

In addition, deletion difficulty and continuous accumulation were processed as two first-order constructs of the second-order construct digital hoarding behavior. The result shows that the weights of deletion difficulty and continuous accumulation are 0.70 and 0.46 and both of these weights are significant with t-values of 19.531 and 15.207, respectively, so both of these two dimensions are included in the later analysis.

Structural model

As shown in Figure 2, the results showed that at the stressor level, information narrowing (β =0.197, t=3.009, p <0.01), information redundancy (β =0.375, t=5.241, p <0.001), information overload (β =0.259, t=3.350, p <0.001) were found to have a positive association with users' perceived value uncertainty of information, which strongly supported H1, H2a, H3a, respectively. In addition, information overload (β =0.351, t=4.097, p <0.001) was found to be positively related to users' cognitive load, supporting H3b. In terms of cognitive appraisal level, user's perceived value uncertainty of the information (β =0.297, t=3.534, P <0.001) and the cognitive load during browsing the information (β =0.190, t=2.631, And p <0.01) were positively related to digital hoarding behaviors, these results support H4 and H5. Nevertheless, a direct relationship between information redundancy and the user's cognitive load was not observed (β =0.034, t=0.432), so the assumption of H2b was not supported. Meanwhile, information-seeking self-efficacy was proven to negatively moderate the impact of perceived value uncertainty on digital hoarding (β =-0.027, t=0.394) while this moderating effect was not significant. Further, opposite to our expectation, the results revealed that information-seeking self-efficacy positively moderates the influence of cognitive load on digital hoarding (β =0.110, t=2.019, p <0.05). Thus, H6a and H6b were not supported. Overall, the structural model explained 44.1%, 13.5% and 27.1% of the variance of users' perceived value uncertainty, cognitive load and digital hoarding behaviors, respectively.

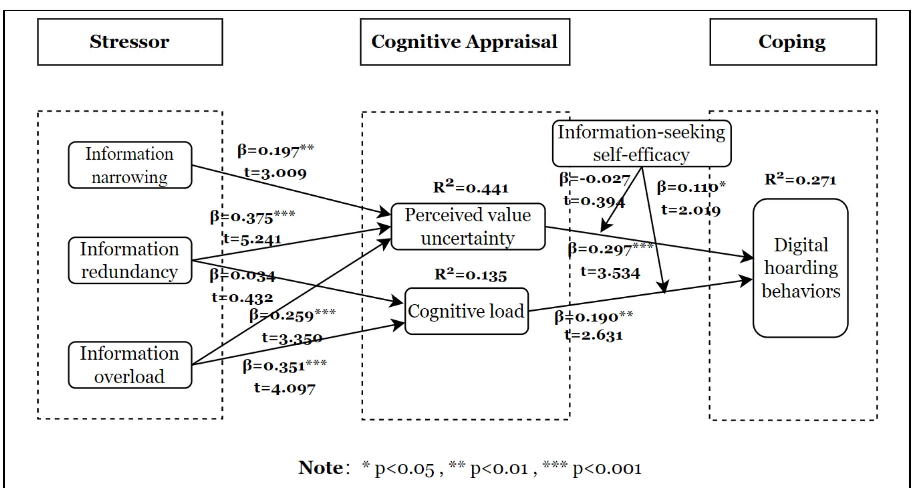

Figure 2. PLS results of the structural model

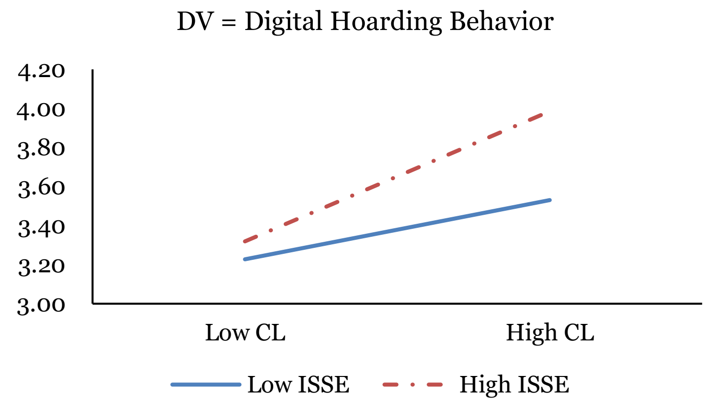

Figure 3. Moderating effect of ISSE

Note: CL=Cognitive load; ISSE=Information-seeking self-efficacy

Discussion

Key findings

The results confirm most of our hypotheses. Specifically, three information characteristics are found to positively affect perceived value uncertainty, while only information overload is found to positively affect cognitive load. Information redundancy does not have a significant impact on users' cognitive load. One possible explanation is that due to the similarity of information, users are relatively easier to process information at the cognitive level (Zhang et al., 2016), so it does not significantly enhance the cognitive load of users.

Further, both perceived value uncertainty and cognitive load are found to positively affect digital hoarding behaviors, while the impact strengths depend on the levels of users' information-seeking self-efficacy. Surprisingly, based on the findings, it can be concluded that information-seeking self-efficacy doesn't moderate the linkage of perceived value uncertainty and digital hoarding but strengthens the correlation between cognitive load and digital hoarding. Regarding the insignificant moderating effect, it may be because perceived value uncertainty is a key determinant of digital hoarding regardless whether users' self-efficacy is high or low. As to the positive moderating effect, this could be attributed to the fact that individuals with high self-efficacy tend to make more efforts to overcome the difficulties encountered while browsing and retrieving information and tend to hoard the information when they have no adequate cognitive resources so as to deal with the information in the future (Kurbanoglu & Akin, 2010). Conversely, for users with low self-efficacy, they may give up the information processing efforts and would not hoard the information at all, thus cognitive load is not a key determinant for their digital hoarding behaviors.

Theoretical implications

This study presents three significant advancements in the field of social media research. First, this study focuses on a new phenomenon of social media (e.g., digital hoarding), theorizes the underlying mechanisms driving digital hoarding, and provides empirical evidences to validate these mechanisms. Digital hoarding behaviors in the realm of social media have been less discussed in prior studies, and in the limited studies, most of these studies either focus on the measurement of constructs or explore the potential mechanisms by conducting qualitative studies. Unlike prior studies, a research model of digital hoarding based on the stress-appraisal-coping (SAC) framework is put forward in this study and subsequently validated through empirical testing. Specifically, this study identifies three information characteristics namely information narrowing, information redundancy, and information overload as the stress-inducing elements which trigger more demands for users to process the information, and two cognitive appraisals namely perceived value uncertainty and cognitive load which respectively capture the benefits and costs brought by information, and digital hoarding behavior as the coping strategy to deal with the information stress. Future research can take the SAC framework as the theoretical foundation for understanding the digital hoarding behaviors of social media.

Second, this study broadens the research context of digital hoarding from the work environment to the social media environment by capturing the unique features of the new research context. Specifically, the study integrates the attributes of information on social media to provide a comprehensive understanding of the factors contributing to digital hoarding. Information characteristics containing information narrowing, information redundancy, and information overload will exert influence on users' perceived value uncertainty and cognitive load.

Finally, this study uncovers the limiting circumstances in which different cognitive appraisals influence digital hoarding by highlighting the moderating role of information-seeking self-efficacy. Specifically, we pay attention to the individual differences in information seeking abilities (e.g., information seeking self-efficacy) and explore when perceived value uncertainty and cognitive load may affect digital hoarding. The results suggest that information-seeking self-efficacy does not alter the impact of perceived value uncertainty on digital hoarding. However, when self-efficacy is high, the relationship between cognitive load and digital hoarding becomes stronger.

Practical implications

First, the results suggest that information narrowing, information redundancy, and information overload positively affect perceived value uncertainty, indicating that social media service providers should enhance the transparency of algorithm, optimize the recommendation performance of algorithm, and balance the personalization (e.g., information overload) and diversity (e.g., information narrowing) of information recommendation. Second, social media platforms should strengthen the information governance to reduce the low-quality and homogeneous information (e.g., information narrowing), and create a clear and user-friendly information environment. It is because of the lack of information quality supervision that users have difficulty grasping the information value. Also, it is easy for users to get cognitive overload by massive information. Thus, platforms should set up an independent regulatory authority to strengthen the governance or regulation. Third, from a personal perspective, users should strive to improve personal information literacy. Individuals with high information literacy can distinguish useful information satisfying their needs because they could evaluate and utilize the useful information from multiple aspects. Moreover, their ability to retrieve and obtain information efficiently from multiple channels is high. Then, their perceived value uncertainty and cognitive load level are low, which can avoid digital hoarding to a certain degree.

Limitations and Future Research

Considering that the relevant research of users' digital hoarding behaviors is a complex systematic engineering, this study still remains some limitations. Given the selection of sample objects and investigation methods, future research areas can be explored and optimized from the following aspects: First, as to the sampling approach, this study used a convenience sampling approach through which the subjects only focus on a specific population (e.g., students in China), therefore, the generalizability of the findings to other populations (e.g., professionals and individuals in other countries) still call for additional investigation. Second, different social media platforms have different features (e.g., TikTok versus RED), thus whether the underlying mechanisms are same across different social media platforms should be further explored. Third, this study primarily examines the effects of information characteristics. However, besides the information characteristics, other important factors such as different intentions for using social media and other personal preferences should be considered in future research. Finally, a cross-sectional rather than longitudinal survey is designed. In future studies, it may be worthwhile to capture the dynamics of digital hoarding behaviors through a longitudinal survey.

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Appendix. Measures

Information narrowing (Huang et al., 2020)

IN1. The recommended content lessens information diversity.

IN2. The recommended content narrows my access to information.

IN3. I have less and less contact with excluded information.

Information redundancy (Ma et al., 2021)

IR1. Sometimes the recommended information is similar.

IR2. Sometimes the recommended information topics are repeated.

IR3. Sometimes the recommended information is redundant.

Information overload (Lee et al., 2016)

IO1. I am often distracted by the excessive amount of recommended information.

IO2. I find that I am overwhelmed by the amount of recommended information.

IO3. I feel some problems with too much recommended information to synthesize instead of not having enough information.

Perceived value uncertainty (Dimoka et al., 2012)

PVU1. I feel that the value of information on social media involves a high degree of uncertainty.

PVU2. I feel the uncertainty associated with information value on social media is high.

PVU3. I am exposed to many uncertainties if I grasp of the value of information on social media.

PVU4. There is a high degree of uncertainty when evaluating the value of information on social media.

Cognitive load (Hu et al., 2017)

CL1. I needed a lot of thinking when browsing the mass of information on social media.

CL2. I often contemplated, among getting lots of information on social media platforms.

CL3. Generally speaking, processing lots of information on social media platforms was cognitively demanding.

Information-seeking self-efficacy (Tang et al., 2022)

ISSE1. I am certain I can find information online that I trust.

ISSE2. I am certain I can avoid online information that is misleading.

ISSE3. I am certain I can find information that is thorough.

ISSE4. I am certain I can avoid online information that is out of date.

ISSE5. I am certain I can avoid online information that is inaccurate.

Digital hoarding behaviors (Deletion difficulty) (Neave et al., 2019)

DD1. I find it extremely difficult to delete old or unused data on social media.

DD2. Deleting certain data on social media would be like deleting a loved one.

DD3. If I delete certain data of social media, I feel apprehensive about it afterwards.

DD4. I strongly resist having to delete certain data on social media platforms.

DD5. Deleting certain data on social media would be like losing part of myself.

DD6. Thinking about deleting certain data of social media causes me some emotional discomfort. (The item loading of the corresponding construct is lower than 0.70, so it is removed when data processing)

Digital hoarding behaviors (Continuous accumulation) (Neave et al., 2019)

CA1. I tend to accumulate data on social media, even when they are not directly relevant to my current needs.

CA2. I feel strongly that some data of social media might be useful one day.

CA3. I lose track of how many data I possess on social media platforms.

CA4. At times I find it difficult to find certain data of social media because I have so many.

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