Assessing IT Usage: The Role of Prior Experience

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Introduction

A variety of models that incorporate attitudinal, social, and control factors have been advanced to explain IT usage (e.g., Davis, 1989; Davis, et al., 1989; Hartwick and Barki, 1994; Mathieson, 1991; Moore and Benbasat, 1991; Thompson, et al., 1991), of which the Technology Acceptance Model (TAM) (Davis, 1989) is the most well known. One goal of such models is to develop diagnostic tools to predict information systems acceptance and facilitate design changes before users have experience with a system (Davis, 1989). However, empirical tests of these models have generally focused on either systems that were already in use by the study participants, or systems that the participants were familiar with, such as word processing packages and spreadsheets. Given this, it is unclear: (1) whether models such as TAM are predictive of behavior for inexperienced users and, more importantly, (2) whether the determinants of IT usage are the same for experienced and inexperienced users of a system.

To address these issues, this paper reports on a study of 430 experienced and 356 inexperienced potential users of an IT system[1]—specifically, a student computing information resource center. Using an augmented version of TAM that incorporates social influences and behavioral control, the experienced and inexperienced user groups are compared. To address issue (1) above, the model was tested to show whether it provides an equivalent understanding of usage for both groups. Then to test issue (2), specific paths in the model were compared between the two groups. The overall goal of this research is to assess the efficacy of the augmented TAM in helping, a priori, to understand the behavior of inexperienced users.

Understanding IT Usage

As noted above, TAM (Davis, 1989; Davis, et al., 1989) has been the most commonly employed model of IT usage, receiving considerable empirical support (e.g., Davis, 1989; Davis, et al., 1989; Mathieson, 1991; Taylor and Todd, 1995). According to TAM, usage behavior (B) is a direct function of behavioral intention (BI). BI is, in turn, a function of: attitude toward usage (A), which reflects feelings of favorableness or unfavorableness toward using the technology, and perceived usefulness (U), which reflects the belief that using the technology will enhance performance. Attitude is determined jointly by perceived usefulness and perceived ease of use (E). Finally, ease of use

[1]IT usage is viewed as not strictly encompassing hardware and software usage, but also the services that surround the technology and the people and procedures that support their use.

is a direct determinant of perceived usefulness. Stated more formally,

$$B \cong BI = w_1A + w_2U$$
$$A = w_3U + w_4E$$
$$U = w_5E$$

Note that TAM does not include the influence of social and control factors on behavior. Such factors have been found to have a significant influence on IT usage behavior (e.g., Barclay, et al., 1996; Compeau and Higgins, 1991; Hartwick and Barki, 1994; Mathieson, 1991; Moore and Benbasat, 1991; Taylor and Todd, 1995; Thompson, et al., 1991). These variables are also key determinants of behavior in the Theory of Planned Behavior (Ajzen, 1991), where social influences (subjective norm) are modelled as determinants of behavioral intention, and perceived behavioral control is modelled as a determinant of both intention and behavior. Because of their predictive utility in IT usage research and because of their widespread application in social psychology, subjective norm (SN) and perceived behavioral control (PBC) are added to TAM to provide a more complete test of the important determinants of IT usage. The full model, which we label the augmented TAM, can be seen in Figure 1. While we anticipate that this model will help understand IT usage for both experienced and inexperienced users, the relative influence of the model determinants may differ between the two groups.

The Influence of Prior Experience

Prior experience has been found to be an important determinant of behavior (Ajzen and Fishbein, 1980; Bagozzi, 1981; Bentler and

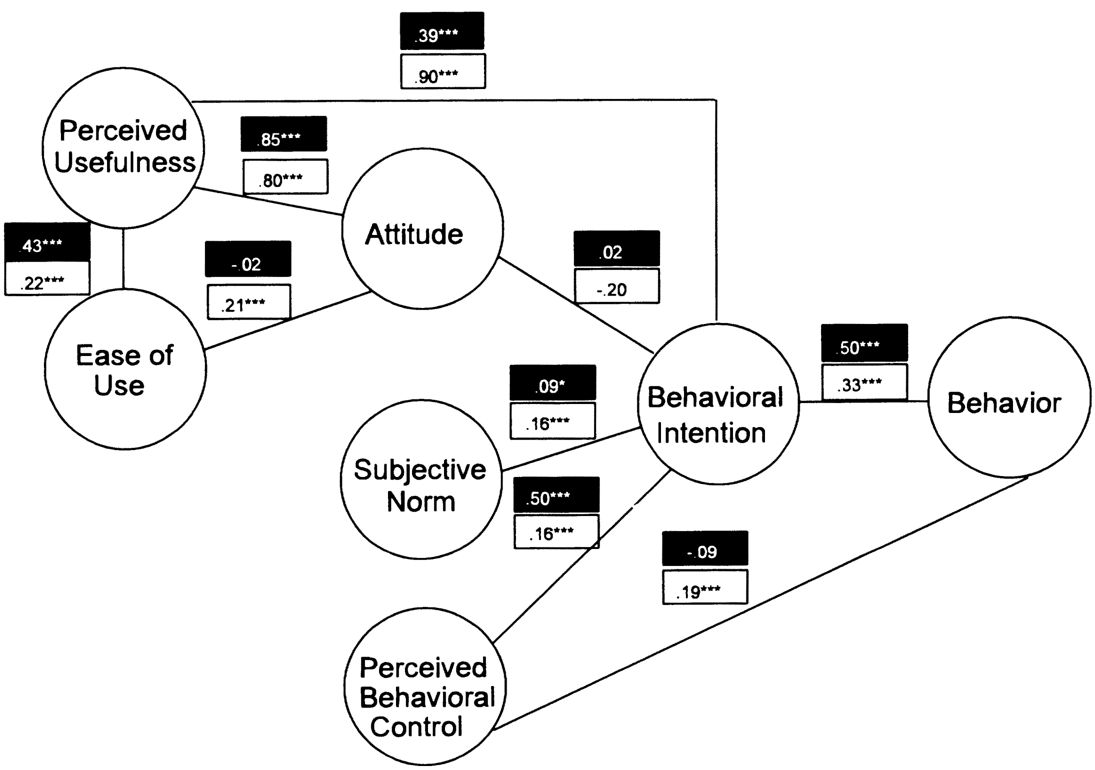

Figure 1. Standardized Path Coefficients[a] for the Experienced and Inexperienced Users

[a]Coefficients for Experienced Users are in the shaded boxes. *p < .05. **p < .01. ***p < .001.

Speckart, 1979; Fishbein and Ajzen, 1975; Triandis, 1979). Specifically, it has been suggested that knowledge gained from past behavior will help to shape intention (Eagley and Chaiken, 1993; Fishbein and Ajzen, 1975), in part because experience makes knowledge more accessible in memory (Fazio and Zanna, 1978; Reagan and Fazio, 1977), and also because past experience may make low probability events more salient, ensuring that they are accounted for in the formation of intentions (Ajzen and Fishbein, 1980). This implies that IT usage may be more effectively modeled for experienced users. Given this, it is important to assess the utility of models such as the augmented TAM for understanding the behavior of inexperienced users. More importantly, there may be differences between experienced and inexperienced users in the *relative influence* of the various determinants of IT usage. Such differences may suggest alternative ways to effectively manage the development and implementation of new systems. The anticipated differences between experienced and inexperienced groups are summarized below.

Behavioral Intention to Behavior. Direct experience will result in a stronger, more stable behavioral intention - behavior relationship (Ajzen and Fishbein, 1980).

PBC to Behavior and Behavioral Intention. For experienced users, BI is expected to fully mediate the relationship between PBC and behavior. By contrast, for inexperienced users with no prior knowledge on which to assess control factors, PBC may directly influence behavior since it is this direct experience that makes the influence of control factors apparent.

Perceived Usefulness and Attitude to Behavioral Intention. Beliefs and attitudes correlate more strongly with behavior for people who have had direct experience with an object (Eagly and Chaiken, 1993; Fazio and Zanna, 1978; Regan and Fazio, 1977), suggesting a stronger influence of perceived usefulness and attitude on BI and subsequent behavior for experienced users.

Subjective Norm to Behavioral Intention. The relative influence of subjective norm on intentions is expected to be stronger for potential users with no prior experience since they are more likely to rely on the reactions of others in forming their intentions (Burnkrant and Cousineau, 1975; Hartwick and Barki, 1994).

Ease of Use and Perceived Usefulness to Attitude. Factors such as ease of use and perceived usefulness may have different relative influences depending on experience. Those without experience may focus first on ease of use. With experience, users have presumably overcome concerns about ease of use and may focus their attention on perceived usefulness. This suggests that the path from ease of use to attitude will be stronger for inexperienced users, while the path from perceived usefulness to attitude will be stronger for experienced users.

The Study

Data for this study were collected as part of a larger project that compared alternative models of IT usage (Taylor and Todd, 1995). Details on the study methodology and procedures are provided there.[2] A summary is provided here. The study focused on usage of a computing resource center (CRC) by business school students. The CRC is a special-purpose computer lab that provides high-end computing and printing services, as well as technical support for students. The CRC is staffed with an attendant on duty. Access is free; however, students are charged a fee for all hardcopy output. Use of the CRC is voluntary since there are alternative facilities and services available on campus.

A survey to measure all constructs except usage was developed and validated through the use of card-sorting procedures and a pilot test. Prior to completing the survey, students had toured the facility and were provided with an information sheet describing the CRC and its services. The final survey was completed by 786 of the approximately 1000 students in the business school. Respondents included 430 participants with prior experience using the

[2] A detailed description of the research method and analytical approach is available from the authors upon request.

CRC and 356 participants with no prior experience using the CRC.

After the survey was completed, usage measures were collected for a 12-week period. The usage measures were based on forms completed each time a student used the CRC. They took about 30 seconds to fill out. Completion of the form was controlled by the CRC attendant. The usage measures derived from these forms were: total number of visits per user, total time spent in the CRC, and total number of projects completed in the CRC.

Of the 786 respondents to the survey, 451 used the CRC over the period that usage was recorded, making a total of 3780 visits. Of these 451 users, 332 had had prior usage experience with the CRC, and 119 had had no prior experience using the CRC.

Results

The augmented TAM (Figure 1) was tested separately for the experienced and inexperienced groups using LISREL8 (Joreskog and Sorbom, 1993) with maximum likelihood estimation.[3] Multiple items were used to measure each construct. For each group, overall fit, predictive power and the significance of paths were considered. To assess fit, the traditional χ^2 fit test, the RNI (Relative Non-Centrality Index) (McDonald and Marsh, 1990), and the RMSEA[4] (Root Mean Square Error of Approximation) (Steiger, 1990) are reported. The covariance matrices used in the analyses are shown in the Appendix.

[3]Analysis of this data indicates that it is not multivariate normal (Mardia's test: x^2 = 70680.97). Given our limited sample size for each group, maximum likelihood estimation was used; although this reduces the confidence of the chi-square estimates, it does not affect the parameter estimates.

[4]For RMSEA, lower numbers represent better fit, while for RNI, higher numbers represent better fit.

Experienced users

Overall, the fit statistics indicate that the model provides an adequate fit to the data for the experienced users (χ_{200}^2 = 1003.66, $p < 0.001$; RNI = 0.86; RMSEA = 0.097).[5] Although the RMSEA is below the 0.10 cutoff suggested as indicative of reasonable model fit (Browne and Cudeck, 1993), the RNI value is slightly below the desired 0.90 level (Marsh, 1994). The model accounts for 21 percent of the variance in behavior and 43 percent of the variance in behavioral intention. As indicated in Figure 1, all path coefficients in the model were significant with the exception of the paths from ease of use to attitude, attitude to behavioral intention, and perceived behavioral control to behavior.

Inexperienced users

The fit statistics indicate that the model fit is approximately equivalent to that for the experienced user group (χ_{200}^2 = 826.75, $p < 0.001$; RNI = 0.88; RMSEA = 0.094). For this group, the model accounts for 17 percent of the variance in behavior and 60 percent of the variance in intention. As indicated in Figure 1, all path coefficients in the model were significant except for the path from attitude to behavioral intention.

Comparisons of experienced and inexperienced users

Multi-sample LISREL8 (Joreskog and Sorbom, 1993) was used to test for differences in the strength of the path coefficients between the two groups. In this analysis, one path co-efficient was constrained to be equal across the two groups, and the resulting model fit was compared to a base model in which all paths were freely estimated using a χ^2 difference test.

The results of these analyses are shown in Table 1. As expected, the path from BI to

[5]The chi-square for the null model for experienced users was: x_{231}^2 = 5851.16. The chi-square for the inexperienced users was: x_{231}^2 = 5495.63.

Table 1. Multisample LISREL Comparison of Paths for Experienced and Inexperienced Users

	χ^2	df	$\Delta\chi^2$ From Base Model
Unconstrained Base Model[a]	1830.41	4e+29	
Constrained Paths[b]			
$\beta(1, 2)$ Intention to Behavior	1859.46		29.05***
$\beta(2, 3)$ Attitude to Intention	1831.82		1.41
$\beta(2, 4)$ Perceived Usefulness to Intention	1838.84		8.43**
$\beta(3, 4)$ Perceived Usefulness to Attitude	1831.17		.76
$\Gamma(1, 2)$ PBC to Behavior	1835.62		5.21*
$\Gamma(2, 1)$ Subjective Norm to Intention	1832.18		1.77
$\Gamma(2, 2)$ PBC to Intention	1837.41		7.00**
$\Gamma(3, 3)$ Ease to Attitude	1841.96		11.55***
$\Gamma(4, 3)$ Ease to Perceived Usefulness	1832.81		2.40

[a]Paths for the two groups were allowed to be freely estimated.

[b]The path specified was constrained to be equal across the two groups.

* $p < .05$. ** $p < .01$. *** $p < .001$.

behavior was stronger for the experienced users ($\Delta\chi^2 = 29.05$; $p < 0.001$). The path from attitude to BI was not significant for either group and did not differ between the experienced and inexperienced groups ($\Delta\chi^2 = 1.41$; $p > 0.05$). Unexpectedly, perceived usefulness was a stronger predictor of intention for inexperienced users ($\Delta\chi^2 = 8.43$, $p < 0.01$); however, it did not differ between the two groups in its impact on attitude ($\Delta\chi^2 = 0.76$, $p > 0.05$) . The path from SN to BI was not significantly different between the two groups ($\Delta\chi^2 = 1.77$; $p > 0.05$). As expected, the path from PBC to BI was stronger for the experienced users ($\Delta\chi^2 = 7.00$; $p < 0.01$), while the path from PBC to behavior was stronger for the inexperienced group ($\Delta\chi^2 = 5.21$, $p < 0.05$). Also as anticipated, ease of use was a more important predictor of attitude for inexperienced users ($\Delta\chi^2 = 11.55$, $p < 0.001$).

Discussion

Overall, the results suggest that the augmented TAM provided an adequate model of IT usage for both experienced and inexperienced users, accounting for a reasonable proportion of the variance in intention and behavior. For both groups, all direct determinants of intention, except attitude, were significant. Thus, the augmented version of TAM can be used to predict subsequent usage behavior *prior* to users having any hands-on experience with a system. This suggests that IT usage models may be employed diagnostically prior to implementation.

More importantly, these results also suggest that there are some significant differences in the relative influence of the determinants of usage depending on experience. Not surprisingly, there was a stronger link between behavioral intention and behavior for the experienced users. This is consistent with the notion that experienced users employ the knowledge gained from their prior experiences to form their intentions (Fishbein and Ajzen, 1975). However, inexperienced users' intentions were better predicted by the antecedent variables in the model than were the intentions of experienced users. This suggests that communicating information to inexperienced users can have a strong effect on intentions but that this intention will not translate completely to behavior. This may be due to their ability to assess the different antecedents of intention. In particular, we note that there are important differences between the groups with respect to the relative influence of perceived usefulness and perceived behavioral control. Contrary to our expectations, perceived usefulness was the strongest predictor of intention for the inexperienced group. By contrast, users with prior experience placed less weight on perceived usefulness, balancing this consideration with an emphasis on perceived behavioral control. For these users, behavioral intention fully mediated the relationship between PBC and behavior. For inexperienced users, perceived behavioral control had less of an impact on intention, but also had a significant influence on behavior. This suggests that inexperienced users tend to discount control information in the formation of intentions, relying instead primarily on perceived usefulness.

This result has implications for the management of user expectations when introducing new information technology. Forming a behavioral intention is not unlike forming an expectation, with the difference between intention and behavior representing an expectation gap. Recall that the path from intention to behavior was stronger for experienced users, suggesting that experience can fill the expectations gap. The challenge, then, is to find a way to close this gap by setting more realistic expectations for inexperienced users. In the simplest terms, expectations are formed by evaluating both the costs and benefits of using a system. Unrealistic user expectations have been suggested as a key factor in systems implementation failure (Szajna and Scamell, 1993). The formation of realistic expectations requires the consideration of control factors (Sheppard, et al., 1988). Our results indicate that inexperienced users may not adequately consider such control information in forming their expectations. In essence, they underestimate costs, instead focusing on the perceived usefulness, or potential benefits, of using a system. One way to close the expectations gap would be to stress to inexperienced users the control factors that may constrain their behavior and suggest alternative strategies to limit the impact of those constraints. Pragmatically, this implies a balanced selling approach that involves communicating to users the facilitating or constraining factors that may limit system usage as well as the benefits of the system, ensuring that both are adequately taken into account.

Our results also have implications for research in the area of information technology usage. In this case we focus on the research implications associated specifically with the effect of experience on IT usage. The relationship of the factors in the augmented TAM to the orignial TAM are discussed in detail elsewhere (Taylor and Todd, 1995).

To date, researchers have primarily taken a static view of the influence of variables such as those in TAM on usage; they have not considered how the influence of those factors may change as users experience with the technology changes over the course of a system's lifecycle. Our findings suggest that different variables within the model may have different influences on intention and usage depending on experience. Researchers should begin to examine this phenomenon at a finer level of analysis to determine the exact magnitude of these effects at various points in the system lifecycle and for users with different experiences.

Before drawing definitive conclusions from these results, it is important to consider the study's limitations. First, this study focuses on a student setting where subjective norms and perceived behavioral control may operate differently than in workplace settings. Second, the role of other factors that may correlate with experience (such as gender, year in the program, etc.) were not examined in this study. Third, our model fits in both cases were adequate, but slightly below desired levels on some indices. Fourth, we examine only one specific form of IT usage, which is the use of a computer information resource center. Finally, our assessments of experience as a dichotomous variable provide only gross distinctions. A finer examination along the continuum of experience would be useful to better understand these relationships.

To conclude, the results from this study suggest that the augmented TAM can be applied to understand the behavior of both experienced and inexperienced users; however it is important to note that inexperienced users place a different emphasis on the determinants of intention and usage. They focus primarily on perceived usefulness, placing less emphasis on control factors. This has implications for systems design and implementation.

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Appendix

Covariance Matrix for Experienced Users

	B1	B2	B3	I1	I2	I3	A1	A2	A3	A4	PU1	PU2	PU3	PU4	SN1	SN2	PBC1	PBC2	PBC3	Ease1	Ease2	Ease3
B1	98.59																					
B2	4184.00	220930.00																				
B3	58.52	2630.60	43.9																			
I1	5.66	231.73	8	1.6																		
I2	5.44	225.74	3.33	0	1.6																	
I3	8.21	335.57	3.23	1.3	9	3.3																
A1	1.04	40.16	4.76	4	1.6	7	0.6															
A2	0.54	16.37	0.58	1.7	0	0.6	2	0.7														
A3	1.88	67.86	0.42	1	0.4	1	0.4	9	1.6													
A4	0.86	32.46	1.16	0.4	5	0.5	7	0.6	9	1.6												
PU1	3.36	141.95	0.60	7	0.3	2	0.6	7	1.1	8	1.65											
PU2	0.65	44.85	1.87	0.3	7	1.1	6	0.5	4	0.6	0.58	2.67										
PU3	1 .41	60.10	1.12	8	0.5	1	0.4	2	0.6	7	0.61	0.60	0.86									
PU4	0.67	7.70	0.88	0.6	2	0.9	5	0.4	6	0.5	0.61	0.55	0.61	1.39								
SN1	0.32	-25.03	0.42	3	0.3	8	0.4	5	0.7	3	0.48	0.71	0.49	0.37	2.24							
SN2	0.30	-10.92	0.00	0.5	3	1.2	3	0.5	0	0.4	0.53	0.81	0.49	0.42	1.71	2.18						
PBC1	2.24	94.63	0.05	0	0.8	8	0.4	3	0.6	5	0.59	0.27	0.35	0.37	0.22	0.21	1.04					
PBC2	0.52	10.94	1.11	0.9	5	0.7	2	0.4	6	0.6	0.45	0.32	0.42	0.56	0.22	0.30	0.57	2.09				
PBC3	3.38	127.48	0.19	4	0.3	9	0.4	0	0.7	5	0.34	0.10	0.30	0.34	-	-	0.55	0.71	1.83			
Ease1	2.64	104 .17	1.64	0.4	7	0.7	1	0.4	0	0.4	0.35	-	0.24	0.32	0.01	0.06	0.31	0.48	0.72	2.22		
Ease2	2.89	99.32	1.36	2	0.4	5	0.4	7	0.6	4	0.44	0.10	0.36	0.61	-	-	0.34	0.82	0.97	1.22	2.34	
Ease3	2.98	114.26	1.47	0.5	2	0.6	8	0.5	3	0.4	0.44	-	0.36	0.50	0.13	0.09	0.48	0.61	1.02	0.89	1.21	1.91
			1.73	5	0.4	3	0.4	5	0.5	7		0.02			0.08	0.19						
				0.4	1	0.6	1	0.5	9	0.3		0.18			0.04	0.05						
				2	0.4	9	0.3	4	0.4	6												
				0.4	0	0.5	9	0.2	0	0.6												
				9	0.4	7	0.2	4	0.5	4												
				0.5	2	0.8	9	0.3	7	0.4												
				2	0.6	0	0.3	5	0.4	1												
				0.7	8	0.5	2	0.1	2	0.3												
				0	0.3	9	0.2	1	0.2	7												
				0.4	7	0.6	1	0.0	8	0.6												
				7	0.4	7	0.0	6	0.5	1												
				0.5	9	0.2	5	0.1	5	0.6												
				5	0.2	6	0.2	7	0.5	2												
				0.3	1	0.7	1	0.1	2													
				1	0.3	1	0.2	9														
				0.4	5	0.7	5															
				3	0.4	1																
				0.4	0																	
				8																		

Covariance Matrix for Inexperienced Users

	B1	B2	B3	I1	I2	I3	A1	A2	A3	A4	PU1	PU2	PU3	PU4	SN1	SN2	PBC1	PBC2	PBC3	Ease1	Ease2	Ease3
B1	35.22																					
B2	1599.60	83605.00																				
B3	25.92	1187.40	21.19																			
I1	3.97	180.92	2.96	3.36																		
I2	4.10	184.20	3.03	2.74	3.56																	
I3	4.31	189.93	3.32	2.75	2.64	3.72																
A1	1.05	44.36	0.82	0.85	0.76	0.76	1.04															
A2	0.84	35.31	0.65	0.80	0.72	0.74	0.70	1.01														
A3	1.27	62.82	1.04	1.22	1.07	1.31	0.78	0.77	1.57													
A4	0.73	29.60	0.50	0.87	0.65	1.07	0.63	0.56	1.10	1.54												
PU1	1.96	90.12	1.31	1.83	1.60	1.58	0.68	0.60	0.89	0.65	2.49											
PU2	0.41	23.23	0.43	1.03	0.85	1.07	0.52	0.51	0.58	0.51	0.59	1.88										
PU3	1.11	42.67	0.82	1.19	1.07	1.05	0.65	0.64	0.89	0.67	0.97	0.70	1.47									
PU4	1.30	58.70	1.03	0.83	0.57	0.78	0.51	0.46	0.68	0.53	0.76	0.35	0.74	1.39								
SN1	-0.14	4.27	-0.12	1.05	0.86	1.13	0.50	0.46	0.48	0.61	0.77	0.86	0.60	0.35	2.50							
SN2	0.02	13.08	-0.04	1.06	0.89	0.95	0.52	0.46	0.56	0.56	0.79	0.79	0.57	0.33	1.94	2.32						
PBC1	2.23	88.67	1.65	1.27	1.07	1.09	0.55	0.45	0.78	0.68	0.84	0.44	0.77	0.70	0.31	0.39	1.93					
PBC2	0.77	18.25	0.53	0.16	0.00	0.06	0.08	0.08	0.16	0.29	0.09	-0.09	0.20	0.18	-0.16	-0.11	0.87	2.01				
PBC3	2.43	96.27	1.77	0.52	0.45	0.54	0.22	0.12	0.48	0.63	0.05	-0.02	0.24	0.26	-0.15	-0.10	1.09	1.22	2.90			
Ease1	0.24	0.48	0.17	0.25	0.17	0.29	0.16	0.19	0.35	0.46	0.16	-0.04	0.21	0.22	-0.15	-0.08	0.56	0.45	0.81	2.20		
Ease2	1.56	67.65	1.03	0.19	0.19	0.26	0.19	0.20	0.51	0.53	0.23	-0.22	0.19	0.33	-0.22	-0.20	0.65	0.54	1.10	1.33	2.38	
Ease3	1.42	64.80	1.01	0.45	0.29	0.50	0.33	0.25	0.62	0.82	0.28	0.12	0.39	0.53	-0.02	-0.08	0.85	0.66	1.18	1.08	1.38	2.03