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Research Note

Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison

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Although much research has examined *conscious use*, which involves deliberate evaluation and decision making, we know less about *automatic use*, which occurs spontaneously with little conscious effort. The objective of this study is to compare two contrasting views in the literature on the nature of automatic use, namely, the habit/automaticity perspective (HAP) and the instant activation perspective (IAP). According to HAP, automatic use occurs because of the force of habit/automaticity without the formation of evaluations and intention; thus, past use—which is a proxy for habit/automaticity—is believed to weaken the evaluations-intention-usage relationship. In contrast, IAP posits that automatic use is simply an expedited form of conscious use; accordingly, as with conscious use, automatic use is still a function of evaluations/intention, so past use will not weaken the evaluations-intention-usage relationship. We tested the competing hypotheses using 2,075 cross-sectional and 990 longitudinal responses from actual users of two online news sites. Our results show that the evaluations-intention-usage relationship is generally weaker among heavier users than among lighter users. These findings suggest that with an increase in past use, user behavior becomes less evaluative and less intentional, in support of the argument that automatic use is driven more by habit/automaticity than by instant activation of cognitions. Overall, this research shows an initial piece of evidence of the moderating role of past use in postadoption phenomena, and it is expected to help the information systems community systematically investigate the important yet underexplored subject of habit/automaticity.

Key words: user evaluation; user behavior; habit; automaticity; structural equation modeling; longitudinal study; cross-validation
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1. Introduction

Information technology (IT) use—defined as the utilization of an IT application by individuals—has long been of interest to researchers in the information systems (IS) field (Straub et al. 1995). According to a review of the literature, much research on IT use assumes that IT use is rational behavior and thus is mainly driven by analytical, reflective, and deliberate cognitive processing (Jasperson et al. 2005, Seddon 1997). In particular, the major premise of this prevailing view is that IT use is activated by an intention to use an IT application, which in turn is determined by conscious evaluations about using the IT application (Jasperson et al. 2005, Venkatesh et al. 2003). Numerous theories that are used to explain IT use center on this evaluations-intention-usage relationship, and such theories include, but are not limited to, the theory of planned behavior (TPB) and the technology acceptance model (TAM) (Ajzen 1991, Davis et al. 1989).

Although conscious use, which involves deliberate evaluations/intention, characterizes many forms of IT use, contemporary research also suggests that automatic use, which occurs spontaneously outside of conscious awareness, represents alternative forms of IT use (Jasperson et al. 2005, Limayem and Hirt 2003, Venkatesh et al. 2000). It is generally known in IS research that such automatic behavior results from the force of habit or automaticity (Jasperson et al. 2005, Limayem and Hirt 2003). According to this point of view, called here the habit/automaticity perspective (HAP), as past use increases, the evaluations-intention-usage path will be diminished to a point at which past use will completely overshadow evaluations/intention as a predictor of subsequent use. Several studies in the IS domain have demonstrated that past use is the sole predictor of subsequent use, implying that habit/automaticity is prevalent in the context of IT use (Davis and Venkatesh 2004, Kim and Malhotra 2005, Venkatesh et al. 2000).

Despite the quantity of research in the IS field that advances the notion of habit/automaticity as the underlying force of automatic use, it is important to acknowledge the existence of a competing perspective that provides a different explanation of why IT use sometimes appears automatic. Specifically, the competing and alternative perspective, called the instant activation perspective (IAP), states that automatic use occurs effortlessly but is still a function of evaluations/intention (as opposed to past use). In essence, IAP maintains that the past use–future use relationship simply occurs when past use is confounded with uncontrolled factors (e.g., moral norms, self-identity, affect) and such uncontrolled factors correlate with subsequent use (Ajzen 2002).

Thus far, empirical investigations in the IS domain have shown merely that after initial adoption, past use has a positive influence on subsequent use (e.g., Davis and Venkatesh 2004, Kim and Malhotra 2005, Venkatesh et al. 2000). However, as mentioned previously, these results do not constitute direct evidence of the utility of HAP over IAP; consequently, it remains uncertain whether, as posited in the IS literature, habit/automaticity really comes into play in IT use. This study is designed mainly to offer a more conclusive statement on the efficacy of HAP over IAP. In particular, this article first offers a theoretical exposition of HAP by drawing on contemporary research in psychology (Bagozzi and Dholakia 1999, Bargh et al. 2001, Gollwitzer 1996). Then this view is thoroughly contrasted with the alternative view, which denies habit/automaticity. Next, we develop research hypotheses—whose results are critical to resolving the controversy surrounding the two competing views—pertaining to the moderating role of past use on the evaluations-intention-usage path. Finally, we present and discuss the results of the hypotheses when they are examined specifically within the context of individuals' use of a Web-based IT application.

2. Automatic Use

2.1. Two Alternative Explanations of Automatic Use

2.1.1. Habit/Automaticity Perspective (HAP). In an effort to explain IT use, IS researchers have relied extensively on the traditional reason-oriented framework that generally states that user evaluations determine usage intention, which in turn influences IT use. Although such traditional models as TPB and TAM are believed to be effective in describing conscious use, contemporary research in psychology also implies that those models will fall short of providing an accurate account of automatic use because automatic use is mainly driven by habit/automaticity rather than by conscious judgments (Aarts and Dijksterhuis 2000, Verplanken et al. 1998).

This particular view of automatic use, or HAP, maintains that conscious behavior is characterized by the mental representation of why-, what-, and how-level goals and their corresponding links. However, with repetition of the same behavior over time, the same set of mental links tends to be repetitively formulated. In such a routinized situation, the knowledge structure linking situational cues and a subsequent action becomes hard wired in the mental representation. As a result, IT use occurs automatically without the process of establishing associated goals (Bargh et al. 2001). In IS research, this "ingrained cognitive script" is assumed to activate subsequent use automatically without requiring conscious processing (Jasperson et al. 2005). Bagozzi and Dholakia (1999) call this type of automatic goal pursuit "habitual goal-directed consumer behavior," and Bargh and Barndollar (1996) use the term "goal-dependent automaticity" to describe such automatic goal-oriented behavior. Consistent with the literature, we use habit and automaticity interchangeably, and they are conceptualized as a principal driver of this automatic process (Kim and Malhotra 2005). In general, the literature suggests that habit/automaticity (and thereby automatic process) is strengthened with an increase in past behavior (Bagozzi 1981, Ouellette and Wood 1998, Triandis 1977). In the context of IT use, this HAP perspective implies that as past use increases, automatic processing displaces conscious processing, and in this automatic mode, evaluations/intention will no longer exert their effects on subsequent use (Kim and Malhotra 2005, Venkatesh et al. 2000).

2.1.2. Instant Activation Perspective (IAP). We previously argued that the evaluations-intention-usage relationship would reasonably represent a causal mechanism underlying conscious use. According to Ajzen (2002), the evaluations-intention-usage relationship should hold not only for conscious behavior but also for automatic behavior. Specifically, Ajzen (2002) states that conscious processing would involve the formation of judgments and intention, and that with repeated performance, such cognitions would become stabilized and ultimately stored in memory. However, contrary to HAP, Ajzen (2002) maintains that the stored judgments and intention would be "instantly activated" in a routine environment and thereby guide subsequent behavior.

A unique point of this competing view of automatic behavior, or IAP, is that automatic behavior is characterized by the same events that define conscious behavior. More specifically, IAP holds that automatic processing is merely an expedited form of conscious processing. According to this view, the only difference between the two forms of behavior is the fact that in automatic mode, a goal is effortlessly retrieved and leads to a next phase of goal setting and pursuit, whereas in conscious mode, the goal is carefully identified through deliberate calculation. Assuming that such instantly activated evaluations/intentions are equivalent to those formed by conscious processing, a causal model designed for reasoned action or planned behavior should work well for explaining not only conscious use, but also automatic use (Ajzen 2002, Ajzen and Fishbein 2000).

Note that IAP is distinguished from HAP in two important ways: First, whereas HAP posits that the formation of evaluations/intention can be bypassed by the hard-wired mental link, IAP argues that automatic use still involves the formation of evaluations/intention; second, whereas HAP considers past use critical to understanding automatic use, IAP ignores the role of past use. More specifically, HAP predicts that past use moderates the evaluations-intention-usage link, but IAP suggests that the evaluations-intention-usage link should stay strong regardless of past use. Therefore, it is important in a legitimate comparison of HAP with IAP to test the moderating role of past use in the evaluations-intention-usage link. Table 1 summarizes the major differences between the two competing perspectives.

2.2. Research Model and Hypotheses

2.2.1. Relationship Between User Evaluations and Usage Intention. Research has shown that three evaluation criteria—utilitarian, hedonic, and social values—succinctly cover a broad set of factors that individuals consider important in the context of IT use (Venkatesh and Brown 2001). First, the utilitarian value relates to the effectiveness and efficiency that result from the use of an IT application (Holbrook 1994). Second, the hedonic value is associated with the fun or pleasure derived from using the application (Davis et al. 1992). Third, the social value refers to enhancement of a user's social image by his or her use of the application (Venkatesh et al. 2003). Of course, the salience of each factor will vary according to the research context. Furthermore, some variables other than the three value factors may emerge as salient factors depending on the research context (Venkatesh et al. 2003). However, this study examines only the essential set of user evaluations to focus on its core topic, that is, automatic use.

As discussed previously, IAP posits that in situations requiring repetitive behavior, IT users do not employ conscious deliberation to arrive at judgments; instead, well-formed judgments stored in memory are activated automatically and guide routine behavior. Because IAP assumes that automatically activated evaluations are equivalent to evaluations formed by careful deliberation, the relationship between evaluations and usage intention is expected to be strong regardless of past use. Furthermore, Ajzen (2002) goes on to argue that with repeated performance, individuals' attitudes tend to be more stable and exhibit

Table 1 Comparison Between Habit/Automaticity and Instant Activation

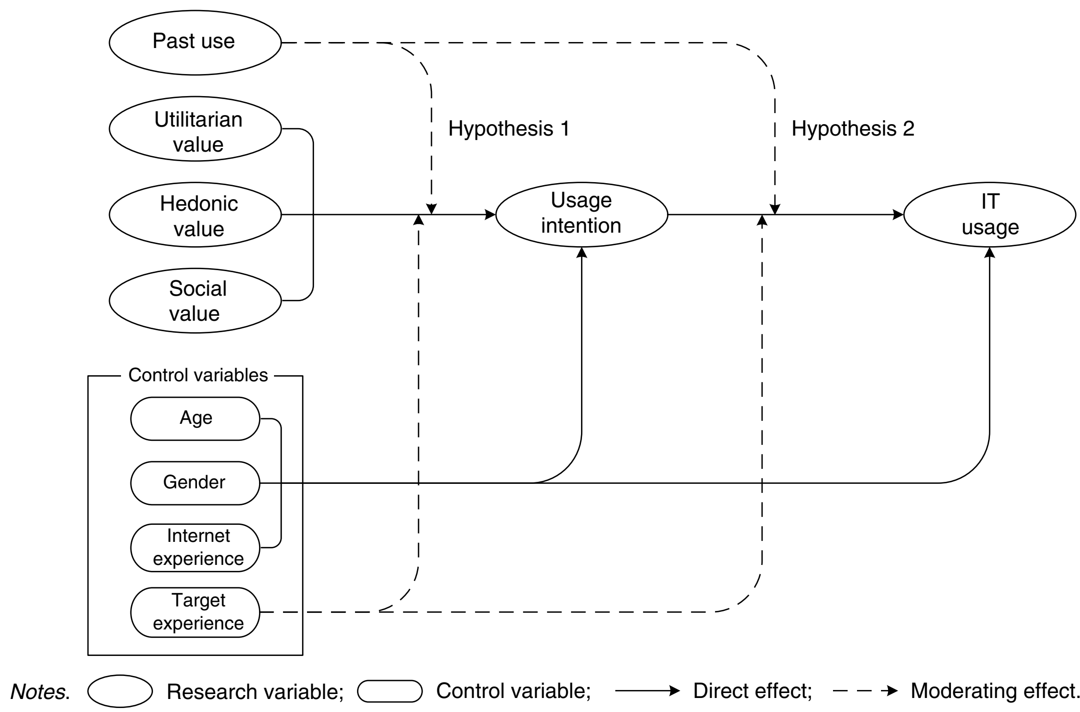
	HAP	IAP
Sources	• Aarts and Dijksterhuis (2000) • Bagozzi and Dholakia (1999) • Bargh et al. (2001) • Gollwitzer (1996)	• Ajzen (2002) • Ajzen and Fishbein (2000)
Conscious process	• Users' evaluations will lead to intention, which will activate IT use.	• Users' evaluations will lead to intention, which will activate IT use.
Automatic process	• With repeated performance, a knowledge structure linking situational cues and an action becomes hard wired. • In a similar situation, the same stimulus cue will automatically activate subsequent IT use. *This process occurs through the hard-wired link without the necessity of forming* evaluations and intention.	• With repeated performance, corresponding evaluations and intention are stored in memory. • In a similar situation, the stored evaluations and intention are automatically activated, and the spontaneous evaluations/intention will determine subsequent IT use. *This process still involves the formation of evaluations and intention to guide subsequent use.*
Difference between conscious and automatic processes	• Automatic processes, which do not require the formation of evaluations or intentions, essentially differ from conscious processes, which involve the formation of evaluations and intention.	• No fundamental differences exist except the speed of processing.
Causal model	• The reason-oriented action framework can explain only conscious use. • To account for automatic use, past use should be added into a causal model as a moderator.	• The reason-oriented action framework is reasonable in explaining both conscious use and automatic use. • The effect of past use is not considered (the effect of past use on IT usage merely indicates that the IT use in question is stable over time).
Predictions	• The evaluations-intention-usage relationship will be stronger for individuals *lower* on past use (i.e., lighter users) than for individuals *higher* on past use (i.e., heavier users).	• The evaluations-intention-usage relationship should stay strong regardless of past use (i.e., for both lighter users and heavier users).

stronger predictive power for intention; thus, the influence of evaluations on behavioral intention will increase as past behavior increases. IAP implies that in the context of IT use, the relationship between user evaluations and usage intention will be stronger among heavier users than among lighter users.

However, HAP expects routine behavior to be controlled by stimulus cues without the need to form user evaluations and intention. The lack of such deliberation, according to HAP, results in the occurrence of a paradoxical event when researchers submit a survey questionnaire to habitual users to learn their perceptions about using an IT application. In this special event, rather than engaging in deliberate calculation, respondents are said to rely simply on past behavior as a basis for gauging their behavioral intentions (Jasperson et al. 2005, Melone 1990). Because of this *self-perception* process (Bem 1972), the unique influence of evaluations on usage intention is expected to decrease as past use increases. That is, HAP predicts that the influence of evaluations on usage intention will be stronger among lighter users than among heavier users. Ouellette and Wood (1998) show in a meta-analysis study that attitudes had a stronger effect on intention in domains in which the respondents had few opportunities to perform behaviors (e.g., blood donation) ($r = 0.51$) than in domains that provided frequent opportunities to perform behaviors (e.g., seat belt use) ($r = 0.44$) ($z_{\text{difference}} = 3.23$, $p < 0.001$). Therefore, the more a behavior is performed, the less effect judgment has on intention.

Consistent with IS literature, we believe that automatic use is influenced by habit/automaticity (Jasperson et al. 2005). Therefore, we predict that the evaluations-intention path will decrease as past use increases. Figure 1 depicts the research model with this HAP-based hypothesis of the moderating effect of past use on the evaluations-intention path. Note that this HAP-based hypothesis directly contradicts the IAP's prediction that the evaluations-intention path will increase or that it will at least stay the same with an increase in past use. The null and alternative

Figure 1 **Causal Model of IT Use**



hypotheses, representing the two competing views, are summarized in the "Hypothesis 1" column in Table 2.

It is interesting to note that our hypothesis is generally consistent with the unified theory of acceptance and use of technology (UTAUT) proposed by Venkatesh et al. (2003). Specifically, UTAUT proposes that as user experience—defined as the time elapsed since the initial use of the IT application—increases, nonutilitarian factors such as effort expectancy and social influence will be less important in determining behavioral intention because, among experienced users, "performance expectancy," which is similar to utilitarian value, will be perceived as the primary criterion in the context of IT use. In fact, Venkatesh et al. (2003) empirically show that the effects of nonutilitarian factors (e.g., effort expectancy, social influence) on behavioral intention decreased as user experience increased. These findings are generally consistent with HAP, which posits that the influence of user evaluations on usage intention will decrease as past use (i.e., system usage in the past) increases. However, our hypothesis differs from UTAUT in two important ways: First, whereas UTAUT holds that experienced users consider the utilitarian factor important in forming behavioral intention, we propose that the relationship between utilitarian value and behavioral intention will be weakened in a routine context. Second, user experience, measured by time elapsed since IT adoption (e.g., "How long have you been using the application since your initial

Table 2 **Summary of Research Hypotheses on Automatic Use**

Theories		Hypothesis 1 (evaluations-intention path)	Hypothesis 2 (intention-usage path)
Null hypothesis	(IAP)	$H1_0$: As past use increases, the influence of users' evaluations on usage intention will increase or at least stay the same.	$H2_0$: As past use increases, the influence of usage intention on IT use will increase or at least stay the same.
Alternative hypothesis	(HAP)	$H1_A$: As past use increases, the influence of users' evaluations on usage intention will decrease.	$H2_A$: As past use increases, the influence of usage intention on IT use will decrease.

use?"), is not the same as past use (e.g., "How much have you used the application in the past month?"), which is an essential driver of habit/automaticity. Thus, the concept of habit/automaticity has not yet been confirmed; it is vital to empirically test the moderating role of past use on the evaluations-intention relationship.

2.2.2. Relationship Between Usage Intention and IT Use. Our research model in Figure 1 shows that usage intention determines IT use. However, IAP and HAP disagree on how the relationship changes with an increase in past use. In particular, IAP holds that newly formed intentions are unstable and thus that intentions formed with little prior experience are a poor predictor of subsequent behavior. According to IAP, automatically activated intentions are considered stable because they have been formed with ample opportunities to perform the behavior of interest. As such, spontaneous intentions in a routine environment are said to have predictive power as strong as, or stronger than, deliberate intentions formed in a novel environment. That is, IAP predicts that the influence of usage intention on IT use will stay the same or increase with an increase in past use.

In contrast, HAP predicts that routine behavior becomes automatic and guided by situational cues (Jasperson et al. 2005). Therefore, though important at an initial stage, the influence of usage intention on IT use decreases as past use increases. Several findings in psychology suggest that past behavior moderates the influence of intention on later behavior. For example, Verplanken et al. (1998) demonstrate in a study of car use that past car use reduces the influence of intention on future car use ($p < 0.01$). In addition, Ouellette and Wood (1998) find that the influence of intention on behavior is significantly lower in high-opportunity contexts than in low-opportunity contexts. Taken together, these findings suggest that the influence of usage intention on IT use will be stronger for lighter users than for heavier users. Thus, drawing on HAP, we hypothesize that past use moderates the relationship between usage intention and IT use. Note that though IAP and HAP both recognize that repeated behavior is performed rather effortlessly, they differ in explaining the underlying mechanism that makes repeated behavior automatic. As a result, the two competing views differ in their predictions of the change in the intention-usage link with respect to past use. The second hypothesis is represented in Figure 1, and the "Hypothesis 2" column in Table 2 summarizes the null and alternative hypotheses that represent IAP and HAP.

3. Method and Results

3.1. Data Collection and Sample Splitting

According to a recent survey, reading online news is one of the three most popular activities on the Internet, thus suggesting that in everyday life a large number of online users routinely visit Web-based news sites (UCLA Center for Communication Policy 2003). Because this study is primarily intended to understand the nature of automatic use, online news was deemed an appropriate target application. Thus, to collect data necessary for testing the research model and its hypotheses, we specifically investigated individuals' use of online news. To increase the generalizability of the findings, two different online news sites, as opposed to a single website, were examined. One of the sites, Target A, mainly featured national and local news of interest to the public in a major city in the Southeast. Meanwhile, the other site, Target B, focused on recreation information and local events in a resort city on the East Coast. The procedures for data collection are summarized in Table 3.

To collect data, we developed a structured questionnaire. Specific items used for measuring research constructs are listed in Appendix A (an online supplement is available at http://www.informs.org / Pubs / Supplements / ISR / 1526-5536-2005-16-04-0418-app.pdf). In Target A, a banner link was posted on the home page for a month. Individuals who wanted to participate in the survey could click on the link and fill out a Web-based questionnaire. No incentives to participate were provided. In Target B, the site manager had kept a list of e-mail addresses for 4,251 registered users. An e-mail invitation message, including the link to a Web-based questionnaire, was sent to each registered user. As incentives for this group, we offered gift certificates ($100 or $20) based on a random drawing from entries.

We conducted two waves of surveys to collect longitudinal data on usage behavior. In the first survey,

Table 3 Data-Collection Procedures

	Target A	Target B
Target system	An online news site featuring national news and local news in a major city in the Southeast	An online news site featuring recreation information and local news in a resort city on the East Coast
Cross-sectional data	A banner link to a Web-based survey was posted on the home page of the online news site for one month.	The news site had kept a list of e-mail addresses for 4,251 registered users. An e-mail invitation message including the link to a Web-based survey was sent to each of the registered users.
Longitudinal data	E-mail was sent asking a respondent's target site usage since the first survey for the following month.	E-mail was sent asking a respondent's target site usage since the first survey for the following month.
Incentives	No incentives were provided.	Gift certificates ($100 or $20) were given based on a random drawing of entries.
Size of sample	• Cross-sectional data: 886 • Longitudinal data: 398	• Cross-sectional data: 1,189 • Longitudinal data: 592
Response rate	• Cross-sectional data: n/a • Longitudinal data: 47.4% (398/840, 46 messages undeliverable)	• Cross-sectional data: 28.0% (1,189/4,251) • Longitudinal data: 51.3% (592/1,154, 35 messages undeliverable)
Cross-validation	• Calibration data: 536 (243 follow-ups) • Validation data: 350 (154 follow-ups)	• Calibration data: 789 (393 follow-ups) • Validation data: 400 (199 follow-ups)

respondents were asked about demographic information (including an e-mail address for a follow-up survey), their evaluations of the target website, and their usage of the website during the past month. In Wave 1, we collected a total of 886 and 1,189 responses from users of Targets A and B, respectively. As a way of checking nonresponse bias, we compared demographic profiles between early and late Wave 1 respondents. No significant differences between samples were found in terms of age, gender, Internet experience, or target system experience distributions. The second survey was conducted one month after the first survey to measure the usage of the same site between the surveys, which is consistent with the time interval used in other longitudinal studies (e.g., Venkatesh 2000, Venkatesh et al. 2000). We sent an e-mail invitation message, including the link to the Web-based survey questionnaire, to each of the respondents in the first survey. We found that 46 and 35 messages, for Targets A and B, respectively, were undeliverable for several reasons (e.g., typos in e-mail addresses, unavailability of the e-mail account). In Wave 2, a total of 398 and 592 responses were collected for Target A and Target B, respectively, out of correctly sent messages. This resulted in a 47.4% response rate for Target A (398/840) and 51.3% for Target B (592/1,154). We compared Wave 2 participants and nonparticipants in terms of demographic variables but found no significant differences. The demographic profiles of the respondents are summarized in Appendix B (an online supplement is available at http://www.informs.org/Pubs/Supplements/ISR/1526-5536-2005-16-04-0418-app.pdf).

We adopted a cross-validation procedure to rigorously evaluate the proposed model and research hypotheses (Cudeck and Browne 1983). Following the procedure of Novak et al. (2000), we split the data unevenly into calibration and validation samples. Specifically, 350 respondents (155 with follow-up) for Sample A and 400 respondents (199 with follow-up) for Sample B—approximately 35% of the respondents—were randomly assigned to validation samples. The remainder—536 respondents (243 with follow-up) for Sample A and 789 respondents (393 with follow-up) for Sample B—were used for calibration samples. We first estimated measurement and structural models based on the calibration samples and then tested the robustness of the calibration results based on the validation samples.

3.2. Measurement Model Results

To check the properties of our measurement scales, confirmatory factor analysis (CFA) was conducted using LISREL 8.7 (Jöreskog and Sörbom 1996). In this study, model fit was assessed in terms of four different indices, namely, the root mean square error of

Table 4 Properties of Measurement Scales

A. Means, Standard Deviations, Composite Reliabilities, and Average Variance Extracted

	Sample A				Sample B			
Variables	Mean	SD	CR	AVE	Mean	SD	CR	AVE
1. Age	4.12	1.31	na	na	4.62	1.26	na	na
2. Gender	1.31	0.46	na	na	1.44	0.49	na	na
3. IEXP	3.49	0.84	na	na	3.21	0.92	na	na
4. TEXP	3.05	1.09	na	na	2.70	1.28	na	na
5. UV	5.39	1.05	0.89	0.72	5.48	1.14	0.94	0.83
6. HV	4.65	1.31	0.91	0.72	5.03	1.22	0.94	0.81
7. SV	2.13	1.31	0.92	0.80	2.56	1.53	0.97	0.90
8. UI	6.68	0.84	0.87	0.78	6.22	1.33	0.93	0.87
9. Past use	3.73	1.00	0.69	0.53	3.14	1.10	0.76	0.61
10. IT use	3.66	1.12	0.77	0.63	3.08	1.20	0.83	0.71

B. Correlations

Variables	1	2	3	4	5	6	7	8	9	10
1. Age	1	−0.16***	−0.06	0.08*	−0.04	0.00	−0.07	−0.06	−0.05	−0.02
2. Gender	−0.09*	1	−0.09**	−0.07	0.06	0.10**	−0.02	0.02	0.09*	0.16***
3. IEXP	−0.12**	−0.13**	1	0.22***	0.00	−0.07*	−0.06	−0.02	−0.02	0.00
4. TEXP	0.08	−0.18***	0.19***	1	0.13***	0.07*	−0.01	0.16***	0.26***	0.15***
5. UV	−0.06	0.01	−0.10*	0.08	1	0.65***	−0.06	0.41***	0.39***	0.36***
6. HV	−0.07	0.03	−0.15***	0.05	0.54***	1	0.09*	0.30***	0.25***	0.22***
7. SV	0.02	0.00	−0.04	−0.07	−0.01	0.11*	1	−0.03	0.12**	0.12**
8. UI	−0.10*	−0.02	0.03	0.20***	0.32***	0.22***	−0.01	1	0.63***	0.59***
9. Past use	−0.03	−0.09	−0.08	0.34***	0.24***	0.19***	0.03	0.51***	1	0.71***
10. IT use	0.04	−0.23***	−0.03	0.28***	0.25***	0.27***	0.19***	0.44***	0.67***	1

Notes. Sample A ($n = 536$); Sample B ($n = 789$). SD = standard deviation; CR = composite reliability; AVE = average variance extracted. IEXP = Internet experience; TEXP = target system experience; UV = utilitarian value; HV = hedonic value; SV = social value; UI = usage intention. Correlations below the diagonal are for Sample A; correlations above the diagonal are for Sample B.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ (two tailed).

approximation (RMSEA), the comparative fit index (CFI), the nonnormed fit index (NNFI), and the standardized root mean square residual (SRMR). According to Hu and Bentler (1999), the criteria for an acceptable model are as follows: RMSEA of 0.06 or lower; CFI of 0.95 or higher; NNFI of 0.95 or higher; and SRMR of 0.08 or lower.

The measurement model included six latent constructs (i.e., utilitarian value, hedonic value, social value, usage intention, past use, and IT use). It should be noted that because the items for past use and IT use were identical, the CFA model was specified to correlate the measurement errors of the same indicators between the two factors. More specifically, the measurement error of the past frequency item was allowed to correlate to the measurement error of the current frequency item. Similarly, the measurement error of the past duration item was allowed to correlate to the measurement error of the current duration item. We ran a CFA for each set of samples, and the results indicated that the measurement model fit the data well [Sample A $\chi^2(87) = 183.96$, RMSEA = 0.046, CFI = 0.98, NNFI = 0.97, and SRMR = 0.034; Sample B $\chi^2(87) = 247.61$, RMSEA = 0.048, CFI = 0.99, NNFI = 0.98, and SRMR = 0.030]. Table 4 shows the construct means, standard deviations, composite reliabilities, average variance extracted, and correlations estimated based on the measurement model.

In addition to model fit, we checked the reliability, convergent validity, and discriminant validity of the scales. First, reliability is acceptable if the composite reliability is 0.70 or higher and the average variance extracted is 0.50 or higher (Bagozzi and Yi 1988, Fornell and Larcker 1981). As shown in Table 4, all factors meet both criteria for acceptable reliability. Second, convergent validity can be established if item loadings are 0.60 or higher (Chin et al. 1997). The lowest loading of the LISREL 8.7 outputs was 0.60 for Sample A and 0.67 for Sample B. These results suggest satisfactory convergent validity for the scales. Third, as a way to test discriminant validity, we conducted a chi-square difference test for each pair of latent variables. More specifically, an unconstrained model in which the two factors in question were freely correlated was compared with a constrained model in which the correlation between the two factors was set to 1. The results of 15 chi-square difference tests indicate that unconstrained models were consistently superior to constrained models, suggesting discriminant validity. To summarize, with evidence of good model fit, reliability, convergent validity, and discriminant validity, the measurement instrument was considered satisfactory and therefore used for subsequent tests of the research model and its related hypotheses.

3.3. Structural Model Results

Our proposed model was tested with four control variables that could potentially affect IT users' reactions to a Web-based IT application (Figure 1). First, age and gender were specified to explain usage intention and usage behavior, because research shows that such demographic variables influence online users' evaluations and behaviors (Kraut et al. 1999). Second, Internet experience was considered another control variable, because individuals' experience with the Internet may affect their reactions to a specific Internet-based application (Marakas et al. 1998). Third, target system experience was taken into account to control for user experience with an IT application. Recently, several cross-sectional and longitudinal studies have shown that target system experience tends to reduce the well-known evaluations-intention-usage relationship (e.g., Davis and Venkatesh 2004, Venkatesh et al. 2000). Thus, we attempted to explicitly control for the moderating effect of target system experience on the evaluations-intention-usage relationship.

Note that our proposed model involves latent interaction effects. In this study; such interaction effects were estimated using the "means of latent variable scores" (MLVS) technique (Jöreskog 1998). In essence, MLVS generates factor scores, the correlations of which stay exactly the same as the estimated factor correlations from the measurement model; then interaction terms are created based on the factor scores. To produce interaction terms, we used the residual centering method in which residuals obtained from regressing the cross-product term ($X_1 \times X_2$) on the main variables (X_1 and X_2) are used to represent the interaction effect (Lance 1988). Obviously, this method produces no correlations between the interaction and its constituent terms; consequently, it offers several advantages over the typical cross-product term procedure in the test of interaction effects.

The proposed model and its two nested models were tested through the structural equations modeling (SEM) technique with LISREL 8.7. The proposed model was specified to include the main and interaction effects of past use on postadoption phenomena, which is consistent with HAP. In contrast, the first nested model, or Nested Model 1, did not control for any past use effects. Therefore, this nested model is considered consistent with IAP. Meanwhile, the second nested model, or Nested Model 2, controlled only for the main effects of past use without its interaction effects. Although this nested model appears to be in line with HAP, this similarity does not put it in opposition to IAP because the past use–future use link may simply indicate the stability over time of the IT use in question (Ajzen 2002).

Each model was tested on each of the two samples. Thus, six separate SEM analyses were conducted. Table 5 reports the results of path coefficients, explained variance, and model fit. The fit indices considered in this study (i.e., RMSEA, CFI, NNFI, and SRMR) indicated that the proposed model explained both sets of the data better than the two nested models. As Table 5 shows, the improvement in fit between the proposed model and each of the competing models is statistically significant for both samples ($ps < 0.01$). In addition to the model-data fit, the proposed model surpassed the competing models in explaining variance in usage intention and IT use. Specifically, the difference in squared multiple correlations (SMC) between the proposed model and its competitors was found to be as much as 31% (the SMC of UI in Sample B is 52% in the proposed model and 21% in Nested Model 1). Taken together, these

Table 5 Results of SEM Analyses with Maximum Likelihood Estimation

Effect	Cause	Nested Model 1		Nested Model 2		Proposed model	
		Sample A	Sample B	Sample A	Sample B	Sample A	Sample B
UI	Age	−0.08	−0.06	−0.06	−0.04	−0.05	−0.04
	Gender	−0.01	−0.02	0.03	−0.05	0.02	−0.07*
	IEXP	0.01	−0.04	0.08	−0.01	0.08	0.00
	TEXP	0.17***	0.12***	0.02	−0.02	0.02	−0.04
	UV	0.29***	0.37***	0.19***	0.10*	0.18***	0.10*
	HV	0.07	0.06	0.04	0.11*	0.04	0.10*
	SV	0.00	−0.01	−0.04	−0.11***	−0.05	−0.10**
	TEXP ∗ UV	−0.23***	−0.14**	−0.25***	−0.13**	−0.21***	−0.06
	TEXP ∗ HV	−0.03	0.07	0.01	0.13**	0.01	0.14***
	TEXP ∗ SV	0.00	0.04	−0.04	−0.02	−0.03	−0.04
	Past use	0[a]	0[a]	0.46***	0.60***	0.45***	0.61***
	Past use ∗ UV	0[a]	0[a]	0[a]	0[a]	−0.10**	−0.19***
	Past use ∗ HV	0[a]	0[a]	0[a]	0[a]	−0.04	−0.07
	Past use ∗ SV	0[a]	0[a]	0[a]	0[a]	0.00	0.05
IT use	Age	0.03	0.04	0.06	0.05	0.04	0.04
	Gender	−0.22***	0.16***	−0.17***	0.10**	−0.17***	0.09**
	IEXP	−0.11*	0.02	0.00	0.04	0.01	0.03
	TEXP	0.25***	0.07*	−0.01	−0.06	0.00	−0.04
	UI	0.32***	0.56***	0.07	0.20***	0.11*	0.20***
	TEXP ∗ UI	−0.05	0.00	−0.08*	−0.03	−0.04	0.02
	Past use	0[a]	0[a]	0.65***	0.63***	0.63***	0.59***
	Past use ∗ UI	0[a]	0[a]	0[a]	0[a]	−0.11**	−0.17***
SMC							
UI (%)		23	21	39	46	40	52
IT use (%)		27	36	53	58	54	59
Model fit							
χ^2		640.26	832.39	492.39	574.48	475.00	491.55
df		224	224	222	222	218	218
RMSEA		0.059	0.059	0.048	0.045	0.047	0.040
CFI		0.93	0.95	0.95	0.97	0.96	0.98
NNFI		0.88	0.91	0.92	0.95	0.92	0.96
SRMR		0.063	0.060	0.039	0.030	0.037	0.024
Comparison[b]							
$\Delta\chi^2$		165.26	340.84	17.39	82.93		
Δdf		6	6	4	4		
p-value		<0.001	<0.001	0.01	<0.001		

Notes. All parameters are completely standardized estimates. Sample A ($n = 536$); Sample B ($n = 789$). IEXP = Internet experience; TEXP = target system experience; UV = utilitarian value; HV = hedonic value; SV = social value; UI = usage intention; SMC = squared multiple correlation; df = degrees of freedom; RMSEA = root mean square error of approximation; CFI = confirmatory fit index; NNFI = nonnormed fit index; SRMR = standardized root mean square residual.

[a]Fixed parameters.

[b]Compared with the proposed model.

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ (two tailed).

results (i.e., fit statistics, chi-square difference tests, and SMC) strongly suggest that the proposed model, which reflects HAP, is a more reasonable representation of postadoption phenomena than nested models that in one way or another reflect IAP.

The research hypotheses were formally tested on the basis of the results of the proposed model. Hypothesis 1 predicts that the evaluations-intention link would be stronger for lighter users than for heavier users. We found that utilitarian value, which is one of the three value factors, positively influenced usage intention, but its effect also interacted with past use. Meanwhile, we found that the other value factors (i.e., hedonic and social) had little impact on usage intention, and these results did not vary with past use, at least in this particular context. Considering that not all of the three components of value are expected to be relevant in a given context, these results were not surprising. Therefore, as a whole, our results provide general support for Hypothesis 1 that past use would moderate the evaluations-intention link. Meanwhile, Hypothesis 2 predicts that the influence of usage intention on IT use would be stronger for lighter users than for heavier users. We found that usage intention significantly interacted with past use to influence subsequent use. Thus, these results support Hypothesis 2, which predicts that past use would moderate the intention-usage link. Recall that a moderating role of past use on the relationships of evaluations-intention-usage was considered strong evidence that contradicts IAP and affirms HAP. Thus, these results offered additional credibility to our central proposition that HAP is better than IAP in explaining automatic use.

To further check the robustness of our findings, we conducted several ad hoc tests. First, we examined whether a major assumption of HAP—past use is a good indicator of habit/automaticity—is reasonable. This test of the basic assumption was conducted in a separate study that involved 243 actual users of a portal website. The detailed procedure and results of this additional study are described in Appendix C (an online supplement is available at http://www.informs.org/Pubs/Supplements/ISR/1526-5536-2005-16-04-0418-app.pdf). In essence, we found from the separate study that past use strongly correlates with habit/automaticity ($r = 0.91$, $p < 0.001$). Thus, it seems safe to conclude that the basic assumption of HAP is realistic and that the findings of this study built on this assumption are dependable.

To further test the robustness of our results, we attempted to cross-validate the results of the calibration samples based on the validation data. Initially, the proposed model was estimated on the validation samples in the same way that it was on the calibration samples (Novak et al. 2000). The results demonstrated that the proposed model represented the validation data as well as it did the calibration data [Sample A $\chi^2(218) = 344.51$, RMSEA $= 0.041$, CFI $= 0.96$, NNFI $= 0.94$, and SRMR $= 0.037$; Sample B $\chi^2(218) = 376.89$, RMSEA $= 0.043$, CFI $= 0.97$, NNFI $= 0.95$, and SRMR $= 0.033$]. Subsequently, we employed an even more stringent procedure for cross-validation. In this second procedure, structural path estimates from the calibration samples were imposed on the proposed model. Then the constrained model was tested on the validation samples. Model fit comparable to that of the unconstrained model would suggest that parameter estimates from the calibration samples were reliable. We found from the results of SEM analyses that the constrained model also fit the validation data well [Sample A $\chi^2(240) = 405.05$, RMSEA $= 0.044$, CFI $= 0.95$, NNFI $= 0.93$, and SRMR $= 0.048$; Sample B $\chi^2(240) = 408.60$, RMSEA $= 0.042$, CFI $= 0.97$, NNFI $= 0.95$, and SRMR $= 0.044$]. Research suggests that extra constraints are reasonable if the difference of NNFI is within 0.05 (Childers et al. 2001). Given little difference in fit between the constrained and unconstrained models (ΔNNFI ≤ 0.01), the results of the cross-validation add even more credibility to the already established soundness of the proposed model.

4. Discussion and Conclusion

This study compared two contrasting views of automatic use using extensive data that include 2,075 cross-sectional and 990 longitudinal responses from actual users of two online news sites. Our findings show that the evaluations-intention-usage relationship is generally weaker among heavier users than among lighter users, suggesting that with an increase in past use, user behavior becomes less evaluative and less intentional. Thus, this study supports the notion of habit/automaticity over the competing view of the instant activation of cognitions. Overall, this research shows an initial piece of evidence of the moderating role of past use in postadoption phenomena, and it is expected to help the IS community systematically investigate the important yet underexplored subject of habit/automaticity.

4.1. Theoretical Implications

4.1.1. Relationship Between User Evaluations and Usage Intention. Our findings, based on two large field surveys, indicate that the influence of user evaluations on usage intention decreases with an increase in past use. Although this moderating effect of past use on the evaluations-intention link has been found in psychology (e.g., Verplanken et al. 1998), we are the first to show it in the context of IT use. Recall that Venkatesh et al. (2003) also showed that the effects of user evaluations (i.e., effort expectancy and social influence) on usage intention decreased with an increase in user experience, which, similar to the findings of our study, favors HAP over IAP. Nevertheless, the present study is unique because it demonstrates the moderating role of *past use*, which is a major driver of automatic processing, while controlling for the moderating role of *user experience*, which does not necessarily reflect habit/automaticity. Thus, though the superiority of HAP over IAP has been suggested in a study by Venkatesh et al. (2003), our study goes further by showing this superiority more directly. Furthermore, it is important to note that the moderating effect of past use on the utilitarian value–usage intention relationship is somewhat unexpected from the viewpoint of UTAUT. This is because, according to UTAUT, experienced users continue to focus on performance-oriented factors in weighing whether to continue to use the IT application in question. If so, the utilitarian value–usage intention relationship should not decrease with an increase in user experience and/or past use. In contrast, we find in this study that the effect of utilitarian value on usage intention decreases as past use increases. This finding supports our conceptual framework that asserts that with repeated use the overall role of evaluation diminishes in importance as a determinant of behavioral intention.

4.1.2. Relationship Between Usage Intention and IT Use. Given that many people visit online news sites on a daily basis, the context examined in this study seems conducive to habit. Unsurprisingly, the findings of this study indicate that the influence of past use on IT use is stronger than that of usage intention. Interestingly, Ouellette and Wood (1998) found a similar result in their meta-analysis study in which, for repeatedly performed behaviors, past behavior became a stronger determinant of subsequent behavior than did behavioral intention. Their findings, in conjunction with ours, suggest that for numerous IT applications that are used on a daily basis (e.g., using an online search engine), past use is the best predictor of subsequent use. In contrast, we expect that for those applications that are rarely used (e.g., visiting an online calendar retailer), behavioral intention will still be the best predictor of subsequent behavior. Certainly a systematic investigation is required to examine the role of behavioral contexts, especially behavioral opportunities, on the nature of IT use.

Moreover, our findings show that past use indeed interacts with usage intention in determining IT use. Certainly this research offers an initial piece of evidence of the moderating role of past use in the relationship between usage intention and IT use. Several studies have shown that in postadoption stages past use is the only predictor of subsequent use and overshadows usage intention (Davis and Venkatesh 2004, Kim and Malhotra 2005, Venkatesh et al. 2000). However, those studies do not explicitly clarify whether the weakened intention-usage relationship was because of user experience or past use. In contrast, we explicitly account for the two types of moderating effects simultaneously and demonstrate that the moderating effect of *past use* on the intention-usage path ($ps < 0.01$) overshadowed the moderating effect of *user experience* ($ps = \text{ns}$) (Table 5). Thus, our findings suggest that it is past use rather than user experience that actually reduces the influence of usage intention on IT use. Taken together, this research is believed to contribute to IS literature by offering a solid conceptual foundation on which further research can build.

4.2. Managerial Implications

A number of important managerial implications arise from our findings. First, our findings indicate that usage patterns of habitual users differ considerably from those of nonhabitual users; thus, to better serve their customers, online firms should try to categorize customers according to their habit/automaticity levels. For example, for websites dominated mainly by nonhabitual users (e.g., newly launched sites), we recommend that practitioners watch closely what the majority of their customers think of the firm's service. Compared with habitual users, nonhabitual users are more conscious of the benefits and costs associated with using the website, and thus, user value plays an important role in determining subsequent use. Specifically, we advocate that managers focus on improving user value by, for example, enriching content, enhancing the user interface, and implementing features that the customers really need/want.

Meanwhile, managers of websites of which the majority of customers are habitual users would be well advised to handle change carefully lest they rouse the customers into conscious, and perhaps critical, use of the site. This advice is based, first, on our research that indicates, all things being equal, that habitual use is dictated by the mental link created through repeated use, and second, on others' research that suggests that the shift from automatic processing to conscious processing takes place when "unexpected events occur" or "something stands out of the ordinary" (Louis and Sutton 1991, p. 60). Therefore, changes to a website (whether for website improvements or promotional/marketing purposes) may risk causing habitual users to fall back onto conscious processing (Bamberg et al. 2003). Accordingly, we suggest that managers of habit-driven websites should consider implementing changes only gradually while carefully examining the effects of such changes on the behavioral patterns of their customers. In this way, online firms will be able to improve the quality of their websites as well as maintain customers' habitual inertia—which seems critical to a firm's long-term profitability.

4.3. Limitations and Further Research

This study is subject to several limitations. Our study focused on online news services, which are high-opportunity contexts conducive to automatic use. Thus, our findings may not apply to low-opportunity contexts (e.g., online shopping for an automobile).

Another limitation is related to the self-reported behavioral measure that was employed for capturing past use and IT use. Even though this practice is typical in IS (Davis et al. 1989) and other research domains (Bagozzi et al. 1992), the results of our study should be compared carefully with those based on objective data (Straub et al. 1995).

A third limitation of this study is that we examined a limited set of user evaluations to focus on the core contribution of this article. Other factors—beyond the three value factors that we employed—may contribute to the prediction of usage intention and IT use (Venkatesh et al. 2003). In a similar vein, the four covariates incorporated in this study (i.e., age, gender, Internet experience, and target system experience) may fall short of accounting for most of the miscellaneous effects. Thus, our findings could have been strengthened with additional control variables and their first-order and high-order interaction effects (e.g., Venkatesh et al. 2003).

Finally, it should be mentioned that in this study, usage behavior (i.e., IT use and past use) is conceptualized as a latent construct with *reflective* indicators, that is, the frequency and duration items. Under this approach, the latent variable is expected to vary along a continuum from light to heavy in a simple, linear fashion. In fact, our conceptualization of usage behavior is consistent with IS literature (Straub et al. 1995); furthermore, for the operationalization of usage behavior, the multi-item scale adopted here is generally favored in the literature over a single-item scale (Chin et al. 1997). Alternatively, however, frequency and duration can be conceptualized as different concepts, and then investigators may examine how the different concepts independently and jointly affect habit formation (e.g., high frequency/low duration versus low frequency/high duration). Thus, although our dealing with the usage behavior construct appears reasonable and consistent with past IS research, future research may pursue an alternative route to the conceptualization and operationalization of the construct in the study of habit formation.

This study suggests additional directions for further research. First, as discussed earlier, this study only examined individuals' use of online news, which provides a high-opportunity context conducive to habit formation. Thus, future research may further examine how habit affects subsequent perceptions, intention, and behavior in a low-opportunity context. One interesting avenue is to systematically compare between low- and high-opportunity contexts the effects of habit on perceptions, intentions, and behaviors. In this way, investigators will be able to show the underlying mechanism through which contextual factors regulate the role of habit in IT use.

In addition, future research should examine the relationship between habit/automaticity and task performance. Given that website traffic has important implications for online companies, we mainly focused on the relationship between habit/automaticity and IT use. However, unlike individual customer IT use, organizational workers' IT use is not directly translated into the profitability of a firm (Seddon 1997). Therefore, further research is required to understand how conscious and automatic use differ in their influence on organizational productivity. Research in other disciplines generally suggests that in "business-as-usual" situations, automatic processing is superior to conscious processing (Ackerman 1992, Louis and Sutton 1991) because conscious processing requires establishing a complex structure of goals that often involves a number of errors, whereas automatic processing is free from such errors associated with goal setting and pursuit (Ackerman 1992). However, the literature also notes that unmindful, repetitive action is not always desirable because its problems and opportunities may be ignored as well. For this reason, Louis and Sutton (1991) argue that a shift from automatic processing to conscious processing should occur when (1) a situation is perceived to be unusual, (2) a gap exists between expectations and performances, and/or (3) other alternatives are available. According to them, if organizational workers fail to respond to such exceptional conditions, their productivity will suffer in the long run. Thus, to better understand the missing link between IT use and performance, we encourage researchers to examine (1) whether automatic processing can really enhance task performance under normal conditions and (2) how habitual users' reactions to exceptional conditions affect their performance in an organizational setting. This line of research will help us more efficiently and effectively leverage organizational IT investments.

4.4. Conclusions

Our knowledge of automatic use is severely limited compared with what we know about conscious use. Lack of knowledge about less evaluative, less intentional behavior is especially problematic, given the pervasiveness of routinized use in everyday life. To clarify the nature of automatic use, this study presents a conceptual framework that highlights the role of habit/automaticity as an underlying mechanism shifting from conscious processing to automatic processing. We hope that more researchers will examine this underexplored area of habit/automaticity and that our theoretical framework will serve as a useful conceptual tool for their endeavors.

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