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Review

Models of information systems habit: An exploratory meta-analysis

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ABSTRACT

Habit has been modeled in different ways in information systems (IS) research. It is theorized to directly impact system use (SU), moderate the impact of behavioral intention (BI) on SU, indirectly impact SU through BI and other variables, mediate the effects of other variables on BI and SU, and moderate the effects of other variables on BI. Prior studies empirically examined models of habit in various settings such as different types of respondents and geographic regions. Unsurprisingly, empirical findings on the relationships involving habit have been inconsistent and mixed. This study proposes that the variations in empirical results may be due to the various models of habit and the study characteristics. An exploratory meta-analysis and review of habit and its relationships is conducted by synthesizing findings across 130 samples reported in 114 published studies. Implications for research and practice are discussed.

1. Introduction

Habit has gained prominence in information systems (IS) research and practice over the last decade. As IS engender considerable investments and become more prevalent within organizations and societies, the adoption, use, and continuance of IS by individuals continue to garner attention among researchers and practitioners. Although traditional explanations of individuals' IS adoption, use, or continuance are largely based on rational calculations (e.g., ease of use) and affective emotions (e.g., satisfaction), there is greater recognition of the role of habit in the IS domain (Ashraf, Tek, Anwar, Lapa, & Venkatesh, 2021).

Habit is of considerable importance to practice since it implies and underlies individuals' repeated engagements with IS (Limayem, Hirt, & Cheung, 2007). It relies on the automaticity of responses of individuals to environmental cues in using IS rather than rational or affective responses (Kim, Malhotra, & Narasimhan, 2005; Limayem et al., 2007; Ortiz de Guinea & Markus, 2009; Venkatesh, Thong, & Xu, 2012). Habit is applicable in both voluntary use contexts such as online shopping, social media, and instant messaging (Lankton, McKnight, & Tripp, 2020; Pahnila & Warsta, 2010; Sun et al., 2017) and mandatory use contexts such as learning management systems (Ain, Kaur, & Waheed, 2016; Kumar & Bervell, 2019). Habit can maximize IS use by individuals and enable organizations to realize returns on their IS investments.

Consistent with the notion of automatic response, habit was initially portrayed as an antecedent to explain the system use (SU) behaviors of individuals, and also a moderating influence on the relationship between behavioral intention (BI) and SU (e.g., Limayem & Hirt, 2003; Limayem et al., 2007). Over time, habit has been modeled in different ways including as a direct effect on BI (Liao, Palvia, & Lin, 2006), an indirect effect on SU through BI (Baptista & Oliveira, 2015) or other variables (Wilson, Mao, & Lankton, 2010), and as a mediator of other effects on SU (Khang, Han, & Ki, 2014) or BI (Chiu, Hsu, Lai, & Chang, 2012).

Prior empirical studies have examined such different models of habit in a variety of research contexts including types of respondents (e.g., students), geographic region (e.g., Europe), types of IS (e.g., enterprise system), context of use (e.g., mandatory), and data collection design (e.g., longitudinal). Unsurprisingly, empirical results related to habit have been mixed. For instance, habit had positive (Chang et al., 2010) and no (Shareef et al., 2017) effect on SU, and strengthened (He & Wei, 2009), weakened (Ye & Potter, 2011), and had no effect (Han, Shen, & Farn, 2016) on the relationship between BI and SU.

The foregoing underscores two related issues regarding research on habit. First, there is considerable diversity in how habit has been modeled in prior IS research. Habit has been theorized to have direct and indirect effects as well as mediating and moderating roles on other relationships, which may cloud the role of habit and its relationships in practice. Second, the empirical studies on habit have been conducted in various contexts and the results involving habit in prior studies have been inconsistent and even contradictory. The variation in empirical results may thus be attributable to the diversity in research contexts or

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the variations in habit models employed in prior studies.

This study seeks to better understand the role of habit by synthesizing prior literature based on the models of habit and the empirical findings related to habit. Specifically, this examines the questions: *How has habit been modeled in prior studies? How do models of habit and research contexts influence the empirical results related to habit?* The modeling and empirical findings on habit reported in 114 prior studies (involving 130 samples) published in journals between 2003 and 2021 are reviewed and synthesized using a combination of exploratory meta-analysis (Jeyaraj & Dwivedi, 2020) and critical review. This study thus provides additional insights into IS habit beyond prior meta-analytic studies that have examined habit in specific contexts such as UTAUT2 (Tamilmani, Rana, & Dwivedi et al., 2019; Tamilmani, Rana, Prakasam, & Dwivedi, 2019) and identifies directions for future research.

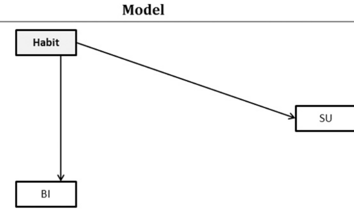
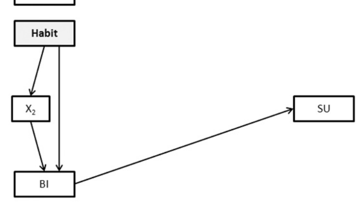
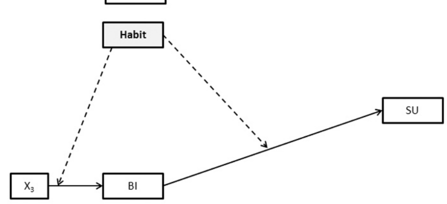
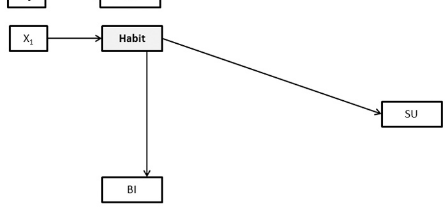
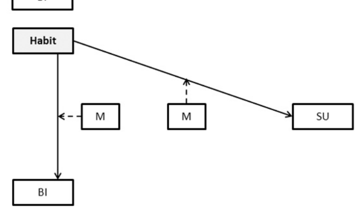
The remainder of the paper is organized as follows. The next section introduces the theoretical background for IS habit. The subsequent sections discuss the research methods and the results. The discussion section provides a summary of the findings and identifies potential directions for research on IS habit, followed by a conclusion section.

2. Theoretical background

Habit is defined as "the extent to which people tend to perform behaviors (use IS) automatically because of learning" (Limayem et al., 2007). It refers to automatic behaviors of individuals based on prior history of interactions with the IS without self-instruction (Triandis, 1980) and occurs outside of conscious awareness (Kim & Malhotra, 2005; Polites & Karahanna, 2012). Habit thus complements rational assessments found in the theory of reasoned action or the theory of planned behavior (Ajzen, 1985; Fishbein & Ajzen, 1975; Gefen, 2003; Limayem et al., 2007). It represents automatic responses to system use when faced with similar situations as before or particular stimuli (Limayem & Hirt, 2003; Wu & Kuo, 2008). Repetitions of prior behavior over time lead to the automaticity of the same behavior without repeatedly and consciously setting goals (Kim et al., 2005) although they may be subconsciously intentional and goal-oriented (Polites & Karahanna, 2012). Such automatic and habitual behaviors may be influenced by, but are different from, experience or continued use (Gefen, 2003; Venkatesh et al., 2012). Habit itself is distinct from actual behavior and represents a mindset or behavioral preference that can result in actual behavior (Gefen, 2003; Limayem et al., 2007).

Within the literature on IS acceptance and use, which aims to explain SU and BI, habit (H) has been modeled in different ways, as summarized in Table 1, in which X_1, X_2, and X_3, represent different independent variables and M refers to different moderating variables (as identified later). It influences actual behavior (SU), intention (BI), and moderates the impact of BI on SU (Limayem & Hirt, 2003; Limayem et al., 2007). Prior studies have also examined the antecedents of habit (Limayem et al., 2007; Lankton, Wilson, & Mao, 2010) and how other variables moderate the effect of habit on SU or BI (Ameri, Khajouei, Ameri, &

Table 1
Modeling of IS Habit.

Type	Paths	Model	Reference
Direct effects of habit	H→SU H→BI		Limayem and Hirt (2003) Hong et al. (2011)
Indirect effects of habit	H→BI→SU H→X_2→BI		Baptista and Oliveira (2015) Polites and Karahanna (2012)
Moderating effects of habit	H→[BI→SU] H→[X_3→BI]		Limayem et al. (2007) Hsu et al. (2015)
Mediating effects of habit (due to antecedents of habit)	X_1→H→SU X_1→H→BI due to X_1→H		Limayem et al. (2007) Lankton et al. (2010) Ray and Seo (2013)
Moderation on direct effects of habit	M→[H→SU] M→[H→BI]		Venkatesh et al. (2012) Ameri et al. (2020)

Jahani, 2020; Venkatesh et al., 2012).

2.1. Direct effects of Habit: H→SU and H→BI

Habit influences both SU and BI in extant literature (Hong, Thong, Chasalow, & Dhillon, 2011; Limayem & Hirt, 2003). Since habit is developed over time based on the past history of engagement with an IS such that it becomes an automatic response to particular stimuli (Limayem & Hirt, 2003), it is expected to have a direct effect on SU. Prior studies found positive (Chopdar & Sivakumar, 2019) and no (Han et al., 2016) effect of habit on SU.

Contrary to this habituation perspective, repeated engagements with an IS help establish attitudes and intentions, which in turn influence behavior according to the instant activation perspective based on the theory of planned behavior (Kim et al., 2005; Venkatesh et al., 2012). Thus, habit is theorized to also influence BI (Baptista & Oliveira, 2015; Liao et al., 2006; Wu & Kuo, 2008). Habit had positive (Kumar & Bervell, 2019) and no (Gwebu, Wang, & Guo, 2014) effect on BI in prior literature.

2.2. Indirect effects of Habit: H→BI→SU and H→X_2→BI

Habit exerts indirect effects on both SU and BI in prior literature (Baptista & Oliveira, 2015; Polites & Karahanna, 2012). The indirect effect of habit on SU is through BI, which implies that BI mediates the effect of habit on SU. This view is consistent with the general consensus in the technology acceptance literature that intention influences behavior (Ajzen, 1985; Davis, 1989; Fishbein & Ajzen, 1975). Along with other variables such as performance expectancy and social influence (Venkatesh, Morris, Davis, & Davis, 2003), habit also influences BI, which in turn influences SU. Results for H→BI→SU have been mixed—both H→BI and BI→SU were positively significant (Chopdar, Korfiatis, Sivakumar, & Lytras, 2018), H→BI was significant while BI→SU was not significant (Kumar & Bervell, 2019), and H→BI was non-significant while BI→SU was significant (Dai, Teo, & Rappa, 2020).

The indirect effect of habit on BI is through other variables (represented by X_2) such as affect and perceived usefulness (Limayem & Hirt, 2003; Wilson et al., 2010). This stems from the idea that the perceptions and beliefs of an individual may be shaped by habit developed over time (Gefen, 2003). For instance, as an individual habitually engages with an IS, the individual's beliefs about ease of use, usefulness, enjoyment, and satisfaction may increase, which in turn influences future BI (Shiau & Luo, 2013; Yen & Wu, 2016). The results for H→X_2→BI are mixed. For instance, perceived usefulness mediated the effect of habit on BI (Kumar & Bervell, 2019) and did not mediate the effect of habit on BI (Wilson et al., 2010). Similar inconsistencies were found for perceived ease of use (Kumar & Bervell, 2019; Shiau & Luo, 2013).

2.3. Moderating effects of Habit: H→[BI→SU] and H→[X_3→BI]

Habit moderates the effect of BI on SU in prior literature (Limayem et al., 2007; Limayem and Cheung 2008). This view is rooted on the distinction between reasoned and automatic responses, i.e., as automaticity of habit becomes more prevalent over time, the need to rely on reason or intention diminishes (Limayem et al., 2007; Verplanken, Aarts, van Knippenberg, & Moonen, 1998). Thus, the effect of BI on SU is weakened as habit is established to a greater extent. Prior studies have shown that habit had negative (Serenko & Turel, 2019), positive (He & Wei, 2009), and no (Han et al., 2016) effects on the relationship between BI and SU.

Habit is proposed to also moderate the effects of other variables (represented by X_3) on BI. Such variables include usefulness, trust, and satisfaction (Chou & Hsu, 2016; Gwebu et al., 2014; Hsu, Chang, & Chuang, 2015). This implies that the direct effects of such variables on BI may be altered based on habit—for instance, two individuals may intend to use an IS based on satisfaction with the IS; but all else being equal, the individual with a greater intensity of habit may intend to use the IS to a greater extent than the other individual (Khalifa & Liu, 2007). Results for the H→[X_3→BI] were mixed. For instance, the effect of user satisfaction on BI increased (Hsu et al., 2015) and decreased (Chou & Hsu, 2016) with increase in the level of habit.

2.4. Mediating effects of Habit: X_1→H→SU and X_1→H→BI

Habit mediates the effects of other variables (represented by X_1) on both SU and BI in prior literature.[2] With regard to SU, habit mediates the effects of hedonic motivation, different types of outcomes, experience, task characteristics, and technology characteristics (e.g., Kumar & Bervell, 2019; Khang et al., 2014; Clements & Boyle, 2018; Lankton et al., 2010). Empirical results for X_1→H→SU have been mixed—for instance, user satisfaction had a positive (Clements & Boyle, 2018) and no (Lankton et al., 2010) effect on habit although habit had a significant effect on SU. With regard to BI, habit mediates the effects of perceived usefulness, perceived ease of use, prior SU, user satisfaction, attitude, hedonic motivation, enjoyment, and value (e.g., Barnes, 2011; Herrero, Martín, & Salmones, 2017; Huang, Wu, & Chou, 2013; Wilson et al., 2010; Amoroso & Lim, 2017; Chiu et al., 2012). Prior studies show mixed results for X_1→H→BI. For instance, user satisfaction had a positive (Chiu et al., 2012) and no (Ray & Seo, 2013) effect on habit although habit had a significant effect on BI.

2.5. Moderation on direct effects of Habit: M→[H→SU] and M→[H→BI]

The direct effect of habit on SU and BI is moderated by other variables (represented by M) in prior literature. Variables such as age, gender, and experience are theorized to alter the effect of habit on both SU and BI (e.g., Venkatesh et al., 2012; Hu, Laxman, & Lee, 2020; Moghavvemi, Paramanathan, Rahin, & Sharabati, 2017). When all else is equal, both H→SU and H→BI become possible as described earlier based on the habituation and instant activation perspectives respectively (Kim et al., 2005). However, the effect of habit may be altered under different conditions. For instance, an individual who has used an IS for a longer period of time relative to another individual is more likely to have developed stronger habits that may influence SU and BI (Moghavvemi et al., 2017; Venkatesh et al., 2012). Prior studies found social presence to diminish the effect of habit on SU (Cui, Zhang, & Lowry, 2017), gender to increase the effect of habit on BI (Ameri et al., 2020), and experience to have no effect on H→SU or H→BI (Hu et al., 2020).

3. Research methods

3.1. Data collection

Articles published in journals between 2003, consistent with the publication of Limayem and Hirt (2003), and 2021 were considered for inclusion in the analysis. The search for articles was conducted on multiple electronic databases; specifically, *Business Source Complete*, *IEEE Xplore*, *ACM Digital Library*, and *Electronic Journal Center* were used. The primary key words for the search were "habit" and "information systems" on the abstract and title fields of the electronic databases. The initial search yielded more than 400 articles.

The articles were subjected to a screening process with the goal of maximizing the number of studies that may be included in the analysis. Duplicate articles (due to cross-listing on multiple databases) and unrelated articles (based on the titles and keywords) were first dropped.

[2] Few studies portray X_1→H but not H→SU or H→BI, i.e., the direct effects on habit. Such studies propose habit as the moderator of the H→BI relationship (i.e., Kang, Min, Kim, & Lee, 2013; Serenko & Turel, 2019; Limayem et al., 2007), or the effect of habit on BI to be mediated by other variables (i.e., Pahnila & Warsta, 2010 depicts affect to mediate H→BI).

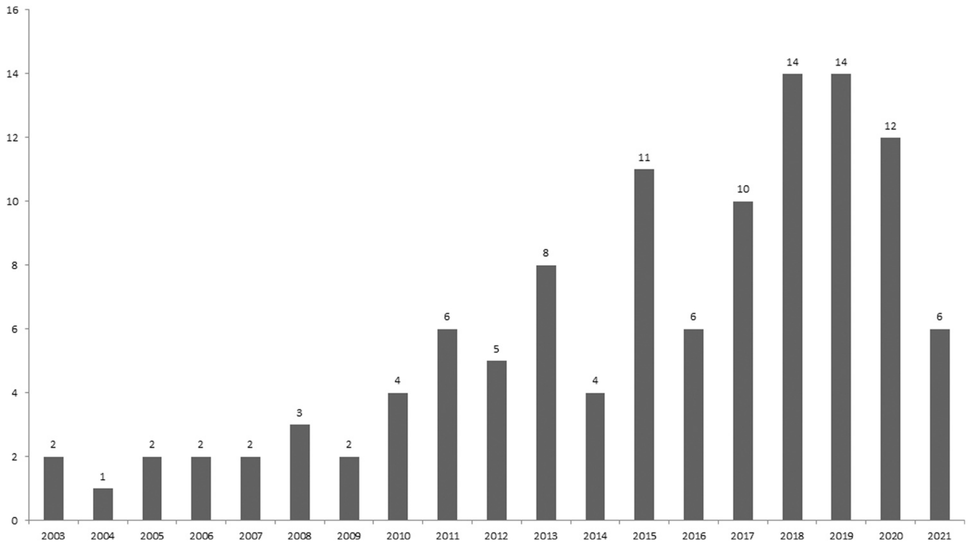


Fig. 1. Publication years of studies.

Table 2
Study variables.

Variable		Frequency or Mean (SD)
Relationship	H→SU	63
	H→BI	73
	H→BI→SU	18
	$H\rightarrow X_2$	21
	$H\rightarrow X_2\rightarrow BI$	20
	H→[BI→SU]	12
	$H\rightarrow [X_3\rightarrow BI]$	7
	$X_1\rightarrow H$	37
	$X_1\rightarrow H\rightarrow SU$	18
	$X_1\rightarrow H\rightarrow BI$	17
	M→[H→SU]	13
	M→[H→BI]	11
Geographic region	Americas	32
	Europe	19
	Asia	56
	Middle East	13
	Africa	8
Type of respondents	Students	42
	Employees	20
	Customers	31
	Others	41
Research design	Cross-sectional	90
	Longitudinal	40
Research model	# of IVs for SU	5.71 (5.85)
	# of IVs for BI	7.59 (7.30)
	# of IEs for SU	4.38 (7.47)
	# of IEs for BI	6.76 (11.85)

IV: Independent variable; IE: Interaction effect

Table 3
Results for relationships involving Habit.

Relationship	Studies	+	0	-
H→SU	63	49 (78%)	13 (21%)	1 (1%)
H→BI	73	60 (82%)	10 (14%)	3 (4%)
H→BI→SU	18	12 (67%)	6 (33%)	
$H\rightarrow X_2$	21	20 (95%)	1 (5%)	
$H\rightarrow X_2\rightarrow BI$	20	10 (50%)	6 (30%)	4 (20%)
H→[BI→SU]	12	2 (17%)	3 (25%)	7 (58%)
$H\rightarrow [X_3\rightarrow BI]$	7	2 (29%)	1 (14%)	4 (57%)
$X_1\rightarrow H$	37	26 (70%)	10 (27%)	1 (3%)
$X_1\rightarrow H\rightarrow SU$	18	11 (61%)	7 (39%)	
$X_1\rightarrow H\rightarrow BI$	17	13 (76%)	4 (24%)	
M→[H→SU]	13	6 (46%)	6 (46%)	1 (8%)
M→[H→BI]	11	2 (18%)	9 (82%)	

Subsequently, the abstract and research model were scrutinized to determine if the study had empirically examined habit along with BI or SU based on a primary data collection effort. Thus, studies were excluded from the analysis if: a) they provided theoretical or conceptual reviews (e.g., Polites & Karahanna, 2013), b) they dealt with quantitative meta-analysis (e.g., Tamilmani et al., 2019a, 2019b); c) empirical results involving habit were not reported (e.g., Naranjo-Zolotov, Oliveira, Casteleyn, & Irani, 2019), and d) SU or BI was not included in the research model (e.g., Ang, Talib, Tan, Tan, & Yaacob, 2015; Li, Zhang, Song, & Wu, 2017). This process resulted in 114 studies that may be considered for analysis. Nine studies (i.e., Ameen, Willis, & Shah, 2018; Ashraf et al., 2021; Chopdar et al., 2018; El-Masri & Tarhini, 2017; Kim et al., 2005; Kim, 2009; Liu, Shao, & Fan, 2018; Mehta, Morris, Swinnerton, & Homer, 2019; Merhi, Hone, & Tarhini, 2019) reported results of multiple samples based on different geographic regions or technologies, which were coded as separate observations. Thus, the analysis was based on 130 samples.[3] Fig. 1 shows the distribution of studies by publication year and Appendix A shows the studies[4] included in this analysis.

3.2. Coding

A uniform coding process was used to gather data from each study. First, the empirical findings related to habit were coded. This involved identifying the type of effect (e.g., H→SU, H→BI, H→[BI→SU], X1→H, etc. as shown in Table 1), the variables examined in the relationship, and

[3] Five studies (Frederik & Jan, 2015; He & Wei, 2009; Kim et al., 2005; Lee, 2014; Soror, Hammer, Steelman, Davis, & Limayem, 2015) examined multiple dependent variables, of which only one was coded to preserve the independence of samples.

[4] The majority of studies were published in Computers in Human Behavior (20), International Journal of Information Management (16), Information & Management (12), Behaviour & Information Technology (7), Information Development (5), Education and Information Technologies (5), MIS Quarterly (4), European Journal of Information Systems (4), Information Systems Frontiers (4), IEEE Transactions on Engineering Management (3), Decision Support Systems (3), Communications of the Association for Information Systems (3), Journal of the Association for Information Systems (2), Journal of Management Information Systems (2), Technological Forecasting & Social Change (2), Industrial Management & Data Systems (2), and Government Information Quarterly (2). The remaining articles were published in 18 different journals.

Table 4
Differences in the effects of H→SU, H→BI, and H→[BI→SU].

Category	Variable		H→SU		H→BI		H→[BI→SU]	
			Mean (SD) k	t	Mean (SD) k	t	Mean (SD) k	t
Region	Americas	= 1	0.82 (0.52) 17	0.63	0.67 (0.65) 12	-0.85	-0.67 (0.57) 3	-0.61
		= 0	0.74 (0.44) 46		0.80 (0.47) 61		-0.33 (0.86) 9	
	Europe	= 1	1.00 (0.00) 10	4.16***	0.73 (0.64) 11	-0.37	0.50 (0.70) 2	2.02**
		= 0	0.72 (0.49) 53		0.79 (0.48) 62		-0.60 (0.69) 10	
	Asia	= 1	0.71 (0.46) 24	-0.71	0.77 (0.50) 30	-0.19	-0.57 (0.78) 7	-0.78
		= 0	0.79 (0.46) 39		0.79 (0.51) 43		-0.20 (0.83) 5	
	Middle East	= 1	0.50 (0.54) 6	-1.46	0.92 (0.28) 12	1.06	n/a (n/a) 0	n/a
		= 0	0.79 (0.45) 57		0.75 (0.53) 61		-0.42 (0.79) 12	
	Africa	= 1	0.50 (0.57) 4	-1.16	0.88 (0.35) 8	0.55	n/a (n/a) 0	n/a
		= 0	0.78 (0.45) 59		0.77 (0.52) 65		-0.42 (0.79) 12	
Respondents	Students	= 1	0.79 (0.53) 19	0.30	0.74 (0.61) 23	-0.47	-0.83 (0.40) 6	-2.07**
		= 0	0.75 (0.43) 44		0.80 (0.45) 50		0.00 (0.89) 6	
	Employees	= 1	0.83 (0.38) 12	0.58	0.73 (0.46) 11	-0.37	0.25 (0.95) 4	2.50**
		= 0	0.75 (0.48) 51		0.79 (0.51) 62		-0.75 (0.46) 8	
	Customers	= 1	0.72 (0.46) 18	-0.42	0.80 (0.41) 15	0.16	n/a (n/a) 0	n/a
		= 0	0.78 (0.47) 45		0.78 (0.53) 58		-0.42 (0.79) 12	
	Others	= 1	0.73 (0.45) 15	-0.27	0.81 (0.48) 27	0.43	-0.50 (0.70) 2	-0.15
		= 0	0.77 (0.47) 48		0.76 (0.52) 46		-0.40 (0.84) 10	
Design	Longitudinal	= 1	0.73 (0.52) 30	-0.46	0.88 (0.35) 8	0.55	-0.50 (0.75) 8	-0.49
		= 0	0.79 (0.41) 33		0.77 (0.52) 65		-0.25 (0.95) 4	

SD: Standard deviation, k: Number of findings.
*** $p < 0.01$
** $p < 0.05$

the result reported for the effect. The result was coded as 1 for positive effect, 0 for no effect, and 1 for negative effect. Second, the characteristics of each study were coded. These included geographic location, respondents, and research design.[5] The geographic location of the study, captured as country, was used to construct categorical variables representing different regions: Americas, Europe, Asia, Middle East, and Africa. Data on respondents was used to create categorical variables representing different types: students, employees, customers, and others. The research design was coded as longitudinal (i.e., data collection was done over multiple points in time) or cross-sectional (i.e., data collection was completed at one point in time). One categorical variable was coded to indicate the type of research design. Finally, the research model characteristics were coded. These included data on the number of independent variables theorized to impact BI or SU and the number of interaction effects modeled to impact BI or SU. Table 2 shows the variables coded and the corresponding descriptive statistics.

3.3. Data analysis

The coded data on the 12 variations of relationships involving habit were analyzed to identify patterns using descriptive statistics. The differences in the results of the variables representing X_1, X_2, and M were also analyzed using descriptive statistics. The differences in the results for the H→SU, H→BI, and H→[BI→SU] relationships were examined by using *t*-tests on the study variables coded for this research.

Table 5
Variables representing X_2 in H→X_2→BI.

Variable (X_2)	H→X_2	X_2→BI	Study	+	0	-
Affect	■	■	Limayem & Hirt (2003); Limayem, Khalifa, & Chin (2004); Pee, Woon, & Kankanhalli (2008); Panhila & Warsta (2010)	4		
Attitude	■	■	Dai et al. (2020)	1		
Enjoyment	■	■	Yen & Wu (2016)	1		
Inertia	■	■	Polites & Karahanna (2012); Sun et al. (2017); Wang, Wang, & Lin (2018)	3		
Mooring effects	■	■	Ye & Potter (2011)	1		
Online shopping satisfaction	■		Khalifa & Liu (2007)	1		
Perceived ease of use	■	■	Gefen (2003); Kumar & Bervell (2019); Sezgin, Özkan-Yildirim, & Yildirim (2018); Shiau & Luo (2013); Wilson et al. (2010); Yen & Wu (2016)	6		
Perceived usefulness	■	■	Gefen (2003); Kumar & Bervell (2019); Liao et al. (2006); Liao, To, & Liu (2013); Liao, To, Liu, Kuo, & Chuang (2011); Wilson et al. (2010); Wu & Kuo (2008); Yen & Wu (2016)	8		
Resistance to change	■	■	Gan (2016)	1		
Social influence	■	■	Kumar & Bervell (2019); Wilson et al. (2010)	2		
Trust	■	■	Liao et al. (2006)	1		
User satisfaction	■	■	Shiau & Luo (2013)		1	

[5] The focal IS, use context, analysis method, and measurement instrument for habit were also coded but were unused in the analysis due to skewed data. The focal IS was used to determine the type of IS such as functional, network, and enterprise IS (e.g., McAfee, 2006). The vast majority of the studies dealt with network IS such as Facebook, Second Life, m-Learning, m-Banking, instant messaging, web portals, blogs, online auctions, digital games, B2C web sites, and public cloud storage. Few studies had examined function or enterprise IS such as knowledge management systems and business intelligence systems used within organizations (e.g., Han et al., 2016; He & Wei, 2009). The use context was coded as voluntary or mandatory, indicating the extent to which individuals may have control over their choice to use the focal IS. The majority of studies reported voluntary use (or did not explicitly mention the use context) while a few studies reported mandatory use (e.g., Ain et al., 2016; Kumar & Bervell, 2019). The analysis method represented whether the study used structural equation modeling (SEM) or other methods. The vast majority of studies employed SEM methods using various software tools such as LISREL, SmartPLS, or AMOS. Few studies (e.g., Musarurwa, Flowerday, & Cilliers, 2019; Tsai & LaRose, 2015) applied regression methods to analyze the data. The measurement instruments for habit are shown in Appendix B.

4. Results

Table 3 shows the results for the relationships involving habit across all prior studies included for analysis. Overall, the results are mixed—i.e., positive (+), negative (-), and no (0) effects have been reported in prior studies.

H→SU was positively significant in 49 of the 63 studies (78%) and not significant in 13 of the 63 studies (21%). H→BI was positively significant in 60 of the 73 studies (82%) and not significant in 10 of the 70 studies (14%) while H→X_2 was positively significant in 20 of the 21 studies (95%). Among the mediating relationships due to the inclusion of H→BI and H→X_2 in prior studies, H→BI→SU was positively significant in 12 of the 18 studies (67%) whereas H→X_2→BI was positively significant in 10 of the 20 studies (50%).

Among the moderating effects of habit, H→[BI→SU] was negatively significant in 7 of the 12 studies (58%), positively significant in 2 of the 12 studies (17%), and not significant in 3 of the 12 studies (25%). H→[X_3→BI] was positively significant in 2 of the 7 studies (29%).

The antecedents of habit (X_1→H) were positively significant in 26 of the 37 studies (70%) and not significant in 10 of the 37 studies (27%). Of the mediating relationships due to the inclusion of X_1→H in prior studies, X_1→H→SU was positively significant in 11 of the 18 studies (61%) and X_1→H→BI was positively significant in 13 of the 17 studies (76%).

For the moderating effects of other variables on relationships involving habit, M→[H→SU] was positively significant in 6 of the 13 studies (46%) and not significant in 6 of the 13 studies (46%) while M→[H→BI] was positively significant in 2 of the 11 studies (18%) and not significant in 9 of the 11 studies (82%).

The differences in the results for the H→SU, H→BI, and H→[BI→SU] relationships across studies are shown in Table 4. Specifically, the results were evaluated by applying *t*-tests on the data coded for the geographic region, type of respondents, and type of research design. The analysis generally showed no significant differences in the results of the relationships due to geographic region, type of respondents, or research design, except in few situations: H→SU was higher for studies set in Europe while H→[BI→SU] was significantly different between students and others, employees and others, and Europe and other regions. The differences for the H→[BI→SU] relationship collectively show that H→[BI→SU] is positive for employees and the European region and negative for other types of users and other geographic regions. These results should be interpreted with caution due to the lower number of times H→[BI→SU] has been examined.

5. Discussion

5.1. Findings

This research was aimed at reviewing and synthesizing empirical findings on IS habit, considering the many ways in which it has been modeled in prior studies. This study found 12 variations of relationships involving habit portrayed in prior research.

Table 6
Variables representing X_3 in H→[X_3→BI].

Variable (X_3)	Reference	+	0	-
Gratification	Chiu & Huang (2014)			1
Learning	Chou & Hsu (2016)		1	
Online shopping satisfaction	Khalifa & Liu (2007)	1		
Perceived usefulness	Gwebu et al. (2014)	1		
Perceived value	Hsu et al. (2015)		1	
Satisfaction with output quality	Chou & Hsu (2016)	1		
Satisfaction with process quality	Chou & Hsu (2016)	1		
Trust	Chou & Hsu (2016)	1		1
	Hsu et al. (2015)			
User satisfaction	Hsu et al. (2015)	1		
Utilitarian value	Kim et al. (2005)			1

H→SU received considerable support in prior research. These results are consistent with the theoretical argument that habit, portrayed as an automatic response due to learning, influences SU. The non-significant findings for the H→SU relationship did not reveal discernible patterns for explanation.

H→BI was the most frequently examined relationship involving habit (n = 73). Along with BI→SU, this finding implies that the effect of habit on SU may be mediated by BI. That is, the automatic habitual response may trigger intention, which suggests that BI may be a necessary condition for the effect of habit on SU, although habitual responses would be expected to influence behavior rather than intention. Nevertheless, results for both the H→BI and BI→SU relationships show moderate support for H→BI→SU, which is inferior to the empirical findings for H→SU.

Habit influenced variables other than SU and BI as represented by H→X_2. Studies typically modeled X_2→BI when examining H→X_2 thus resulting in H→X_2→BI. Table 5 shows the variables represented by X_2 and the overall results for the H→X_2 and X_2→BI relationship. The most frequently examined impacts of habit were perceived usefulness, perceived ease of use, and affect. Habit had positive significant effects on all examined variables except user satisfaction. When considering H→X_2 alone, the vast majority of the findings in prior studies were significant despite the diversity of variables representing X_2. However, the results for X_2→BI were mixed. Overall, the results show mixed support for the H→X_2→BI relationship, which suggests that the effect of habit on BI may not always be mediated by other variables.

The H→[BI→SU] relationship received reasonable support, which demonstrates that habit moderates the BI→SU relationship, although the direction of moderation seems inconclusive. Habit is generally expected to negatively moderate the BI→SU relationship, i.e., when habit as an automatic response becomes stronger, the impact of BI on SU diminishes. This notion implies that individuals may use systems even when not intending to use due to automatic habitual responses. However, prior studies found that habit positively moderates the BI→SU relationship (e.g., He & Wei, 2009) or has no effect on the BI→SU relationship (e.g., Han et al., 2016).

Table 6 identifies the variables representing X_3 in H→[X_3→BI], which represents the moderating effects of habit on relationships other than BI→SU. Habit seems to positively affect several relationships but such relationships have been examined only a few times.

Denoted by X_1→H, several antecedents of habit had been examined in prior literature. In combination with H→SU and H→BI, this also implies that habit mediated the effects of X_1 on both SU and BI. Table 7 shows the variables representing X_1 in both X_1→H→SU and X_1→H→BI, and the results for the X_1→H relationship. User satisfaction and prior system use were the most frequently examined variables that influenced habit—user satisfaction was positively significant in 10 of the 12 studies (83%) and prior system use was positively significant in 7 of the 8 studies (88%).

The results for both X_1→H and X_1→H→SU were mixed, which implies that habit may not be consistently influenced by X_1 or mediate the effects of X_1 on SU. In other words, automatic habitual responses may not always be influenced by other variables, and habit may not always mediate the impact of X_1 on SU. The results for both X_1→H and H→BI in X_1→H→BI were mixed, which implies that habit may not always be influenced by other variables and that habit may not always impact BI. A more salient consideration pertains to the role of habit in the H→BI relationship since automatic habitual responses are expected to impact SU more than BI.

When considered from the perspective of X_1→H→SU and X_1→H→BI, habit mediated the effects of user satisfaction and prior system use on both SU (e.g., Lankton et al., 2010) and BI (e.g., Huang et al., 2013). But habit mediated the effects of user satisfaction on either SU (e.g., Han et al., 2016) or BI (e.g., Ray & Seo 2012) and the effects of prior system use on either SU (e.g., Chiu et al., 2012) or BI (e.g., Wilson et al., 2010) but not both. Limayem et al. (2007) showed that habit did not mediate the effects of user satisfaction and prior system use on either SU or BI. Similar patterns can be determined in the mediating role of habit for

Table 7
Variables representing X_1 in $X_1 \rightarrow H \rightarrow SU$ or $X_1 \rightarrow H \rightarrow BI$.

Variable (X_1)	$X_1 \rightarrow H$	$H \rightarrow SU$	$H \rightarrow BI$	Study	+	0	-
Activity outcomes	■	■		Khang et al. (2014)	1		
Attitude	■		■	Amoroso & Lim (2017)	1	1	
	■			Serenko & Turel (2019)			
Breadth	■		■	Teng (2018)		1	
Convenience comfort	■		■	Baudier, Ammi, & Deboeuf-Rouchon (2020)	1		
Deficient social regulation	■	■		Khang et al. (2014)	1		
Depth	■		■	Teng (2018)	1		
Enjoyment	■		■	Barnes (2011)	1		
Familiarity	■		■	Chiu et al. (2012)	1		
Game-internal outcomes	■	■		Frederik & Jan (2015)	1		
Health	■		■	Baudier et al. (2020)	1		
Hedonic motivation	■	■	■	Kumar & Bervell (2019)	2		
	■		■	Herrero et al. (2017)			
Moral outcomes	■	■		Frederik & Jan (2015)	1		
Past experience	■	■		Khang et al. (2014)	1		
Perceived ease of use	■		■	Herrero et al. (2017)	3		
	■	■		Ashraf et al. (2021)			
	■		■	Ray & Seo (2013)			
Perceived effectiveness	■	■		Cui et al. (2017)	1		
Perceived usefulness	■		■	Barnes (2011)	3		
	■		■	Huang et al. (2013)			
	■		■	Ray & Seo (2013)			
Prior system use	■		■	Barnes (2011)	7	1	
	■		■	Huang et al. (2013)			
	■	■	■	Lankton et al. (2020)			
	■			Limayem et al. (2007)			
	■		■	Liu et al. (2018)			
	■		■	Ray & Seo (2013)			
	■	■		Han et al. (2016)			
	■	■	■	Wilson et al. (2010)			
Rationality	■	■		Cui et al. (2017)		1	
Regret	■			Kang et al. (2013)			1
Relation length	■		■	Teng (2018)	1		
Safety security	■		■	Baudier et al. (2020)	1		
Self-image congruity	■			Kang et al. (2013)	1		
Sense of belonging	■		■	Liu et al. (2018)	1		
Social context	■	■		Frederik & Jan (2015)	1		
Social influence	■			Pahnila &Warsta (2010)	1		
Social outcomes	■	■		Khang et al. (2014)	1		
Sustainability	■		■	Baudier et al. (2020)		1	
Switching cost	■		■	Teng (2018)	1		
Task behavior	■	■		O'Connor & O'Reilly (2018)	1		
Task importance	■	■		Lankton et al. (2010)	1		
Technology complexity	■	■		Clements & Boyle (2018)	1		
Technology instability	■	■		Clements & Boyle (2018)	1		
Technology-enabled triggers	■	■		Clements & Boyle (2018)	1		
User satisfaction	■		■	Amoroso & Lim (2017)	10	2	
	■		■	Alalwan (2020)			
	■		■	Chiu et al. (2012)			
	■	■		Clements & Boyle (2018)			
	■	■		Han et al. (2016)			
	■		■	Huang et al. (2013)			
	■			Kang et al. (2013)			
	■	■		Lankton et al. (2010)			
	■			Limayem et al. (2007)			
	■		■	Mouakket (2015)			
	■		■	Veeramootoo, Nunkoo, & Dwivedi (2018)			
	■		■	Ray & Seo (2013)			
Value	■		■	Chiu et al. (2012)	2		
	■		■	Setterstrom, Pearson, & Orwig (2013)			
Winning experience	■	■		Cui et al. (2017)	1		

other variables, although such variables have not been examined as frequently as user satisfaction or prior system use.

Table 8 shows the variables representing M for the M→[H→SU] and M→[H→BI] relationships. The most frequently examined moderators were age, gender, and experience as specified in the UTAUT2 models (e.g., Venkatesh et al., 2012). The moderators were largely non-significant in altering the effects of habit on SU or BI.

The analysis to uncover differences in effects of habit due to differences in study characteristics did not show significant differences except in a few situations involving the geographic region and type of respondents. These results have to be interpreted with caution since the sample sizes for each group are low and the analysis was not conducted on all possible study characteristics due to skewed data.

Fig. 2 depicts the consolidated model of IS habit based on the findings. (It does not represent the moderating effects of other variables on H→SU and H→BI since the majority of those effects were non-significant as shown in Table 8. Also not shown in the figure are the moderating effects of habit on the antecedents of BI due to low sample size as shown in Table 6). The antecedents and consequents of habit can be understood from the figure.

Table 8
Variables representing M in M→[H→SU] and M→[H→BI].

Variable (M)	H→SU	H→BI	Reference	M→[H→SU]			M→[H→BI]		
				+	0	−	+	0	−
Age		∎	Ameri et al. (2020)		3			7	
	∎	∎	Hu et al. (2020)						
		∎	Nikolopoulou, Gialamas, & Lavidas (2020)						
	∎	∎	Kwateng, Appiah, & Atiemo (2021)						
		∎	Moghavvemi et al. (2017)						
		∎	Tsai & LaRose (2015)						
	∎	∎	Venkatesh et al. (2012)						
Blogging time		∎	Shiau & Luo (2013)					1	
Discipline	∎	∎	Hu et al. (2020)		1			1	
Education level	∎	∎	Kwateng et al. (2021)		1			1	
Experience	∎	∎	Hu et al. (2020)		2			5	
		∎	Nikolopoulou et al. (2020)						
		∎	Moghavvemi et al. (2017)						
		∎	Tsai & LaRose (2015)						
	∎	∎	Venkatesh et al. (2012)						
Gender		∎	Ameri et al. (2020)	1	2		2	5	
	∎	∎	Hu et al. (2020)						
	∎	∎	Kwateng et al. (2021)						
		∎	Nikolopoulou et al. (2020)						
		∎	Moghavvemi et al. (2017)						
		∎	Tsai & LaRose (2015)						
	∎	∎	Venkatesh et al. (2012)						
Masculinity/ femininity		∎	Chopdar & Sivakumar (2019)					1	
Privacy restrictiveness		∎	Lankton, McKnight, & Thatcher (2012)				1		
Readiness	∎		Ashraf et al. (2021)	1					
Social presence	∎		Cui et al. (2017)			1			
Web personalization		∎	Krishnaraju, Mathew, & Sugumaran (2016)					1	

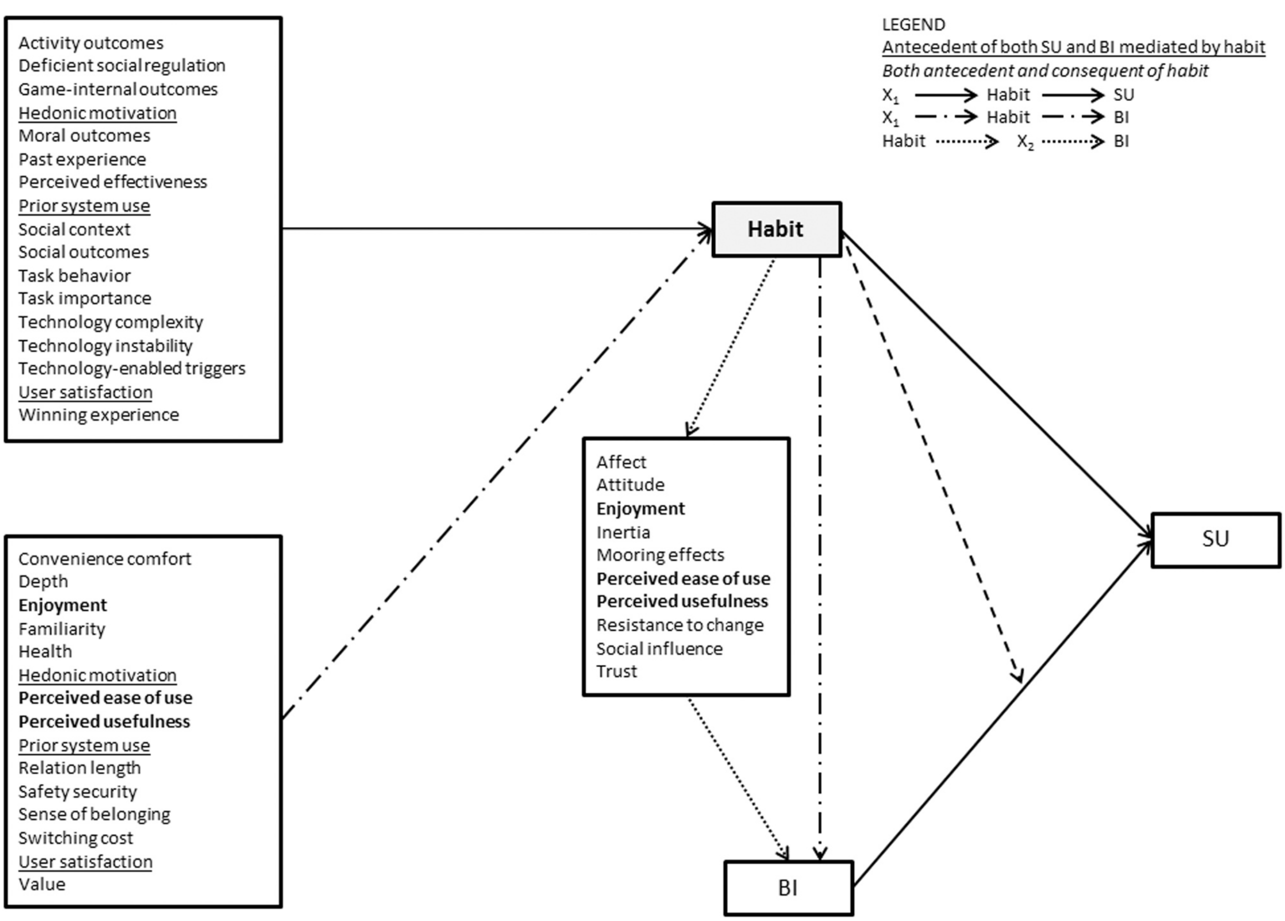


Fig. 2. Consolidated Model of IS Habit.

The antecedents of habit (X_1) seem to differ between the $X_1 \rightarrow H \rightarrow SU$ and $X_1 \rightarrow H \rightarrow BI$ paths examined in prior studies. In the context of SU, habit mediates the effects of variables representing task characteristics (importance), technology attributes (complexity), individual attributes (past experience), and outcomes (effectiveness). In the context of BI, habit mediates the effects of technology attributes (usefulness, ease of use) and individual attributes (enjoyment). Prior system use, user satisfaction, and hedonic motivation seem common to both $X_1 \rightarrow H \rightarrow SU$ and $X_1 \rightarrow H \rightarrow BI$. That is, these variables impact both BI and SU through habit. The antecedents of habit also include potential negative effects on BI, which can serve as barriers to usage. Such variables include inertia, resistance to change, and mooring effects (Gan, 2016; Sun et al., 2017; Ye & Potter, 2011).

There are commonalities between the antecedents of habit (X_1) in $X_1 \rightarrow H \rightarrow BI$ and the consequents of habit (X_2) in $H \rightarrow X_2 \rightarrow BI$. Specifically, perceived usefulness, perceived ease of use, and enjoyment influenced and were influenced by habit. In the larger context, habit mediates the effects of perceived usefulness, perceived ease of use, and enjoyment on BI (Barnes, 2011; Ray & Seo, 2013) whereas the effect of habit on BI is also mediated by perceived usefulness, perceived ease of use, and enjoyment (Kumar & Bervell, 2019; Yen & Wu, 2016). Given their roles as antecedents and consequents of habit, and given that habit is built over time as a result of SU, these variables most likely share a relationship with SU; however, these variables have been examined in the context of BI and not SU.

5.2. Limitations

The findings may be viewed in light of the limitations of this study. First, this research relied on data reported in published studies and did not have access to the original data on habit. The study assumes the quality, rigor, and accuracy of prior studies included in the meta-analysis. Second, data were coded using the descriptions given in the published studies. When such descriptions were not complete, certain assumptions were made when coding, particularly in the case of study characteristics such as the context of use, which may have biased the coded data. Third, data analysis was not possible on certain study characteristics such as type of IS due to skewed or low sample sizes. While such omissions do not necessarily question the validity of the findings, additional insights may have been possible if other study characteristics had been examined. Fourth, studies included in this analysis were obtained from journals and not from other sources such as dissertations or conference proceedings, which could have introduced bias in the sample. Finally, the study employed an exploratory meta-analysis of derived statistics and not a confirmatory meta-analysis of effect sizes (Jeyaraj & Dwivedi, 2020) that may have yielded an understanding of the magnitude of effects involving habit.

5.3. Implications for research

The findings of this study raise several implications for research. First, the question of whether habit influences SU, BI, or both seems crucial for modeling habit. While $H \rightarrow SU$ is based on the notion of automaticity of response, $H \rightarrow BI$ is rooted in rational calculations, both of which run counter to the other. If, in fact, habit is automatic and it diminishes the power of intention (Limayem et al., 2007), then it is unclear why rational processes and intention are appropriate in the context of habit. On the other hand, the role of automaticity seems redundant if habit relies on intentional considerations (Venkatesh et al., 2012). Prior studies of habit have more frequently examined its relationship with BI than SU; however, the results are generally inconsistent for both. Perhaps, automaticity and intentions belong to different stages of technology acceptance—for instance, BI may be necessary for SU during the early stages when the technology is new or not well-understood whereas habit may be more prominent during the later stages when the technology has been in use for a period of time and users are more knowledgeable of the technology and more comfortable using it. This implies that comparative studies of intention and habit in different stages may be necessary. Future studies that compare intention and habit in the early and later stages of technology acceptance may be needed for a more definitive conclusion about $H \rightarrow SU$ and $H \rightarrow BI$ (and also $H \rightarrow BI \rightarrow SU$).

Second, assuming that $H \rightarrow BI$ is appropriate at least during the later stages of technology acceptance, the question of whether habit has a direct effect on BI or whether the effect of habit on BI is mediated by other variables assumes importance. Technology acceptance studies have argued that rational evaluations of perceived usefulness and perceived ease of use impact BI (Venkatesh et al., 2003). These foundations have been used to argue that habit impacts such variables, which in turn impacts BI (Yen & Wu, 2016). Prior studies, for instance, have argued for both $H \rightarrow BI$ (Chipeva, Cruz-Jesus, Oliveira, & Irani, 2018) and $H \rightarrow X_2 \rightarrow BI$, in which X_2 is represented by different variables such as perceived usefulness and perceived ease of use (Kumar & Bervell, 2019). Such alternate treatments of habit on BI raise questions about whether habit is a sufficient condition for BI or if rational considerations beyond habit are necessary for BI. Future studies that examine the necessary and sufficient conditions for habit in the context of BI may help address these questions.

Third, the relevance of the antecedents of habit examined in prior studies is another candidate for debate. It would be important to know the variables that influence habit from the perspective of developing automatic responses (Limayem & Hirt, 2003). For instance, automatic responses may be influenced by prior system use (Limayem et al., 2007). To some extent, variables such user satisfaction, perceived usefulness, and perceived ease of use may influence habit since they may serve as proxies for prior system use (DeLone & McLean, 2003) and also since they could be influenced by system use as users learn the technology and identify different and effective ways to use it (Limayem et al., 2007; Ray & Seo, 2013). Outcome-related variables such as social outcomes, moral outcomes, and perceived effectiveness (Cui et al., 2017; Frederik & Jan, 2015; Khang et al., 2014), possibly shaped by prior system use, and emotion-related variables such as hedonic motivation and enjoyment (Kumar & Bervell, 2019) have also been proposed to influence habit. These seem counter to the general consensus that habitual and automatic responses result from prior system use (Limayem et al., 2007; Venkatesh et al., 2012). Future studies that strive to examine these aspects might be fruitful in fostering a more precise understanding of habit and its antecedents.

Fourth, the moderating effects of other variables on $H \rightarrow SU$ and $H \rightarrow BI$ may need further examination. They have been examined in only a limited number of prior studies, with age, gender, and experience (Hu et al., 2020; Venkatesh et al., 2012) receiving the most attention. Barring few exceptions (Ameri et al., 2020), the moderating effects on both relationships have been largely non-significant. This raises few questions about such moderators. For instance, if habit is based on unconscious automatic behaviors, why would its effect on SU or BI vary by age, gender, or experience? It seems habit would drive the behaviors (SU) and intentions (BI) of individuals regardless of their individual differences. Future studies may employ qualitative research designs to determine if moderators are likely to influence the effects of habit on SU and BI.

Finally, the question of how habit develops over time may be examined. Although it is expected that habit may stem from SU, it is unclear if $SU \rightarrow H$ can be assumed. On the other hand, prior studies show perceived usefulness (PU), perceived ease of use (PE), and enjoyment (EN) influence habit (Barnes, 2011; Ray & Seo, 2013), but it is unclear if they may be influenced by SU. In other words, could $SU \rightarrow H$ be expected or would $SU \rightarrow PU \rightarrow H$ or $SU \rightarrow PE \rightarrow H$, $SU \rightarrow EN \rightarrow H$ be more appropriate? The causal path remains unclear. Could it be $PU \rightarrow H \rightarrow SU \rightarrow PU$ or just $H \rightarrow SU \rightarrow H$ or something else? It may be more confusing when BI is also considered. Could it be: $PU \rightarrow H \rightarrow BI \rightarrow SU \rightarrow PU$ for instance? Future research using longitudinal designs are needed to address these questions to better understand the relationship between the trifecta of habit, BI, and SU.

5.4. Implications for practice

This study also offers implications for practice. First, organization leaders could find it useful to engender IS habit among individuals to maximize return on their investments in IS. Habit provides an alternate path to SU without relying on the intentions of individuals and has the capability to reduce the cognitive processing typically involved in choosing to use IS. Use of IS may be embedded in daily work routines or mandated by organizational managers to motivate individuals.

Second, organizations may strive to make everyday engagements with the IS pleasurable and satisfying for individuals. This has the potential to tap into the hedonic motivation of individuals, which also influences habit. Further, individuals may use the system to a greater extent if they are more satisfied with its capabilities or information provision. Everyday use fosters automatic responses, which further influence habit.

Finally, organizations could institute mechanisms by which users can enhance their evaluations of usefulness and ease of use of systems. While repeated use of systems can also facilitate a finer understanding of usefulness and ease of use (i.e., habit can help appreciate the system capabilities), systems of higher complexity and those that lag on usability may hinder user evaluations. Training sessions or other interventions may be helpful in maintaining a virtuous cycle of user evaluations and habits.

6. Conclusion

This study reviewed and synthesized empirical findings involving IS habit reported in extant research. Identifying the various models of habit in prior literature, this study offers a critical review of the theoretical relationships and synthesizes the empirical findings on habit. The study identifies the different ways in which habit is modeled in extant research including its direct effect on SU, indirect effect on SU through BI, mediating effect of other variables on SU and BI, and moderating effect on BI→SU. The analysis showed that certain study characteristics influenced the empirical results although the results should be interpreted with caution due to low sample sizes. Several directions for future research are suggested to foster a clearer understanding of IS habit.

Appendix A. Prior studies included in this review

Study	Region	Respondents	Technology	Design
Açıkgül & Şad (2021)	Turkey	Students	Mobile technology	C
Agudo-Perregrina et al. (2014)	Spain	Students	e-Learning system	C
Ain et al. (2016)	Malaysia	Students	LMS	C
Alajmi (2019)	Kuwait	Faculty	Library electronic info res.	C
Alalwan (2020)	Jordan	Customers	Mobile food ordering apps	C
Alalwan (2018)	Jordan	Customers	Social media advertising	C
Alharbi et al. (2017)	Saudi Arabia	General public	e-Government services	C
Ameen et al. (2018)	Jordan	Users	Smartphone	C
Ameen et al. (2018)	UAE	Users	Smartphone	C
Ameri et al. (2020)	Iran	Students	LabSafety application	C
Amoroso & Lim (2017)	Philippines	Consumers	Financial mobile app	C
Arain et al. (2019)	Pakistan	Students	m-Learning	C
Ashraf et al. (2021)	9 countries	Smartphone users	m-Commerce	L
Baabdullah et al. (2019)	Saudi Arabia	Customers	m-Banking	C
Baptista & Oliveira (2015)	Mozambique	Customers	Online banking	C
Barnes (2011)	UK	Users	Second Life	C
Baudier et al. (2020)	France	Digital natives	Smart home concept	C
Bhattacherjee & Lin (2015)	Taiwan	Insurance agents	Work system	L
Bhattacherjee et al. (2012)	USA	Students	Internet browser	L
Chang et al. (2010)	Taiwan	Employees	Real-estate IS	C
Cheng et al. (2019)	China	Users	Mobile personal cloud storage	C
Chipeva et al. (2018)	2 countries	Alumni	ICT	C
Chiu & Huang (2014)	Taiwan	Users	Facebook	C
Chiu et al. (2012)	Taiwan	Customers	Online shopping	C
Chopdar & Sivakumar (2019)	India	Consumers	Mobile shopping apps	L
Chopdar et al. (2018)	USA	Consumers	Mobile shopping apps	C
Chopdar et al. (2018)	India	Consumers	Mobile shopping apps	C
Chou & Hsu (2016)	Taiwan	Customers	Online shopping	C
Clements & Boyle (2018)	USA	Students	Mobile applications	C
Cui et al. (2017)	China	Bidders	Online auction	C
Dai et al. (2020)	China	Students, Teachers	MOOC	C
Dhir et al. (2018)	India	High school students	Social networking	C
Duarte & Pinho (2019)	Portugal	Users	Mobile health	C
El-Masri & Tarhini (2017)	Qatar	Students	e-Learning system	C
El-Masri & Tarhini (2017)	USA	Students	e-Learning system	C
Eneizan et al. (2019)	Jordan	Customers	Mobile marketing	C
Frederik & Jan (2015)	Belgium	Students	Digital games	C
Gan (2016)	China	Students	Instant messaging	C
Gefen (2003)	USA	Students	Online store	C
Goncalves et al. (2018)	Angola	Students, Faculty	ICT	C
Guo & Barnes (2011)	UK	Users	Second Life	C
Gwebu et al. (2014)	USA	Users	Facebook	C
Han et al. (2016)	Taiwan	Employees	Business intelligence system	L
He & Wei (2009)	Hong Kong	Employees	KMS	L
Herrero et al. (2017)	Spain	Tourists	Facebook	C
Hew et al. (2015)	Malaysia	Students	Mobile app	C
Hong et al. (2011)	USA	Employees	Agile information systems	L
Hsu et al. (2015)	Taiwan	Customers	Online group-buying	C

(continued on next page)

(*continued*)

Study	Region	Respondents	Technology	Design
Hu et al. (2020)	China	Academics	Mobile technology	C
Huang et al. (2013)	Taiwan	Employees	Data mining tools	C
Kamdjoug et al. (2021)	Cameroon	Users	Mobile banking	C
Kang et al. (2013)	Korea	Users	Social network site	C
Kesharwani (2020)	India	Students	Quicforce (LMS)	L
Khalifa & Liu (2007)	USA	Online shoppers	Online store	C
Khang et al. (2014)	USA	Users	Social media	C
Khansa et al. (2015)	USA	Users	Yahoo! Answers	L
Kim (2009)	USA	Employees	Enterprise-wide system	L
Kim & Malhotra (2005)	USA	Students	Personalized portal web site	L
Kim et al. (2005)	USA	Users	Online news	L
Kim et al. (2005)	USA	Users	Online news	L
Krishnaraju et al. (2016)	India	Students	e-Government service	C
Kumar & Bervell (2019)	Malaysia	Students	Google classroom	L
Kwateng et al. (2021)	Ghana	Healthcare workers	Health information system	C
Lankton et al. (2020)	USA	General population	Facebook	C
Lankton et al. (2012)	USA	Students	Facebook	C
Lankton et al. (2010)	USA	Students	University internet app	L
Lee (2014)	Korea	Students	Social network service	L
Liao et al. (2006)	Taiwan	Online shoppers	B2C site	C
Liao et al. (2013)	Taiwan	Blog users	Blogs	C
Liao et al. (2011)	Taiwan	Users	Web portal	C
Limayem & Cheung (2008)	Hong Kong	Students	Internet-based learning tech	L
Limayem & Cheung (2011)	Hong Kong	Students	Blackboard	L
Limayem and Hirt (2003)	Hong Kong	Students	WebBoard	L
Limayem et al. (2004)	Canada	Students	Piracy [not specific tech]	L
Limayem et al. (2007)	Hong Kong	Students	WWW	L
Lin & Wang (2006)	Taiwan	Students, Others	Mobile commerce	C
Liu et al. (2018)	China	Users	Social networking (Renren)	L
Liu et al. (2018)	China	Users	Microblogging (Weibo)	L
Macedo (2017)	Portugal	Older adults	ICT	C
Maier et al. (2021)	Germany	Users	Facebook	L
Mehta et al. (2019)	Gambia	Employees	e-Learning	C
Mehta et al. (2019)	UK	Employees	e-Learning	C
Merhi et al. (2019)	England	Customers	Mobile banking	C
Merhi et al. (2019)	Lebanon	Customers	Mobile banking	C
Moghavvemi et al. (2017)	Malaysia	Students	e-Learning (Facebook)	C
Moody & Siponen (2013)	Finland	Employees	Internet	C
Mouakket (2015)	UAE	Students	Facebook	C
Musarurwa et al. (2019)	Zimbabwe	Employees	BYOD	C
Mutterlein et al. (2019)	Germany	Students	Mobile augmented reality	C
Nikolopoulou et al. (2020)	Greece	Students	Mobile technology/phone	C
O'Connor & O'Reilly (2018)	Canada	Healthcare prof.	Mobile health	C
Osatuyi & Turel (2018)	USA	Students	Social networking site	L
Pahnila & Warsta (2010)	Finland	Students, net users	Online shopping	C
Pal et al. (2021)	India	Executive students	Mobile payments	C
Pee et al. (2008)	Singapore	Employees	Nonwork related computing	C
Polites & Karahanna (2012)	USA	Students	e-mail, Google Docs	L
Ray & Seo (2013)	Taiwan	Users	Information web sites	C
Serenko & Turel (2019)	USA	Students	Facebook	C
Setterstrom et al. (2013)	USA	Students	Wireless technology	C
Sezgin et al. (2018)	Turkey	Physicians	Mobile health apps	C
Shareef et al. (2017)	Bangladesh	Customers	Short messaging service	C
Shaw & Sergueeva (2019)	Canada	Consumers	Mobile commerce	C
Sheikh et al. (2017)	Saudi Arabia	Social media users	Social commerce	C
Shiau & Luo (2013)	Taiwan	Blog users	Blogs	C
Song et al. (2020)	South Korea	Users	Public cloud storage services	C
Soror et al. (2015)	USA	Users	Mobile phones	C
Sun et al. (2020)	China	Customers	Omnichannel service	C
Sun et al. (2017)	China	Users	Instant messaging	C
Tam et al. (2020)	Portugal	Users	Mobile apps	C
Teng (2018)	Taiwan	Gamers	Online games	C
Thusi & Maduku (2020)	South Africa	Clients	Mobile banking apps	C
Tsai & LaRose (2015)	USA	Residents	Broadband	C
Turel (2015)	USA	Students	Facebook	C
Veeramootoo et al. (2018)	Mauritius	Citizens	e-Government service	L
Venkatesh et al. (2012)	Hong Kong	Consumers	Mobile internet	L
Wang et al. (2018)	Taiwan	Users	Computer operating system	C
Wilson & Lankton (2013)	USA	Students	University Internet app	L
Wilson et al. (2010)	USA	Students	University Internet app	L
Wu & Kuo (2008)	Taiwan	Consumers	Google search	C
Ye & Potter (2011)	USA	Students	Browser	L
Yen & Wu (2016)	Taiwan	Consumers	Mobile financial services	C

Appendix B. Measurement instruments for Habit

Origin	Measurement items	Studies
Verplanken & Orbell (2003)	Behavior X is something … a) I do frequently. b) I do automatically. c) I do without having to consciously remember. d) that makes me feel weird if I do not do it. e) I do without thinking. f) that would require effort not to do it. g) that belongs to my (daily, weekly, monthly) routine. h) I start doing before I realize I'm doing it. i) I would find hard not to do. j) I have no need to think about doing. k) that's typically "me". l) I have been doing for a long time.	Chang et al. (2010); Chiu and Huang (2014); Lee (2014); Moody & Siponen (2013); Wu & Kuo (2008)
Gefen (2003)	a) This is where I usually go to buying CDs/books. b) This is my preferred online CDs/books vendor. c) When I need to buy CDs/books online this is where I go first. d) I often buy CDs/books online from this vendor.	Liao et al. (2006); Lin & Wang (2006)
Limayem & Hirt (2003)	a) The use of WebBoard has become a habit for me. b) I am addicted to using WebBoard. c) I must use WebBoard. d) I don't even think twice before using WebBoard. e) Using WebBoard has become natural to me.	Cheng et al. (2019); He & Wei (2009);Lankton et al. (2010);Shiau & Luo (2013);Sun et al. (2017);Wilson et al. (2010)
Limayem et al. (2007)	a) Using the WWW has become automatic for me. b) Using the WWW is natural to me. c) When faced with a particular task, using the WWW is an obvious choice for me.	Barnes (2011);Gwebu et al. (2014);Hsu et al. (2015);Serenko & Turel (2019);Wang et al. (2018)
Venkatesh et al. (2012)	a) The use of mobile Internet has become a habit for me. b) I am addicted to using mobile Internet. c) I must use mobile Internet. d) Using mobile Internet has become natural to me. *(dropped)*	Ameen et al. (2018);Chopdar & Sivakumar (2019);Merhi et al. (2019);Moghavvemi et al. (2017); Tam et al. (2020)

Note: The measurement instrument in Polites and Karahanna (2012) is not reported here since it had not been used in studies included in this meta-analysis.

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