Journal of Organizational and End User Computing
Volume 33 • Issue 6 • November-December 2021

Revisiting How Perceived Uncertainty and Herd Behavior Influence Technology Choice

Ali Vedadi, Middle Tennessee State University, USA

Timothy H. Greer, Middle Tennessee State University, USA

ABSTRACT

Understanding how herd behavior occurs in the information systems context is important because such behavior influences many choice decisions, is the reason for some decision anomalies, and explains the reasons behind the rise or collapse of technology trends. Perceived uncertainty is a critical factor that triggers herding, but despite its influential role, prior research has not adequately investigated this broad concept. This research contributes to the literature by decomposing perceived uncertainty to its dimensions and analyzing the influence of each one on triggering individuals' herd behavior. The findings show that unlike state uncertainty, only effect and response uncertainty are the triggers herd behavior.

KEYWORDS

Discounting Own Information, Herd Behavior, Imitation, Perceived Uncertainty

INTRODUCTION

People's decisions are often not only determined by their own perceptions and information, but also by the behavior of those around them. The influence of others' behavior is usually more significant in uncertain circumstances, which are characterized by complexity and information deficiency. Similarly, individuals often make information technology (IT) adoption decisions in complex and multidimensional settings, which could lead to certain behavioral anomalies. As technologies become increasingly advanced, the accurate evaluation of their functionalities may require a substantial amount of information and analysis, thus making choices difficult for most users. In uncertain circumstances, end users' information about the technology options is most likely incomplete, and their understanding of the technology capabilities could be limited. The lack of enough information usually motivates users to find ways of coping with the resulting uncertainty (Banerjee, 1992). In such circumstances, observing other users' decisions and learning about the popularity of alternatives could significantly influence users' decision making. When uncertain about what to do, individuals may simply "follow the herd" and imitate others (Bikhchandani et al., 1992).

The widespread use of the Internet and various online social media platforms has made it convenient to observe other users' decisions pertaining to the adoption of technologies and to assess how popular each technology is. The combination of perceived uncertainty and observing the behavior of other users may lead to the phenomenon of herd behavior, which is defined as the imitation of others' behavior in uncertain circumstances (Banerjee, 1992). An instance of herd behavior can occur

DOI: 10.4018/JOEUC.20211101.oa1

in online auctions, in which numerous buyers tend to bid for products that already have numerous bids while ignoring similar or more attractive products that do not have any bids (Wang et al., 2018)[1].

Herd behavior is primarily comprised of two complementary cognitive mechanisms: 1) “discounting own information” (i.e., the degree to which one disregards personal beliefs about a technology when making an adoption decision), and 2) “imitating others” (i.e., the degree to which one follows previous adopters in choosing a certain form of technology) (Sun, 2013). Herd behavior theory explains that in uncertain circumstances, a reasonable strategy is to simply follow the herd instead of investing one’s own time and efforts in evaluating the alternatives. This approach is based on the premise that the current members of the herd have already made a careful assessment of alternatives and determined that a reasonable decision is to adopt the popular technology. Imitation has also been shown to be a popular IT strategy used by late-mover firms (Zhang & Ravishankar, 2019).

Although some previous information systems (IS) studies attempted to investigate how herd behavior occurs in the IS context, there are still important questions that need to be addressed, which is evidenced by surprising and mixed results in the literature. For instance, Sun (2013) found that perceived uncertainty about adopting a wiki technology and learning about its popularity did not directly cause individuals to imitate each other. The non-significant relationship between perceived uncertainty and imitation suggested that decision making was not a function of others’ behavior. Similarly, the findings of Vedadi and Warkentin (2020) showed that perceived uncertainty and imitation tendency were negatively correlated, indicating that the more uncertain individuals are, the less likely they are inclined to imitate. These findings, which are inconsistent with herd behavior theory, suggest that perceived uncertainty may not necessarily lead to imitation in technology adoption and that herd behavior in the IS context should be reconceptualized. Therefore, we aim to answer the following overarching research question:

- *How does perceived uncertainty lead to herd behavior in the choice of technology?*

We argue that there are two main reasons for these unexpected findings in the IS literature. First, despite the complex and multidimensional nature of perceived uncertainty, it has been measured rather simplistically and needs further operationalization and specification. Multiple studies have called for measuring the different types of perceived uncertainty such as state uncertainty (the uncertainty about how components of the environment could be changing), effect uncertainty (the inability to predict what a future state will impact the decision maker), and response uncertainty (the inability to predict the likely consequences of a response alternative) (Ashill & Jobber, 2010; Lueg & Borisov, 2014; Milliken, 1987). However, in the related studies in the literature, perceived uncertainty has been measured as a generic and one-dimensional construct. Furthermore, from a theoretical standpoint, “discounting own information” mediates the relationship between perceived uncertainty and imitation because when users discount their personal information, they rely less on their initial information and beliefs than on the insights obtained from their observations of others’ behavior. Thus, the more a user discounts his or her personal information, the more likely he or she will be to imitate the behavior of others.

The findings of prior studies showed that herd behavior explains numerous phenomena such as users’ technology choices and design decisions (Chang et al., 2019; Duan et al., 2009; Trenz et al., 2018; Weinmann et al., 2016), the reasons for some IS-related decision anomalies (Muchnik et al., 2013; Wang et al., 2018), and the rapid rise or collapse of various technology fads (Walden & Browne, 2009); and therefore, because perceived uncertainty is a main trigger of herd behavior, decomposing this broad concept to its dimensions and analyzing the influence of each dimension on users’ behavior could enhance the current understanding herd behavior in the IS context. Therefore, by positioning the multidimensionally conceptualized perceived uncertainty in the herd behavior theoretical framework, we investigate what types of perceived uncertainty lead to herd behavior. Although the different types of perceived uncertainty are conceptually distinct, prior studies in the

IS literature have not addressed how each dimension influences herd behavior. Thus, this research contributes to the literature by differentiating among these three types of perceived uncertainty in the attempt to clarify the mixed results reported in past research. Our findings indicate that only certain types of perceived uncertainty influence herd behavior.

This paper proceeds as follows. First, we discuss the theoretical foundations of herd behavior, the multidimensional nature of uncertainty, and we develop the hypotheses. Then, we explain the research methodology, including the experimental design and the instrument. Next, we describe the results of the data analysis. Finally, we discuss the results, implications for practice, and future research avenues.

THEORY AND HYPOTHESIS DEVELOPMENT

The Multidimensional Nature of Uncertainty

Milliken (1987) defined perceived uncertainty as the perceived inability to predict something accurately, mainly because of information deficiency and inability to distinguish between relevant and irrelevant information. Perceived uncertainty is also referred to as "perceived environmental uncertainty", which suggests that the source of the uncertainty is the external environment and that uncertainty should be studied in relation to specific components of the environment (e.g., stakeholders such as suppliers, customers, and government) (Gifford et al., 1979). Understanding the specific components of perceived uncertainty that are experienced by the decision maker is essential. Specifying the source of uncertainty identifies the domain of the environment about which the decision maker is uncertain about, whereas identifying the type of uncertainty addresses the nature of the uncertainty being experienced (Duncan, 1972).

One type of uncertainty that a decision maker can experience is uncertainty about the state of the environment. *State uncertainty* is experienced when an individual perceives the environment or a certain component of it to be unpredictable. An individual might be uncertain about the probability or the nature of changes in the state of the relevant environment (e.g., emerging technological trends, cybersecurity regulations, and software pricing). In other words, state uncertainty indicates that a person does not understand how the components of the environment could be changing. State uncertainty can also include an incomplete understanding of the relationships among the elements of the environment (Milliken, 1987). For instance, a person might be uncertain about the likelihood of the advent of a transformative technology as well as the likely reaction of individuals if such technology becomes available.

Milliken (1987) argued that of the three types of uncertainty about the environment, state uncertainty is the conceptually closest to using the term "environmental uncertainty" in delineating the state of environments. Experiencing state uncertainty could be the result of the characteristics of the environment in which decision making occurs. To the extent that volatility, complexity, and heterogeneity make environments less predictable, it is likely that decision makers who function in environments with high volatility and complexity will perceive more uncertainty about the nature of their environment than those who operate in more stable environments.

The second type of uncertainty, *effect uncertainty*, is defined as the inability to predict how the nature of a future state will impact the decision maker. For instance, being aware that a dangerous malware has spread on the Internet does not necessarily mean that the decision maker knows how it will affect his or her own IT infrastructure and critical systems. Duncan (1972) stated that effect uncertainty includes a lack of understanding of causal relationships. For instance, if state uncertainty is related to uncertainty about the nature of the new malware, effect uncertainty involves uncertainty about the consequences of IT infrastructure being infected by the virus and the likely impact of a company's ability to function in the future. Another example is uncertain circumstances, such as how using a strategic information system could impact firm performance (Choe, 2003). Lastly, *response uncertainty* is defined as a lack of information about response alternatives and the inability to predict the likely consequences of a response alternative (Milliken, 1987). This type of uncertainty is most likely to occur when the decision maker needs to act, and an immediate decision should be made.

To summarize, state uncertainty refers to a situation in which the decision maker lacks information about the nature of the environment. Effect uncertainty, conversely, may not certainly be the result of lacking information about the nature of the environment, but a lack of information about how environmental events will affect the decision maker (or the organization/industry) in which he or she operates. Finally, response uncertainty refers to a lack of information about what the response alternatives are.

In the IS literature, Sun and Fang (2010) adapted these three types of uncertainty to the context of technology adoption, explaining that users may be unclear about what a technology is for (state uncertainty), uncertain about what a technology can do for them (effect uncertainty), and whether they can deal with potential changes of the technology, such as upgrades to support it following adoption (response uncertainty). Sun (2013) hypothesized that perceived uncertainty in technology adoption is the reason that users imitate the actions of others instead of making decisions based solely on their own limited information. Therefore, in high uncertainty, potential adopters are not adequately capable of analyzing the relationships between their adoption and the possible adoption outcomes. However, the findings of Sun (2013) showed that the relationship between perceived uncertainty and imitation was not significant. This surprising finding is particularly important because, theoretically, the positive relationship between perceived uncertainty and imitation is a fundamental premise of herd behavior theory. Vedadi and Warkentin (2020) also used the reflective measurement scale, developed by Sun and Fang (2010), to measure these types of uncertainty, and found that perceived uncertainty and imitation were negatively correlated.

Ashill and Jobber (2010) argued that the studies on environmental uncertainty have focused on a single perceptual measure of uncertainty and have not attempted to measure further the process of understanding, interpreting, and responding to changes in the external environment as separate phenomena. Therefore, they developed a full psychometric development and tested the scales to measure the three conceptually discriminant constructs. Consequently, their empirical findings showed that individuals make meaningful distinctions between different types of uncertainty. Similarly, we argue that in order to understand better the influence of perceived uncertainty on herd behavior in the IS context, the effects of its different types should be investigated. Specifically, we hypothesize that all three types of perceived uncertainty will prompt individuals to discount their own limited information about a technology, therefore becoming susceptible to herd behavior; thus, we hypothesize that:

H1a: *State uncertainty positively influences users' tendency to discount their own information.*
H1b: *Effect uncertainty positively influences users' tendency to discount their own information.*
H1c: *Response uncertainty positively influences users' tendency to discount their own information.*

Intermediating Role of Discounting Own Information

When individuals discount their limited personal information, they rely less on their own beliefs and information than on the information obtained from their observations of others' actions. Theoretically, the more users discount their personal information, the more likely they will be to imitate the behavior of others (Banerjee, 1992). Discounting own information can increase the possibility of users' imitating the actions of others instead of making decisions merely based on their own information because as one reduces the use of one's own information, following others could become a legitimate strategy. In circumstances when a user discounts his or her own opinion, a reasonable strategy is to imitate the actions of others (Au & Kauffman, 2003; Thies et al., 2016; Tucker & Zhang, 2011). Therefore, we argue that uncertainty alone does not necessarily lead to imitation because, in some cases, the level of uncertainty can be too high; thus, hindering the decision-making process. Furthermore, being uncertain without receiving popularity information might lead users to simply prefer the status quo.

Thus, we argue that in uncertain circumstances, imitation becomes an authentic alternative strategy through discounting own information because users may believe that others have better and more complete information regarding a technology. Therefore, we hypothesize the following:

H2: *Discounting own information positively influences imitation tendency.*

Imitation vs. Personal Assessment

Herd behavior theory posits that perceived uncertainty causes people to discount personal information and mimic the decisions of others (Banerjee, 1992). For instance, the finance literature suggests that some investors imitate the investment decisions of professional investment managers to avoid being considered incompetent if the investments perform poorly in the future (Scharfstein & Stein, 1990). Sun's (2013) findings showed that when the subjects were uncertain about adopting a wiki system and received information about its high popularity, they decided to "follow the herd" and imitate the decision of the current users. Similarly, Vedadi and Warkentin (2020) found that receiving popularity information about an IT security tool increased their subjects' imitation tendency and, subsequently, their intention to use the technology. These findings indicate that herd behavior (i.e., imitation) influences behavioral intention simultaneously with the user's own perceptions (i.e., perceived usefulness). Therefore, we hypothesize the following:

H3: *Imitation tendency positively influences users' intention to adopt a technology.*

According to herd behavior theory, the ultimate adoption decision is mainly based on a combination of individuals' limited information about the alternatives and what they learn from observing the actions of others. Hence, even in uncertain circumstances, users may attempt to individually evaluate and explore the capabilities of a technology based on personal judgment and perceptions of the usefulness of the technology[2] (Venkatesh et al., 2003). Accordingly, we offer the following hypothesis:

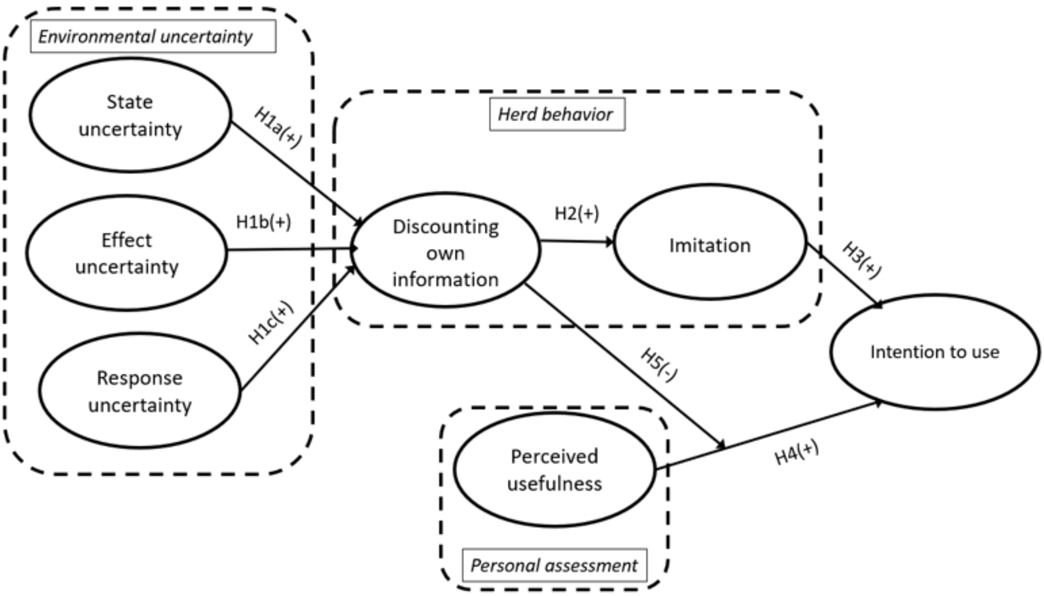
H4: *Perceived usefulness positively influences users' intention to adopt a technology.*

Discounting one's own information refers to a situation in which an uncertain individual relies less on his or her personal beliefs in making adoption decisions. Therefore, the higher the discount, the less critical the personal beliefs and perceptions are in making such decisions, thus indicating the weak anchoring effect of these beliefs (Sun, 2013). In other words, discounting own information emphasizes the effect of herd behavior while diminishing the effect of personal perceptions and beliefs. Therefore, discounting own information could negatively moderate the relationship between perceived usefulness, which is based on the individuals' own assessment, and the intention to adopt technology. Thus, we hypothesize that:

H5: *Discounting own information negatively moderates the relationship between perceived usefulness and behavioral intention.*

Figure 1 depicts the proposed research model:

Figure 1. The research model



METHODOLOGY

Experimental Design

We designed a multigroup experiment and recruited participants with various educational and professional backgrounds from a professional panel of working adults in the United States. The focus of the study was the Blockchain Wallet technology, so we used filter questions to ensure that only individuals who had not used this technology and were unfamiliar with it could participate in the experiment. The qualified participants were randomly assigned to either the treatment group or the control group. After providing their demographic information, the participants read a short narrative, which was designed to encourage them to use Blockchain Wallet. The narrative was discussed by an expert review panel to provide additional ideas for refining the structure and content of the instrument as well as the treatment information. The narrative provided information about the benefits of using Bitcoin and further details about Blockchain Wallet (see Appendix A). Then, only the participants in the treatment group received additional information about the popularity of this technology (i.e., the treatment). Next, all participants reported their intention to use Blockchain Wallet, and they answered the rest of the survey questions (see Appendix B; Table 6).

We chose Blockchain Wallet as the focal technology because there is still a high degree of uncertainty among users about this technology. Several reports, such as one by CNBC[3], have indicated that the adoption rate of this technology is still slow for several reasons, such as the lack of sufficient clarity and standards, an overwhelming number of available cryptocurrencies, and perceptions of immaturity. Therefore, this technology was a suitable focus for the context of our study because it allowed us to investigate whether providing information about its popularity influenced the participants' decisions to adopt it.

Data Collection and Screening

We adapted most of the measures used in this study from previously validated scales (seven-point Likert scale) in the literature (see Appendix C). To ensure data quality, we used several techniques that included several attention checks to eliminate the responses by participants who were not attentive, to check performance speed in the survey platform to discard responses that were recorded in an unreasonably short amount of time, and to drop responses in which response-set bias was detected. We also applied several other techniques, such as item randomization and ensuring the participants' anonymity to reduce common-method bias (CMB), which refers to the spurious variance that is attributable to the measurement method rather than to the constructs that the measures are assumed to represent (Podsakoff et al., 2003). After implementing the data quality checks and obtaining approval from the Institutional Review Board (IRB), we proceeded to the data collection phase and collected 362 usable responses from the participants (87% female and 13% male), whose average age was 27 years (standard deviation = 16.24). There were 168 responses from the control group participants and 194 responses from the popularity information group.

RESULTS

Manipulation Check

We used an experimental manipulation check to determine whether the participants' perceptions were manipulated in the intended manner and whether the treatment (i.e., the information about the popularity of Blockchain Wallet) was effective in obtaining significant evidence for inferring causality (Marett, 2015). The following manipulation check item was presented to the participants immediately after they read the narrative: "Blockchain Wallet seems to be a widely used digital currency technology". The responses were recorded on a seven-point Likert scale from strongly disagree to strongly agree. The results of the one-way ANOVA test showed a significant difference between the two groups in terms of the participants' understanding of the widespread use and popularity of Blockchain Wallet ($F = 17.02$, $p < .001$), which indicated that the manipulation was successful.

Confirmatory Factor Analysis

We used IBM Amos v25 to estimate the model fit statistics, and the results showed that the fit indices met the acceptable threshold (χ^2 /df= 2.03, CFI =.97, IFI =.97, RMSEA =.05). We also assessed the measurement model for composite reliability (CR), convergent validity, and discriminant validity. The CR should be 0.70 or higher (Bagozzi & Yi, 1988). For convergent validity, the items should be loaded highly (loading > 0.70) on their corresponding factors. The average variance explained (AVE) should also be at least 0.5 (Fornell & Larcker, 1981). To ensure discriminant validity, the square root of AVEs should be higher than the variance shared between the construct and the other constructs (Chin, 1998).

Table 1 shows the descriptive statistics, including the average mean and standard deviation of the measurement items, and Table 2 shows the factor loadings for these items. Most factor loadings were higher than .70. Table 2 displays the CRs and the AVEs and the construct validity in terms of square roots of the AVEs and the correlations. The diagonal elements, which are shown in bold in Table 3, are the squared roots of the variance shared between the constructs and their measures. The off-diagonal elements are the correlations. All the diagonal elements were larger than the off-diagonal elements, which indicated discriminant validity. Overall, the analysis results showed that all constructs had acceptable reliability, convergent validity, and discriminant validity. Specifically, our findings showed that the three types of uncertainty were discriminant constructs, thus providing empirical support that perceived uncertainty has a multidimensional nature.

Structural Analysis

To test the hypotheses, we performed a two-group covariance-based structural equation modeling (SEM) using IBM Amos v25. The covariance-based SEM allows researchers to explicitly model the measurement error variance, assess the model fit, and calculate estimates that are less biased than those of component-based SEM techniques, such as partial least squares (PLS) (Gefen et al.,

Table 1. Descriptive statistics

Construct	Item code	Control group		Treatment group	
		Average	Std. deviation	Average	Std. deviation
State uncertainty (STATE)	STATE1	5.07	1.76	4.84	1.77
	STATE2	5.25	1.64	4.88	1.74
	STATE3	4.36	1.65	4.14	1.60
Effect uncertainty (EFFECT)	EFFECT1	4.92	1.58	4.77	1.67
	EFFECT2	4.95	1.52	4.76	1.63
	EFFECT3	4.77	1.53	4.65	1.63
Imitation (IMI)	IMI1	3.03	1.56	3.24	1.70
	IMI2	2.63	1.48	2.79	1.64
	IMI3	3.32	1.51	3.28	1.65
	IMI4	2.69	1.49	2.80	1.16
Perceived usefulness (PU)	PU1	3.98	1.59	4.04	1.78
	PU2	3.96	1.64	3.96	1.77
	PU3	3.98	1.58	4.02	1.76
	PU4	3.86	1.59	3.92	1.71
Discounting own information (DOI)	DOI1	4.23	1.66	4.23	1.756
	DOI2	4.60	1.70	4.69	1.626
	DOI3	4.08	1.47	4.13	1.60
Response uncertainty (RESP)	RESP1	5.26	1.46	4.89	1.66
	RESP2	5.21	1.45	4.83	1.55
	RESP3	5.19	1.43	4.78	1.63
	RESP4	4.99	1.53	4.83	1.62
Behavioral intention (BI)	BI1	2.94	1.75	3.31	1.73
	BI2	2.69	1.56	2.98	1.61
	BI3	2.90	1.66	3.06	1.69
	BI4	2.81	1.68	3.04	1.70
	BI5	2.77	1.67	3.18	1.72

2011). Because of the multigroup nature of this study (i.e., a control group and a treatment group), we used a dummy-coded variable (defined as whether popularity information was received) to split the dataset into two groups to compare the statistical differences between them. We expected that most relationships in the control group analysis would be non-significant because the participants did not receive the treatment.

To test the moderation effects, we referred to the product-of-sums approach recommended by Goodhue et al. (2007). Specifically, the moderating factor (discounting one's own information) and the independent variable (perceived usefulness) were multiplied to generate an interaction factor (DOI × PU), which was then linked to the dependent variable (behavioral intention). We also checked the model fit statistics of the structural model and found that the indices met the acceptable threshold (χ^2 /df= 2.03, degree of freedom = 1.84, CFI =.94, IFI =.94, RMSEA =.04). Table 4 presents the path coefficients and the t-values derived to test the hypotheses, Table 5 shows the results of the hypothesis testing, and Figure 2 depicts the results of the structural analysis. We also measured the participants'

Table 2. Factor loadings

Construct (code)	Item code	Loading
State uncertainty (STATE)	STATE1	0.81
	STATE2	0.84
	STATE3	0.71
Effect uncertainty (EFFECT)	EFFECT1	0.79
	EFFECT2	0.89
	EFFECT3	0.83
Imitation (IMI)	IMI1	0.88
	IMI2	0.82
	IMI3	0.77
	IMI4	0.86
Perceived usefulness (PU)	PU1	0.94
	PU2	0.93
	PU3	0.92
	PU4	0.91
Discounting own information (DOI)	DOI1	0.81
	DOI2	0.71
	DOI3	0.62
Response uncertainty (RESP)	RESP1	0.79
	RESP2	0.91
	RESP3	0.93
	RESP4	0.88
Behavioral intention (BI)	BI1	0.93
	BI2	0.94
	BI3	0.92
	BI4	0.93
	BI5	0.95

Table 3. Square roots of AVEs (bolded) and correlations

Construct (C.R.; AVE)	RESP	BI	PU	DOI	STATE	EFFECT	IMI
RESP (.98; .90)	**0.88**						
BI (.98; .90)	-0.30	**0.93**					
PU (.87;.63)	-0.24	0.71	**0.92**				
DOI (.78;.55)	0.61	-0.23	-0.14	**0.72**			
STATE (.91;.73)	0.65	-0.22	-0.16	0.41	**0.79**		
EFFECT (.97;.91)	0.80	-0.33	-0.32	0.57	0.70	**0.84**	
IMI (.94;.70)	-0.31	0.56	0.54	-0.16	-0.29	-0.35	**0.83**

Table 4. Path estimates

Path	Control group			Treatment group		
	Std. estimate	t-value	p-value	Std. estimate	t-value	p-value
STATE → DOI	-0.00	-0.10	0.91(ns)	-0.17	-1.77	0.07(ns)
EFFECT → DOI	0.01	0.32	0.74(ns)	0.23	2.03	0.04*
RESP → DOI	0.03	1.01	0.31(ns)	0.33	2.75	0.00**
DOI → IMI	0.11	0.12	0.89(ns)	0.27	2.74	0.00**
IMI → BI	0.23	10.59	***	0.25	12.66	***
PU → BI	0.66	4.03	***	0.71	4.75	***
DOI moderating PU ® BI	-0.23	-4.25	***	-0.19	-4.10	***
Control: Age → BI	-0.14	-2.6	0.00**	-0.02	-0.41	0.67(ns)
Control: Gender → BI	0.05	0.97	0.32(ns)	0.00	0.07	0.94(ns)
Control: Education → BI	0.02	0.46	0.64(ns)	-0.04	-0.84	0.39(ns)

ns = non-significant, * p<.05, ** p<.01, *** p<.001

actual behavior by asking them whether they were interested in trying Blockchain Wallet, and we provided them with a download link at the end of the survey. The Pearson correlation analysis showed that the behavioral intention and the actual behavior of the participants, which was measured by a dummy-coded variable including "no = 0, yes = 1," were positively correlated ($r = .108$, $p < .05$).

Dashed line = non-significant path, ns = non-significant p-value, * p<.05, ** p<.01, *** p<.001

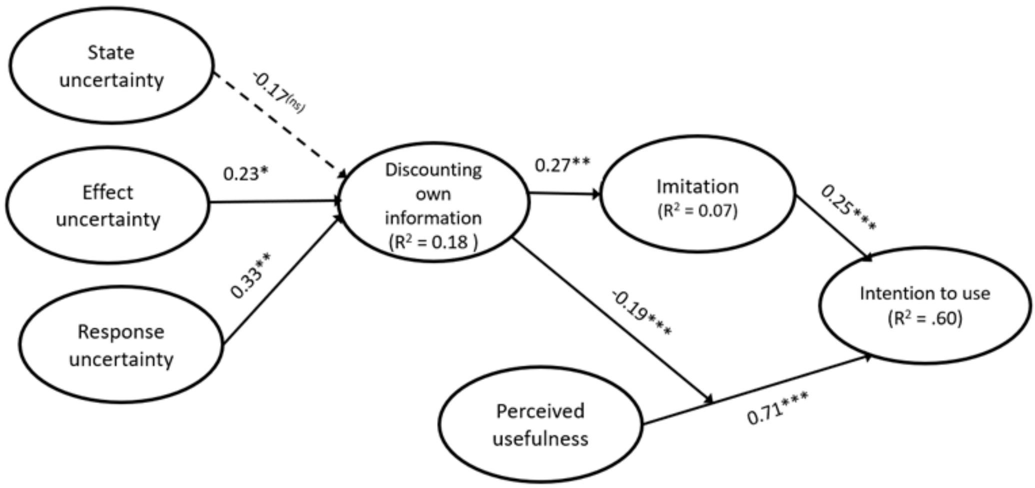
DISCUSSION

As we discussed earlier, the extant IS literature on herd behavior shows inconsistent and mixed results about how perceived uncertainty and herd behavior are linked in the adoption of technology adoption. This research contributes to the literature by further theorization of perceived uncertainty and whether and how it may trigger herd behavior. The empirical findings of this research supported the argument that an in-depth understanding of how herd behavior occurs in uncertain circumstances requires a refined analysis of perceived uncertainty as a key antecedent. Specifically, our findings showed that only effect uncertainty and response uncertainty lead to users' discounting of own information and imitation tendency. Earlier in this paper, we explained that state uncertainty refers to a situation in which the decision maker lacks information about the nature of the environment; effect

Table 5. Results of the hypothesis testing

H#	Path	Result
H1	STATE ® DOI	NOT Supported
H2	EFFECT ® DOI	Supported
H3	RESP ® DOI	Supported
H4	DOI ® IMI	Supported
H5	IMI ® BI	Supported
H6	PU ® BI	Supported
H7	DOI moderating PU ® BI	Supported

Figure 2. Structural analysis



uncertainty refers to the lack of information about how environmental events will affect the decision maker and the environment in which he or she operates; and, response uncertainty refers to a lack of information about what the response alternatives are and the consequences of each alternative. In the IS context, users may be unclear about what a technology is for (state uncertainty), uncertain about what a technology can do for them (effect uncertainty), and whether they are able to deal with potential changes of the technology, such as upgrades to support it following adoption (response uncertainty). One of the main factors that distinguish state uncertainty from the other two types of perceived uncertainty is the degree of the *personal relevance* that a decision maker perceives while evaluating the changes in the characteristics of the environment.

The results of the analysis showed that the participants' tendency to discount their own information was influenced primarily by how uncertain they were about what Blockchain Wallet could do for them and how they should cope with the potential changes associated with this technology. According to Milliken (1987), if perceived uncertainty makes the environment unpredictable, a decision maker is expected to have high levels of state uncertainty and probably lower levels of effect uncertainty and response uncertainty. This is because high levels of state uncertainty could make it difficult to adequately understand the environmental changes, thus raising the questions, "what effect will these changes have on my own tasks, and what should I do about it?" Correspondingly, individuals with high state uncertainty about a technology might not become predisposed to discounting their own information and imitation because they could regard the technology as irrelevant or too complex to understand. Our finding that mere perceived uncertainty about Blockchain Wallet was not an influential factor helps in understanding the reasons for the unexpected findings in the literature, specifically in studies in which perceived uncertainty was measured as a generic and unidimensional concept.

Our findings also showed that when the participants discounted their own information, they tended to rely less on their beliefs and attach more importance to the information obtained in their observations of others' actions. Consequently, discounting one's own information could heighten the possibility of imitating the actions of others instead of making decisions solely based on this information. As the value of one's own limited information is reduced, imitating others could be a legitimate strategy. The results showed that in uncertain circumstances, imitation becomes an authentic alternative strategy through discounting one's own information because users may believe that others have better and more complete information regarding a technology.

Furthermore, consistent with the findings of several studies in the IS literature (Sun, 2013; Vedadi & Warkentin, 2020; Vedadi & Greer, 2020), we found that the greater the discounting, the less influential personal beliefs were in making such decisions, which demonstrates the weak anchoring effect of these beliefs. The result of our analysis showed that the participants' discounting of their own information about Blockchain Wallet negatively moderated the relationship with perceived usefulness, which was based on their own assessments and intention to use this technology.

LIMITATIONS AND FUTURE RESEARCH

Herd behavior can have positive impacts in some cases, such as expediting the process of adopting useful technologies (Lieberman & Asaba, 2006). In contrast, herd behavior can have negative impacts, such as groupthink, misleading expectations, and the manipulation of users' choices (Muchnik et al., 2013). Distinguishing the different impacts of herd behavior and the outcomes of each was not within the scope of this research. Therefore, future studies should investigate how the types of perceived uncertainty and herd behavior lead individuals in positive or negative directions. This phenomenon is referred to as correct and incorrect herding. In a correct herd, imitation is a good strategy for reducing the disconfirmation of negative expectations (Sun, 2013). For instance, Walden and Browne (2009) found that correct herds tended to be robust to contrary information. Conversely, in incorrect herds, users may have unrealistic expectations about a technology, and thus could be more receptive to contrary information, which could signal the poor quality of a certain technology. Incorrect herds tend to collapse easily and rapidly in the presence of contrary information (Walden & Browne, 2009).

The participant population in this research was limited to the United States. This limitation could be addressed in future studies by investigating the role of cultural differences in the context of perceived uncertainty and herd behavior. Different ethnic groups may have different cultural values, which may affect the behavior of individuals within these groups (Hwang & Lee, 2012; Hwang, 2012). For instance, Chang and Lin (2015[a]) found that national culture influenced people's decision making in international stock markets and that herd behavior occurred more often in Confucian equity markets.

The scope of this research was limited to the context of choosing a nascent technology; however, in the IS literature, the role of perceived uncertainty on users' behavior has been investigated in different areas such as online reviews (e.g., Chang et al. 2015[b]), software development projects (e.g., Mellis et al., 2013), functional systems (e.g., Linn et al., 2001), and online bidding (e.g., Park & Keil, 2019); therefore, it is worthwhile to investigate whether and how the different types of perceived uncertainty influence decisions about adopting more mature and familiar technologies and use contexts. In addition, future research can complement the findings of this study by examining how people's perceived uncertainty about the specific features of a technology (compatibility, customizability, compliance, modularity, privacy, etc.) and uncertainty about the vendor of the technology may interact with the different types of environmental uncertainty and lead to herd behavior.

Furthermore, this research employed a cross-sectional experiment to investigate how different types of perceived uncertainty influenced herd behavior in the *initial* technology adoption stage. Future studies should explore the temporal aspects of perceived uncertainty and its influence on herd behavior in the IS context in order to examine the continuance characteristics of these phenomena. It is possible for both pre- and post-adoption herd behavior to exist as an influential factor in users' online behavior (e.g., Mattson & Aurigemma, 2018; Verkijika, 2020). Future work could further differentiate the relative importance of pre- and post-adoption herd behavior in initial and continuous technology usage. For instance, Vedadi and Warkentin (2020) found that imitation tendency influenced users' perceptions about security technology in both the pre- and post-adoption stages. Future research could further investigate whether and how the different types of perceived uncertainty influence herd behavior in the post-adoption stage.

IMPLICATIONS FOR PRACTICE

The results of this research indicate that in uncertain circumstances, people are significantly influenced by the actions of others. Hence, managers could frame their communications to inform employees that the majority of others have accepted a new system or technology to increase the likelihood of its acceptance. In other words, fostering herd behavior could expedite technology adoption (Lieberman & Asaba, 2006). Our findings also showed that only effect uncertainty and response uncertainty and not state uncertainty triggered herd behavior through discounting personal information and imitation. Because state uncertainty addresses only how environmental components could change, practitioners should be aware that individuals are likely to engage in context-relevant interpretations of uncertain circumstances.

Correspondingly, information obtained mindfully is likely to be focused on details that are relevant to current conditions (Fiol & O'Connor, 2003; Sun et al., 2016). This cognitive process emphasizes the importance of creating a sense of perceived personal relevance, which is defined as the belief that a certain object or behavior is associated with one's lifestyle, values, and self-image (Celsi et al., 1992). The cognitive process could be used to target end users because their personal beliefs motivate individuals to assume positive attitudes and intentions related to a specific behavior (i.e., the adoption of an emerging technology) (Dijkstra & Ballast, 2012).

CONCLUSION

Understanding how herd behavior occurs in the IS context is important because such behavior influences many choice decisions, is the main reason for some adoption decision anomalies, and explains the reasons behind the rapid rise or collapse of various technology fads. Perceived uncertainty is a critical factor that triggers herd mentality, but despite its influential role, the IS literature has not adequately conceptualized and operationalized this broad concept. This research contributes to the literature by examining the dimensions of perceived uncertainty and analyzing the influence of each dimension on triggering herd behavior. Our empirical findings showed that only effect uncertainty and response uncertainty, and not state uncertainty, triggered herd behavior, which indicates the importance of fine-grained analyses of the factors that could lead to herd behavior. Future research can build on the findings of this study to further analyze how herd behavior influences users' technology choices.

REFERENCES

Ashill, N. J., & Jobber, D. (2010). Measuring state, effect, and response uncertainty: Theoretical construct development and empirical validation. *Journal of Management*, *36*(5), 1278–1308. doi:10.1177/0149206308329968

Au, Y. A., & Kauffman, R. (2003). What do you know? rational expectations in information technology adoption and investment. *Journal of Management Information Systems*, *20*(2), 49–76. doi:10.1080/07421222.2003.11045764

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94. doi:10.1007/BF02723327

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817. doi:10.2307/2118364

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992–1026. doi:10.1086/261849

Celsi, R. L., Chow, S., Olson, J. C., & Walker, B. A. (1992). The construct validity of intrinsic sources of personal relevance: An intra-individual source of felt involvement. *Journal of Business Research*, *25*(2), 165–185. doi:10.1016/0148-2963(92)90015-4

Chang, C. H., & Lin, S. J. (2015a). The effects of national culture and behavioral pitfalls on investors' decision-making: Herding behavior in international stock markets. *International Review of Economics & Finance*, *37*, 380–392. doi:10.1016/j.iref.2014.12.010

Chang, H. H., Fang, P. W., & Huang, C. H. (2015b). The Impact of on-line consumer reviews on value perception: The dual-process theory and uncertainty reduction. *Journal of Organizational and End User Computing*, *27*(2), 32–57. doi:10.4018/joeuc.2015040102

Chang, H. H., Wong, K. H., & Chiu, W. S. (2019). The effects of business systems leveraging on supply chain performance: Process innovation and uncertainty as moderators. *Information & Management*, *56*(6), 103140. doi:10.1016/j.im.2019.01.002

Chin, W. (1998). Commentary: Issues and opinion on structural equation modeling. *Management Information Systems Quarterly*, *22*(1), xii–xvi.

Choe, J. M. (2003). The effect of environmental uncertainty and strategic applications of IS on a firm's performance. *Information & Management*, *40*(4), 257–268. doi:10.1016/S0378-7206(02)00008-3

Dijkstra, A., & Ballast, K. (2012). Personalization and perceived personal relevance in computer-tailored persuasion in smoking cessation. *British Journal of Health Psychology*, *17*(1), 60–73. doi:10.1111/j.2044-8287.2011.02029.x PMID:22106987

Duan, W., Gu, B., & Whinston, A. B. (2009). Informational cascades and software adoption on the Internet: An Empirical Investigation. *Management Information Systems Quarterly*, *33*(1), 23–48. doi:10.2307/20650277

Duncan, R. B. (1972). Characteristics of organizational environments and perceived environmental uncertainty. *Administrative Science Quarterly*, *17*(3), 313–327. doi:10.2307/2392145

Fiol, C. M., & O'Connor, E. J. (2003). Waking up! Mindfulness in the face of bandwagons. *Academy of Management Review*, *28*(1), 54–70. doi:10.5465/amr.2003.8925227

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *JMR, Journal of Marketing Research*, *18*(3), 382–388. doi:10.1177/002224378101800313

Gefen, D., Rigdon, E. E., & Straub, D. (2011). An update and extension to SEM guidelines for administrative and social science research. *Management Information Systems Quarterly*, *35*(2), iii. doi:10.2307/23044042

Gifford, W. E., Bobbitt, H. R., & Slocum, J. W. Jr. (1979). Message characteristics and perceptions of uncertainty by organizational decision makers. *Academy of Management Journal*, *22*(3), 458–481.

Goodhue, D., Lewis, W., & Thompson, R. (2007). Statistical power in analyzing interaction effects: Questioning the advantage of PLS with product indicators. *Information Systems Research*, *18*(2), 211–227. doi:10.1287/isre.1070.0123

Hwang, Y. (2012). End user adoption of enterprise systems in eastern and western cultures. *Journal of Organizational and End User Computing*, *24*(4), 1–7. doi:10.4018/joeuc.2012100101

Hwang, Y., & Lee, K. C. (2012). Investigating the moderating role of uncertainty avoidance cultural values on multidimensional online trust. *Information & Management*, *49*(3-4), 171–176. doi:10.1016/j.im.2012.02.003

Lieberman, M. B., & Asaba, S. (2006). Why do firms imitate each other? *Academy of Management Review*, *31*(2), 366–385. doi:10.5465/amr.2006.20208686

Linn, G., Casey, K. M., Johnson, G. H., & Ellis, T. S. (2001). Do broad scope managerial accounting systems moderate the effects of budget emphasis, budget participation and perceived environmental uncertainty on the propensity to create budgetary slack? *Journal of Computer Information Systems*, *42*(1), 90–96.

Lueg, R., & Borisov, B. G. (2014). Archival or perceived measures of environmental uncertainty? Conceptualization and new empirical evidence. *European Management Journal*, *32*(4), 658–671. doi:10.1016/j.emj.2013.11.004

Marett, K. (2015). Checking the manipulation checks in information security research. *Information and Computer Security*, *23*(1), 20–30. doi:10.1108/ICS-12-2013-0087

Mattson, T., & Aurigemma, S. (2018). Running with the pack: The impact of middle-status conformity on the post-adoption organizational use of twitter. *Journal of Organizational and End User Computing*, *30*(1), 23–43. doi:10.4018/JOEUC.2018010102

Mellis, W., Loebbecke, C., & Baskerville, R. (2013). Requirements uncertainty in contract software development projects. *Journal of Computer Information Systems*, *53*(3), 97–108. doi:10.1080/08874417.2013.11645636

Milliken, F. J. (1987). Three types of perceived uncertainty about the environment: State, effect, and response uncertainty. *Academy of Management Review*, *12*(1), 133–143. doi:10.5465/amr.1987.4306502

Muchnik, L., Aral, S., & Taylor, S. J. (2013). Social influence bias: A randomized experiment. *Science*, *341*(6146), 647–651. doi:10.1126/science.1240466 PMID:23929980

Park, S. C., & Keil, M. (2019). The moderating effects of product involvement on escalation behavior. *Journal of Computer Information Systems*, *59*(3), 218–232. doi:10.1080/08874417.2017.1328648

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *The Journal of Applied Psychology*, *88*(5), 879–903. doi:10.1037/0021-9010.88.5.879 PMID:14516251

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, *80*(3), 465–479.

Sun, H. (2013). A longitudinal study of herd behavior in the adoption and continued use of technology. *Management Information Systems Quarterly*, *37*(4), 1013–1041. doi:10.25300/MISQ/2013/37.4.02

Sun, H., & Fang, Y. (2010). Toward a model of mindfulness in technology acceptance. *Proceedings of ICIS*, 1–17.

Sun, H., Fang, Y., & Zou, H. M. (2016). Choosing a fit technology: Understanding mindfulness in technology adoption and continuance. *Journal of the Association for Information Systems*, *17*(6), 377–412. doi:10.17705/1jais.00431

Thies, F., Wessel, M., & Benlian, A. (2016). Effects of social interaction dynamics on platforms. *Journal of Management Information Systems*, *33*(3), 843–873. doi:10.1080/07421222.2016.1243967

Trenz, M., Huntgeburth, J., & Veit, D. (2018). Uncertainty in cloud service relationships: Uncovering the differential effect of three social influence processes on potential and current users. *Information & Management*, *55*(8), 971–983. doi:10.1016/j.im.2018.05.002

Tucker, C., & Zhang, J. (2011). How does popularity information affect choices? A field experiment. *Management Science*, *57*(5), 828–842. doi:10.1287/mnsc.1110.1312

Vedadi, A., & Greer, T. H. (2021). The Relationship Between Intention to Use, Popularity Information About a Technology, and Trust in Predecessors and Vendors. [IRMJ]. *Information Resources Management Journal*, *34*(1), 43–65. doi:10.4018/irmj.2021010103

Vedadi, A., & Warkentin, M. (2020). Can secure behaviors be contagious? A two-stage investigation of the influence of herd behavior on security decisions. *Journal of the Association for Information Systems*, *21*(2), 428–459. doi:10.17705/1jais.00607

Venkatesh, M., Morris, , Davis, , & Davis, . (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425–478. doi:10.2307/30036540

Verkijika, S. (2020). Assessing the role of simplicity in the continuance use of mobile APPS. *Journal of Organizational and End User Computing*, *32*(4), 26–42. doi:10.4018/JOEUC.2020100102

Walden, E., & Browne, G. J. (2009). Sequential adoption theory: A theory for understanding herding behavior in early adoption of novel technologies. *Journal of the Association for Information Systems*, *10*(1), 31–62. doi:10.17705/1jais.00181

Wang, C., Zhang, X., & Hann, I. H. (2018). Socially nudged: A quasi-experimental study of friends' social influence in online product ratings. *Information Systems Research*, *29*(3), 641–655. doi:10.1287/isre.2017.0741

Wang, Q., Yang, X., & Xi, W. (2018). Effects of group arguments on rumor belief and transmission in online communities: An information cascade and group polarization perspective. *Information & Management*, *55*(4), 441–449. doi:10.1016/j.im.2017.10.004

Weinmann, M., Schneider, C., & vom Brocke, J. (2016). Digital nudging. *Business & Information Systems Engineering*, *58*(6), 433–436. doi:10.1007/s12599-016-0453-1

Zhang, G., & Ravishankar, M. N. (2019). Exploring vendor capabilities in the cloud environment: A case study of Alibaba Cloud Computing. *Information & Management*, *56*(3), 343–355. doi:10.1016/j.im.2018.07.008

ENDNOTES

[1] Herd behavior can be distinguished from a close concept - subjective norms. The latter emanate from someone's reference group (i.e., important others), such as family members, co-workers, and close friends, whereas the members of a herd (e.g., a large user base) are usually strangers.

[2] Although IS research has identified numerous antecedents to technology adoption, we included only perceived usefulness in the model as the proxy of personal beliefs and judgements because a) it has been shown to have a substantial influence on the adoption decision, b) it is important to keep the research model as parsimonious as possible to emphasize the focus of this study. The main point is to test whether discounting own information weakens the influence of personal assessment.

[3] https://www.cnbc.com/2018/10/01/five-crucial-challenges-for-blockchain-to-overcome-deloitte.html

APPENDIX A. NARRATIVE AND TREATMENT

Bitcoin is a decentralized, peer-to-peer, cryptocurrency system designed to allow online users to process transactions through digital units of exchange called bitcoins. Bitcoin payments are processed through a private network of computers linked through a shared program. Each transaction is simultaneously recorded in a "blockchain" on each computer that updates and informs all accounts. Bitcoin provides users with anonymity, no third-party interruptions, no sales tax, very low transaction fees, no risk of inflation, no paperwork, and ease of use with mobile pay.
Blockchain Wallet: Bitcoin is a digital wallet platform accessible securely from web or mobile devices, making it easy for anyone to transact securely with bitcoin through a clean, intuitive user-interface.

- The following facts indicate that the widespread use of this wallet:
- There are over **30 million users** of this digital wallet.
- Users have engaged in an overall **$200 billion dollar transactions** with this wallet.
- Various sources recognize Blockchain Wallet: Bitcoin as the world's most trusted digital wallet by a **substantially large number of users**.
- In late 2017, this digital wallet became **the most downloaded app** in App Store.
- A 2018 Forbes report predicts that Blockchain Wallet: Bitcoin adoption will experience a **big boost** in near future.

Note: *All participants (in control and treatment groups) received the first two paragraphs, but only the treatment group participants received the bulleted popularity information about Blockchain Wallet.*

APPENDIX B. EXPERIMENTAL PROCEDURE

Table 6. The experimental procedure

<table>
<tr><th rowspan="2">Groups</th><th colspan="4">Phases</th></tr>
<tr><th>Pre-narrative measures
(all groups)</th><th>Narrative
(all group)</th><th>Treatment</th><th>Post-narrative measures
(in order)</th></tr>
<tr><td>Control group</td><td rowspan="2">1. Qualifying filter questions
2.Demographic information
3. Embedding data screening checks</td><td rowspan="2">Providing information about:
1.Introducing Blockchain Wallet
2. The benefits of using this technology</td><td>(none)</td><td rowspan="2">1.BI items
2. PU items
3. Uncertainty and herd behavior items
4. Actual adoption</td></tr>
<tr><td>Treatment group</td><td>Providing popularity information about Blockchain Wallet</td></tr>
</table>

* We included the "discounting own information" and "imitation" items in the control group survey instrument because we needed symmetric data across both groups to be able to run the covariance-based SEM model. We expected that the majority of hypotheses about the relationship between the different types of perceived uncertainty, discounting own information, and imitation be non-significant because the control group participants would not receive the popularity information. Lack of support for H1 to H4 confirmed our expectation.

APPENDIX C. CONSTRUCTS DEFINITION AND MEASUREMENT SCALES

Behavioral Intention

Definition: Users' intention to use a certain technology (Venkatesh et al., 2003).

BI1: I intend to use Blockchain Wallet in future.
BI2: I plan to adopt Blockchain Wallet soon.
BI3: I predict I will use Blockchain Wallet soon.
BI4: I expect to use Blockchain Wallet soon.
BI5: My intention is to use Blockchain Wallet in the near future.

Discounting Own Information

Definition: The degree to which one disregards his or her personal beliefs about a technology when making an adoption decision (Sun, 2013).

DOI1. If I were to use Blockchain Wallet, I wouldn't necessarily be making the decision based on my own assessment.
DOI2. My decision to use or not use Blockchain Wallet would not necessarily reflect my own preferences for doing digital transactions.
DOI3. If I did not know that a lot of people have already accepted Blockchain Wallet, I might choose another option.

Effect Uncertainty

Definition: The degree to which an individual may be uncertain about what a technology can do for him/her (Ashill & Jobber, 2010).

EFFECT1: I feel like I am not able to predict the impact of using Blockchain Wallet.
EFFECT2: I am not sure how Blockchain Wallet will affect my online transactions.
EFFECT3: I believe I do not fully understand the effect of Blockchain Wallet on my online transactions.

Imitation

Definition: The degree to which one follows previous adopters in adopting a certain form of technology (Sun 2013).

IMI1. It seems that Blockchain Wallet is a widely-used technology, therefore I would like to use it too.
IMI2. I follow others in deciding to use Blockchain Wallet.
IMI3. I would choose to use Blockchain Wallet because many others are already using it.
IMI4. I choose to use Blockchain Wallet because it is popular.

Perceived Usefulness

Definition: The degree to which a person believes that using a particular technology would enhance his or her performance (Venkatesh et al., 2003).

PU1: I think Blockchain Wallet would allow me to do my digital transactions more effectively.
PU2: Using Blockchain Wallet could help improve managing my digital transactions.

PU3: Blockchain Wallet would give me greater control over digital transactions.
PU4: Using Blockchain Wallet would enhance my effectiveness in my digital transactions.

State Uncertainty

Definition: The degree to which an individual is unclear about what a technology is exactly for (Ashill & Jobber, 2010).

STATE1: I feel like I do not have adequate information to understand how Blockchain Wallet exactly works.
STATE2: I believe the information I have about Blockchain Wallet is not enough.
STATE3: I feel like I am not able to easily get the necessary information about Blockchain Wallet.

Response Uncertainty

Definition: The degree to which an individual is uncertain about how to deal with potential changes of the technology, such as upgrades or requirements to download software to support it following adoption (Ashill & Jobber, 2010).

RESP1: I feel like I cannot accurately anticipate the consequences/outcomes of using Blockchain Wallet.
RESP2: I am not sure how to respond to changes and updates that may happen in Blockchain Wallet.
RESP3: I feel like I am not able to determine what my options would be if changes occur in Blockchain Wallet.
RESP4: I feel uncertain whether I would be able to respond appropriately to any changes and updates of Blockchain Wallet.