Available online at www.sciencedirect.com
SCIENCE DIRECT
ELSEVIER
Int. J. Human-Computer Studies 59 (2003) 451–474
International Journal of Human-Computer Studies
www.elsevier.com/locate/ijhcs

Predicting e-services adoption: a perceived risk facets perspective

Mauricio S. Featherman[a,*], Paul A. Pavlou[b]

[a] College of Business & Economics, Washington State University, Todd Hall 240C, Box 644729, Pullman, WA 99164-4729, USA
[b] Marshall School of Business, University of Southern California, 401M Bridge Hall, Los Angeles, CA 90012, USA

Received 15 November 2002; received in revised form 24 February 2003; accepted 31 March 2003

Abstract

Internet-delivered e-services are increasingly being made available to consumers; however, little is known about how consumers evaluate them for potential adoption. Past Technology Adoption Research has focused primarily on the positive utility gains attributable to system adoption. This research extends that approach to include measures of negative utility (potential losses) attributable to e-service adoption. Drawing from Perceived Risk Theory, specific risk facets were operationalized, integrated, and empirically tested within the Technology Acceptance Model resulting in a proposed e-services adoption model. Results indicated that e-services adoption is adversely affected primarily by performance-based risk perceptions, and perceived ease of use of the e-service reduced these risk concerns. Implications of integrating perceived risk into the proposed e-services adoption model are discussed.

Keywords: Perceived risk; Risk facets; HCI; Technology adoption; e-Services,SEM

1. Introduction

E-services are interactive software-based information systems received via the Internet. They have been referred to as “assets—information, business processes, computing resources, applications—made available via the Internet as a means of

*Corresponding author. Tel.: +1-509-335-4445; fax: +1-509-335-427.
E-mail addresses: mauricio@cbe.wsu.edu (M.S. Featherman), pavlou@marshall.usc.edu (P.A. Pavlou).

1071-5819/03/$ - see front matter
doi:10.1016/S1071-5819(03)00111-3

driving new revenue streams and creating efficiencies".[1] E-services are important in business to consumer (B2C) e-commerce because they represent ways to provide on-demand solutions to customers strengthening customer–service provider relations, creating transactional efficiencies and improving customer satisfaction (Ruyter et al., 2001). Prominent examples of e-services include integrated trip planning, on-line banking and financial portfolio management. While e-services are convenient and create efficiencies for their users, little is understood about how consumers evaluate them for adoption.

It is important to distinguish the difference between conducting basic e-commerce purchases and adopting e-services. In comparison to one-time e-commerce-based purchases, the e-service adoption decision is typically more complex, as they initiate a long-term relationship between the consumer and service provider. There is more at stake for the consumer as they contemplate entering into a business relationship with distant, faceless e-service providers. Additionally unlike product purchases where consumers receive a tangible good, when consumers purchase an e-service they receive only access to the functionality provided by a web-portal.

Consumers have shown reluctance to complete simple on-line purchase transactions (Hoffman et al., 1999), primarily due to risk concerns (Jarvenpaa and Tractinsky, 1999; Pavlou, 2001) and therefore, perceived risk is similarly posited as a prominent barrier to consumer acceptance of e-services. Consumer perceptions of risks inherent in product adoption and usage have been studied for many years (Bauer, 1967; Dowling and Staelin, 1994); however have not been applied to the relatively new e-services evaluation and adoption context. According to Koller (1988), the degree of importance of the situation determines the potential effect of risk. Given that the adoption of e-services is an important decision for most consumers with long-term implications, the role of risk is likely to become prominent. Hence, even if e-services are an e-commerce application to which some adoption models exist (Pavlou, 2001), it requires a distinct conceptualization. Toward this end, this study employs elements from the perceived risk literature to predict consumer evaluation of e-services adoption of e-services.

As increasing numbers of paper-based processes are digitized and moved to computer environments, it has become more important to study end-user perceptions of these new user interfaces. When e-services are considered as a combination of the client–side user interface and programs run on vendor's servers, the Human–Computer Interaction (HCI) research discipline can be used to guide formal research efforts. HCI research is "the scientific study of the interaction between people, computers and the work environment" (Beard and Peterson, 1988). The HCI research focus enables unique insights into how consumers interact with information, technologies and the tasks they enable (Zhang et al., 2002). This research paper draws on the management information systems (MIS) portion of the HCI literature base as it attempts to gain understanding of end-user's cognitive and affective reactions to the potential risks often perceived inherent in using computerized e-services. These consumer perceptions are important to understand

[1] http://www.hp.com/solutions1/e-services/ (accessed 3/9/02)

as they enable better system development (Compeau et al., 1999) and have implications to both research and practitioners (Davis, 2002). Understanding end-user reactions to an e-service portal interface are also important as they may be perceived as cues of overall service performance. Because the user interface is a central source of e-service pre-adoption information, this research utilizes an MIS focused HCI theoretical approach.

The specific theoretical basis utilized here is the Technology Acceptance literature, which studies individual reactions to computing technology. The Technology Acceptance Model (TAM, Davis, 1989) has been utilized in many on-line contexts to gauge user perceptions of system use, and the probability of adopting an on-line system (Teo et al., 1999; Gefen and Straub, 2000; Moon and Kim, 2001; Pavlou, 2001). Since TAM has been applied to e-commerce transactions, it may aid our understanding of e-service adoption. This study proposes to integrate the perceived risk literature with the basic TAM variables (perceived usefulness and perceived ease of use). The marriage of these literature streams may provide a more comprehensive model of e-services evaluation and adoption, and therefore benefit the MIS HCI research discipline.

The perceived risk variable is first modeled as a singular variable within TAM, and then decomposed into its sub-facets, as theorized by Cunningham (1967). In that way, insight may be gained as to which risk facets are salient for potential consumers of e-services.

Theoretical insight into consumer reactions and perceptions of e-services may be made possible by the inclusion of measures of negative utility (perceived usage risks) into the existing positive utility oriented adoption model. Hence, this study enlarges the scope of the adoption decision to explicitly include both risks (potential negative utility) and rewards (potential positive utility). The research may benefit practitioners as an increased understanding of consumer perceptions can be used to devise risk-reducing strategies to encourage service adoption, especially in the emerging area of e-payments. The following two research questions guide the methodology:

- How important are risk perceptions to the overall e-services adoption decision?
- What types of risk are salient and therefore important to the consumer of e-services?

The paper proceeds with the following sections. First, a brief review of the Perceived Risk and Technology Acceptance literature results in a proposed research model. Exploratory research models are presented and analysed with sample #1 and then confirmed with sample #2. The paper concludes by discussing the implications of the resulting e-services adoption model.

2. Conceptual development

2.1. Perceived risk

Perceived risk (PR) is commonly thought of as felt uncertainty regarding possible negative consequences of using a product or service. It has formally been defined as "a combination of uncertainty plus seriousness of outcome involved" (Bauer, 1967), and "the expectation of losses associated with purchase and acts as an inhibitor to purchase behavior" (Peter and Ryan, 1976). PR has been captured with Likert scales measuring the perception of dangerous events occurring or the presence of the attribute inherent in the service. Alternately it has been measured using an expectancy * value methodology typically multiplying either probability of loss, exposure or danger (uncertainty component) by the cost or importance of that potential loss or exposure (severity component). Following these descriptions, we define perceived risk as " the potential for loss in the pursuit of a desired outcome of using an e-service."

PR enters the information systems adoption decision when circumstances of the decision create (a) feelings of uncertainty, (b) discomfort and/or anxiety (Dowling and Staelin, 1994), (c) conflict aroused in the consumer (Bettman, 1973), (d) concern, (e) psychological discomfort (Zaltman and Wallendorf, 1983), (f) making the consumer feel uncertain (Engel et al., 1986), (g) pain due to anxiety (Taylor, 1974), and (h) cognitive dissonance (Festinger, 1957; Germunden, 1985). The dissonance arises from the evaluation of the product as having costs and benefits, risks and utility. For the current research context, the utility gains are potential increased task performance efficiencies, while the risks include possible task performance related problems and the uncertainty of the Internet as an unsecured communications medium.

2.2. *Facets of perceived risk*

Cunningham (1967) identified two major categories of perceived risk (a) performance and (b) psychosocial. He broke performance into three types (i) economic, (ii) temporal, (iii) effort; and broke psychosocial into two types—(i) psychological and (ii) social. Cunningham (1967) further typified perceived risk as having six dimensions—(1) performance, (2) financial, (3) opportunity/time, (4) safety, (5) social and (6) psychological loss. He also posited that all risk facets stem from performance risk. A rich stream of consumer behavior literature supports the usage of these risk facets to understand consumer product and service evaluations and purchases. The e-services research context does not incur any threat to human life; therefore, measures of (physical) safety risk were not included in this study. A newly developed risk facet tapping privacy concerns, that replaces this safety risk will be introduced below.

Jacoby and Kaplan (1972) inferred from Bauer's seminal work (1967) an overall measure of perceived risk. He theorized it as consisting of several independent varieties of risk after a risk "tradeoff" behavior occurred. For example, a large automobile may reduce physical (safety) risk but increase financial risk. This measure of overall perceived risk is also tested here.

Bellman et al. (1999) reported on the importance of time considerations and found it the significant predictor to on-line buying behavior. Their research found that "harried" consumers with less time were more likely to purchase over the Internet in order to save time. The current research similarly proposes that consumers are very time oriented and concerned about potential risks of "wasting time" implementing, learning how to use,

Table 1
Description and definition of perceived risk facets

Perceived Risk Facet	Description—Definition
1. Performance risk	"The possibility of the product malfunctioning and not performing as it was designed and advertised and therefore failing to deliver the desired benefits." (Grewal et al., 1994)
2. Financial risk	"The potential monetary outlay associated with the initial purchase price as well as the subsequent maintenance cost of the product" (Grewal et al., 1994). The current financial services research context expands this facet to include the recurring potential for financial loss due to fraud.
3. Time risk	Consumers may lose time when making a bad purchasing decision by wasting time researching and making the purchase, learning how to use a product or service only to have to replace it if it does not perform to expectations.
4. Psychological risk	The risk that the selection or performance of the producer will have a negative effect on the consumer's peace of mind or self-perception (Mitchell, 1992). Potential loss of self-esteem (ego loss) from the frustration of not achieving a buying goal.
5. Social risk	Potential loss of status in one's social group as a result of adopting a product or service, looking foolish or untrendy.
6. Privacy risk	Potential loss of control over personal information, such as when information about you is used without your knowledge or permission. The extreme case is where a consumer is "spoofed" meaning a criminal uses their identity to perform fraudulent transactions.
7. Overall risk	A general measure of perceived risk when all criteria are evaluated together.

and troubleshooting a new e-service. These time-conscious consumers likely guard against the possible loss of time risk, and are less likely to adopt the e-service that they consider as have high switching, setup and maintenance costs.

A seventh risk facet; privacy risk was included. Privacy risk may be particularly salient for the e-payments product category. Pilot test results have indicated subjects' concern for the theft of their private information, or simply its misuse by the company collecting it. A focus group drawn from the sample population identified common concerns for the possible loss of privacy of personal financial information and potential "identity-theft". As this focus group indicated privacy risk as a common concern that inhibited adoption, items tapping this phenomenon were developed, grouped and modeled as a deterrent to perceived usefulness and adoption. The risk facets are defined in Table 1. Based on the proposed conceptualizations, for this context we propose:

H1: Perceived risk comprises the facets of (1) performance, (2) financial, (3) time, (4) psychological, (5) social, (6) privacy and (7) overall risk.

2.3. Technology acceptance

TAM was designed to gather evaluative measures of information system (IS) quality and suitability to job requirements, and thereby enable predictions of IS acceptance and usage. Davis wrote "The goal of TAM is to provide an explanation of the determinants of computer acceptance that is general, capable of explaining user behavior across a broad range of end-user computing technologies and user populations" (Davis et al., 1989, p. 985). TAM posits that an attitude toward using an information system is based on two primary antecedent variables—perceived usefulness and perceived ease of use. These are similar to Bandura's (1986) outcome judgment, and self-efficacy. Many recent research articles have utilized TAM as a base model to predict adoption (Teo et al., 1999; Gefen and Straub, 2000; Moon and Kim, 2001; Pavlou, 2001).

Perceived Usefulness (USF) is defined as "The prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context" (Davis et al., 1989, p. 985). Perceived Ease of Use (EOU) is defined as the "…the degree to which the prospective user expects the target system to be free of effort" (Ibid). Software perceived as being helpful in performing important tasks and easy to use are typically evaluated more highly and often deemed desirable. An excellent theoretical review of TAM was provided when it was expanded (Venkatesh and Davis, 2000), and the reader is encouraged to use that source for a more in-depth literature review. The expanded TAM utilizes eight constructs and provides a rich research framework useful to predict end-user adoption intentions. The current research however utilizes the original more parsimonious model (EOU and USF as lone predictors of adoption intention) to more clearly focus on their covariance with the newly introduced seven perceived risk facets. A second-order perceived risk variable is proposed which is based on seven underlying risk facets bringing the model total to 11. To enable the usage of structural equation modeling, the parsimonious TAM version was utilized.

It is deemed necessary to include a measure of perceived risk into TAM because consumers consciously and unconsciously perceive risk when evaluating products and services for purchase and/or adoption (Bauer, 1967). Similarly, Igbaria (1993) identified that information systems adoption has been shown to create anxiety and discomfort for consumers and employees. Usage of the Internet delivery medium also adds additional uncertainties and potential dangers due to its perceived unsecured nature. The combination of uncertainty (probability of loss) and danger (cost of loss) that make up perceived risk have been shown to inhibit product evaluation (e.g. perceived usefulness) and adoption (Dowling and Staelin, 1994). Therefore, it follows that:

H2: E-service perceived risk reduces their perceived usefulness and adoption.
H3: E-service privacy risk adversely affects perceived usefulness and adoption.

User perceptions of an e-service's ease of use are likely to affect perceptions of usage risk. Products or services that are perceived as being complex, with steep learning curves, are likely to also be thought of as risky to adopt and use. Moore and Benbasat (1991) identified that the complexity of the user interface reduces system evaluation and adoption intention. TAM's EOU is a similar construct perhaps at the other end of the usability scale that may reduce system usage uncertainty and risk. E-services that

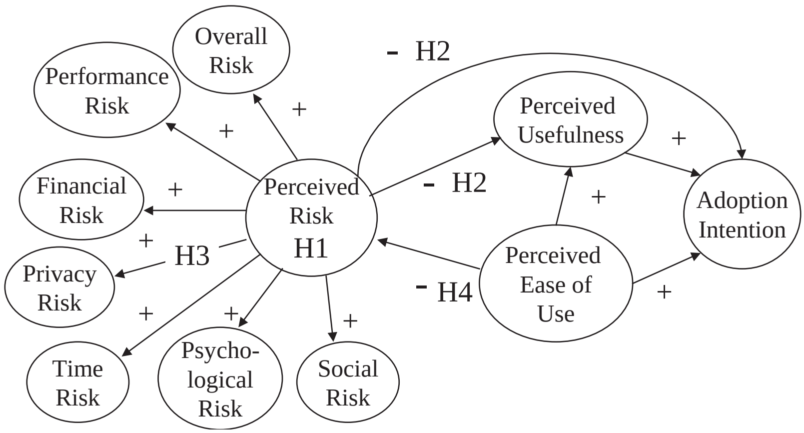


Fig. 1. Research model.

are perceived as being complex, problematic and not free of effort may also be perceived as being plagued with performance problems and usage uncertainties. Conversely, consumers that view e-services as easy to use may increasingly believe they will perform well, evaluate them highly and potentially adopt them. Because these highly usable e-services are less likely to engender usage concerns, EOU may function as an important risk-reducing factor similar to others identified by Roselius (1971). The pre-adoption demonstration software that is utilized here in a hands-on trial may function as a proxy for likely service performance and user interface usability.

It is therefore hypothesized that:

H4: Perceptions of e-service ease of use ascertained from hands-on trial significantly reduce perceived risks of usage.

The proposed model is presented in Fig. 1 above. Perceived risk has been modeled as both a composite variable and decomposed into its theorized sub-facets. Next follows presentation of the research methodology and empirical results.

3. Research methodology

This research follows Featherman (2001) and Pavlou (2001) and incorporated a measure of the perceived risk variable into TAM. Featherman (2001) found that a general measure of perceived risk reduced perceived usefulness (USF) and adoption intentions, but did not utilize the specific risk facets, nor test for the potential risk-reducing effect of system EOU. Pavlou (2001) found that perceived risk reduced subject's intention to transact but did not test for the risk-reducing effect of system EOU or the adverse effect of perceived risk on USF. This research therefore improves previous efforts by studying perceived risk at a more granular level and further refines the nomological fit of perceived risk within the TAM framework.

Two computer lab usability tests utilizing a vendors shopping trial demonstration software were performed. Each test drew a different sample from the population of undergraduate business students of a large university. Subjects were a relatively homogeneous population suitable for theory testing and development. They also represented an important target market for the research context and were therefore considered appropriate. The research context utilized to study e-service evaluation and adoption was Internet-based bill payment services, also known as electronic bill presentment and payment (EBPP), or e-billpay. The initial sample ($N=214$) was used to test the psychometric properties of the indicants and research model. A second sample ($N=181$) was used to confirm the relationships found amongst the risk facets and the research model's nomological validity.

The same methodology was utilized for both samples. Subjects were briefed on the e-billpay product category, then read brand information and performed a 25 min "shopping trial" using an interactive, demonstration software hosted on a vendor's website. After the trial, subjects were asked to evaluate the brand they were exposed to by completing a paper and pencil survey that utilized 7-point Likert and semantic differential scales. Items to capture the perceived risk (PR) facets, e-service ease of use (EOU), and usefulness (USF) were gathered, as well as measures of intention to adopt (AI) the e-billpay service given the proper facilitating conditions were available. Pre-validated TAM measures of EOU, USF and AI were utilized while the PR facet operationalizations used Jacoby and Kaplan's (1972) items and theoretically motivated original items.

Results were evaluated as follows. Psychometric properties for each research variable were measured using Cronbach's alpha and a first-order confirmatory factor analysis (CFA). Because the research model was theory driven and not exploratory, CFA rather than exploratory factor analysis was utilized to measure the ability of each indicant to tap the latent variable. Next, a second-order CFA was performed to measure the relative importance of each risk facet. This higher order perceived risk variable was included into the research model. Path weights and overall fit to the data was then estimated using AMOS-based structural equation modeling (SEM). The model was then refined to test Cunningham's (1967) proposition that all risk facets are caused by performance risk.

4. Sample #1 results

Cronbach's alpha scores shown in Table 2 below indicated that each risk facet exhibited strong internal reliability. Group means for each risk facet measured the probability of the e-billpay service having and therefore causing the specified risk. As compared to the general population, the sample population of university students was younger, more computer literate, and more comfortable with Internet-based transactions. These combined factors likely reduced perceived risk levels as compared to the general population. While this sample may not have perceived high levels of e-service inherent risk, each performance-based risk facet was nevertheless rated as very important. The importance (value) portion of the

Table 2
Psychometric properties and descriptive measures of research variables

Variables	Alpha	GFI	# Items	$\bar{X}$	Importance
Time risk	0.796	[a]	3	2.96	5.26
Psychological risk	0.891	0.982[b]	2	2.34	3.63
Privacy risk	0.857	[a]	2	3.80	6.16
Financial risk	0.857	0.868	4	3.26	6.22
Performance risk	0.797	0.991	4	3.53	5.98
Social risk	0.814	0.982[b]	2	1.98	3.17
Overall risk	0.850	0.987	4	3.51	
Ease of use	0.867	0.987	4	5.42	
Usefulness	0.901	0.982	4	5.12	
Adoption intention	0.968	0.933	4	4.38	

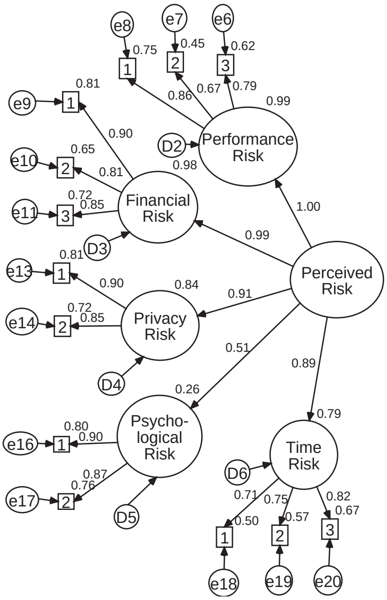
[a] AMOS-based CFA not possible with 3-item variables.
[b] GFI result from combined psychosocial risk facet.

expectancy-value measurement is an insightful indicant of perceived risk as it identifies the facets most important to the sample population. Additionally, many consumers are not able to accurately gauge probability of risk.

The Cronbach's alpha score for adoption intention suggests that the addition of two original items to enable SEM analysis did not harm its internal reliability. Support was also provided for the inclusion of a privacy risk facet for e-services adoption research. It exhibited the highest group mean and ranked only behind financial risk in importance.

A first-order CFA was performed to assess the ability of the indicants to measure the theorized risk facets. Here the overall risk measure was deemed a composite of the other risk facets and was therefore not included (Diamantopoulos, 2000). The CFA model exhibited excellent maximum likelihood estimated fit indices with an X^2/df ratio of 1.58, GFI = 0.939, AGFI = 0.900, NFI = 0.948, CFI = 0.980 and RMSEA = 0.052. These indices indicated that only 5.2% of the variance in the data was unexplained by the risk facets and in general, the model supported H1 and fit the data very well. First-order CFA goodness of fit indices (GFI) are shown in Table 2 above for each individual risk facet as an additional indicant of internal reliability. Due to the low number of items measuring the psychological and social risk facets, these were combined into one psychosocial facet as theorized by Cunningham (1967). The GFI for this latent variable is shown in Table 2 above. The individual items and factor loadings are presented in the appendix.

Perceived risk has been theorized as comprising all of these facets. To identify the strongest underlying facets of this composite perceived risk variable a second-order CFA model was next analysed. Here again the overall perceived risk measure was considered in itself a composite measure and not included to reduce item cross-loadings. Results presented in Fig. 2 were promising, indicated a good fit to the data, and largely supported H1. In addition to the maximum likelihood (ML) estimated fit indices, general least-squares (GLS) fit indices are also presented, as these are less sensitive to small sample sizes as utilized in this study (Diamantopoulos, 2000). The



Sample size to indicant ratio = 16.4:1
ML fit indices after removing Social Risk
X^2/df = 2.39, GFI = 0.901, AGFI = 0.851,
NFI = 0.923, CFI = 0.954, RMSEA = 0.081

GLS fit indices X^2/df = 1.81, GFI = 0.92,
AGFI = 0.88, RMSEA = 0.062

Risk Facet	Std Path weights Sig <0.001	Squared Mult Correl
Performance risk	0.996	0.992
Financial Risk	0.989	0.979
Privacy Risk	0.914	0.836
Time Risk	0.891	0.793
Psychological Risk	0.505	0.255
Social Risk	0.249	0.062

Fig. 2. Sample 1 second-order CFA perceived risk facets model.

model explained only 6.2% of the variation for social risk indicating that for this sample and context the social risk attached to e-services adoption was neither important nor salient. For this reason social risk was dropped from further analysis. This sample appears to have focused on the performance-related risks during system evaluation and adoption decision-making. Psychological risk concerns were also less important than the performance related facets; however, as this affect-based measure of personal frustration was deemed insightful, it was included in further analysis. This second-order perceived risk variable was next positioned within TAM to test the remaining research hypotheses. The research model's correlation matrix and SEM results are now presented.

The correlation matrix of the risk facets and research variables shown in Table 3 below supported the Cunningham (1967) proposition that perceived risk has two main categories, performance related and psychosocial. This is evidenced by the collinearity amongst the financial, time, privacy and performance facets, and between the social and psychological facets. Support for H2 and H3 was found as each risk facet negatively covaried with perceived usefulness and adoption intention.

Fornell and Larcker (1981) asserted that convergent validity is established when the factor is able to extract over 50% of the total variance of each indicant (AVE scores are shown in the diagonal of the lower matrix). For this sample alpha scores were typically >0.8 and the maximum likelihood estimated AVE scores were >0.5 indicating strong internal reliability and therefore convergent validity (Ping, 1996). Discriminant validity refers to the degree that measures of different constructs are internally correlated, distinct from other constructs and unique (Ping, 1996). Partial

Table 3
Sample #1 correlation matrix

	1	2	3	4	5	6	7	8	9	10
1. Overall PR	**0.845**									
2. Performance risk	0.812	**0.725**								
3. Financial risk	0.871	0.832	**0.770**							
4. Privacy risk	0.828	0.770	0.821	**0.801**						
5. Psychological risk	0.353	0.373	0.395	0.296	**0.950**					
6. Social risk	0.203	0.221	0.229	0.157	0.633	**0.917**				
7. Time risk	0.611	0.682	0.635	0.602	0.450	0.313	**0.753**			
8. Ease of use	−0.460	−0.528	−0.470	−0.452	−0.258	−0.185	−0.500	**0.791**		
9. Usefulness	−0.403	−0.485	−0.412	−0.367	−0.146	0.045 (ns)	−0.519	0.560	**0.834**	
10. Adoption intention	−0.516	−0.585	−0.525	−0.499	−0.243	0.006 (ns)	−0.543	0.553	0.714	**0.940**

All correlations significant at $p<0.01$ except where noted. Average variance extracted (AVE) displayed in the diagonal.

evidence for discriminant validity is provided in the lower matrix of squared correlation coefficients and AVE scores. According to Fornell and Larcker (1981) discriminant validity is established if the AVE (within factor shared variance) is larger than the squared correlation coefficients (r^2) between variables. In all but three cases, support was provided for discriminant validity as the performance related risk facets were collinear.

Fig. 3 presents overall fit indices and effect weights for the research model. Each TAM construct was measured by four indicants, and the items for each risk facet were combined to define six indicants for the second-order perceived risk variable. At this higher level of analysis the measure of overall risk was included to enable discussion; however, results were similar when excluded as the individual risk facets more specifically explained consumer concerns.

Fit indices indicated that the model exhibited a good fit to the data for the somewhat small sample size. In particular, the GLS estimated RMSEA measure of 0.058 indicates that only the model has not explained 5.8% of the variance in the data, whereas an RMSEA measure of 5% or less indicates an excellent model fit (Diamantopoulos, 2000). Reported parameter estimations supported hypothesis 2 and 3 as consumer concerns for potential financial losses, system performance problems, loss of time and privacy breaches were salient during e-service evaluation and adoption decision-making.

Further support for inclusion of privacy risk facet (H3) was found using a simplified SEM, which included only privacy risk, USF and AI. The path from the exogenous privacy risk latent variable to the endogenous USF variable was −0.450 and explained 20.2% of its variance. The path from privacy risk to the endogenous AI variable was −0.555 and explained 30.8% of its variance. Both paths were ML estimated and significant at $p<0.001$. The model exhibited a GFI of 0.88, NFI $=0.91$, and CFI $=0.92$.

Strong support for H4 was provided by the significant perceived ease of use to perceived risk path weight. This suggests that e-service software that is perceived as

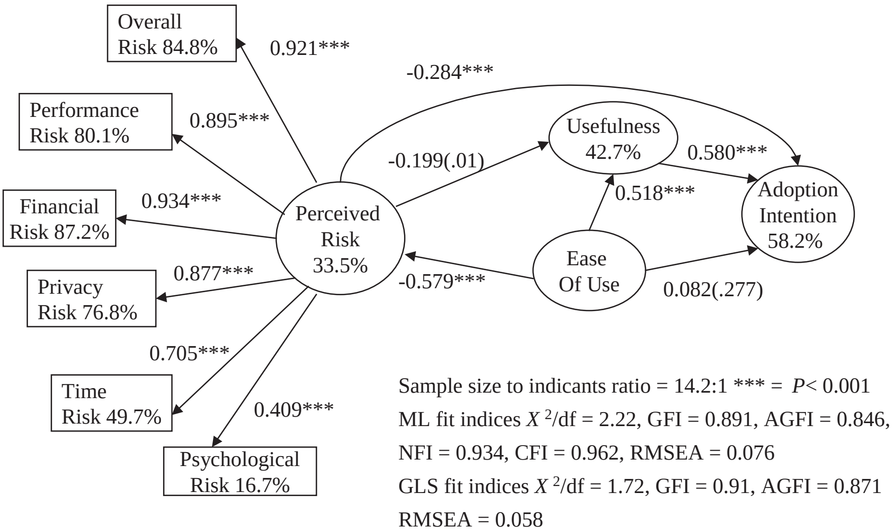


Fig. 3. Sample #1 research model results.

easy to use during system trial reduces resultant risk concerns. This effect is plausible as risks inherent in service performance are shaped in part by the usability of the software interface. If the user cannot easily manipulate the software, they may portend further performance problems. Expected service performance becomes increasingly uncertain and therefore perceived risk increases. This path also indicates that as the e-service increases in usability expected performance risks reduce. This path suggests an important new application for the ease of use variable, whose effects on adoption intention are often minimized during regression analysis by the typically collinear perceived usefulness variable.

An exploratory analysis was performed to test Cunningham's (1967) proposition that all risk facets spring from performance risk concerns. The research model shown in Fig. 4 models performance risk as an antecedent to the remaining risk concerns. Fit indices while suffering from a smaller sample to indicant ratio (10.7:1), supported the model refinement and show a good fit to the data, with only 5% of the variance in the model unexplained by the indicants when using the general least-squares (GLS) estimation method. GLS has been previously shown to perform better than maximum likelihood (ML) estimation for small samples (Hu and Bentler, 1995). All path estimates shown are ML estimated and ML and GLS fit indices are both presented for comparison. The positive EOU→PR emerged unexpectedly using ML estimation; however, was not significant using GLS estimation and therefore is questionable. This path may have been overestimated representing a confound between EOU and PR, when performance risk is simultaneously estimated. Cohen et al. (2003) suggest that confounds typically overestimate relationships and may account for both the spurious EOU→PR path and the large performance risk→ perceived risk path. The analysis does suggest however that EOU primarily exhibits a performance risk reducing effect.

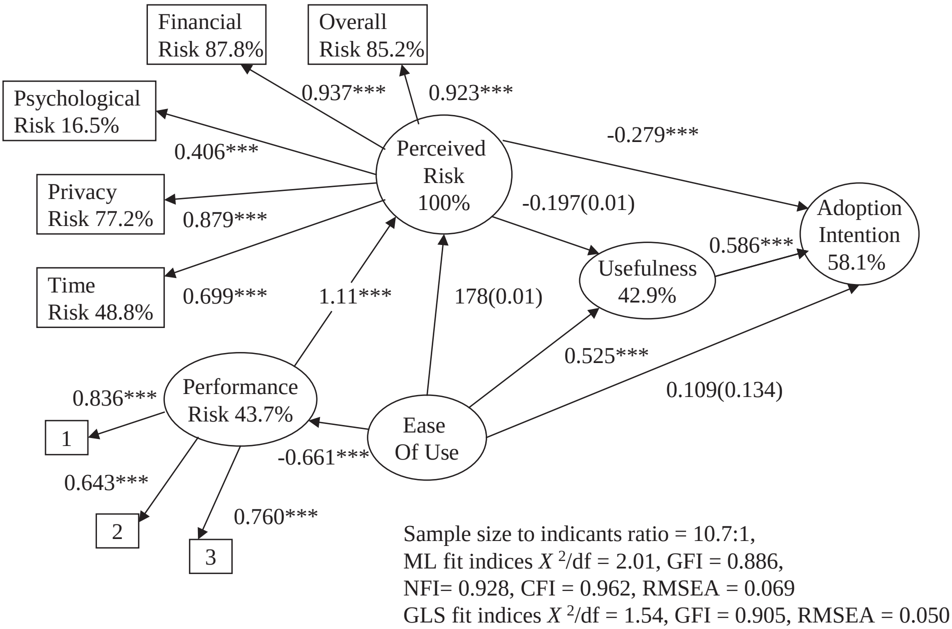


Fig. 4. Final structural equation model.

As a further comparison of the two models the Akaike Information Criterion (AIC) measure was compared for both models. AIC is used to compare different structural equation models. Typically, the model with the lower AIC score is deemed the better model. Here the AIC for the final saturated model shown in Fig. 4 was 306 as compared with 240 for the model shown in Fig. 3. While the final model suffered from a smaller sample to indicant ratio which may have inflated the AIC score, the single composite risk variable performed better than the model with performance risk modeled as an antecedent to the remaining PR facets.

In summary for this sample and the e-service adoption context, empirical evidence supported the inclusion of a second-order perceived risk variable into TAM based on the theorized PR facets. Furthermore, a hierarchical structure may be evident within the risk facets, with performance risk concerns influencing the time, privacy, psychological and financial risk factors and overall PR. These assertions and models must be confirmed with a different data set however and therefore data from a second sample were gathered. The results of that confirmatory study are now presented.

5. Sample #2 results

A second unique sample ($N = 181$) was drawn from the same undergraduate university population and the same methodology was administered to this new sample. In this iteration, one-half of the sample tested and evaluated a second e-billpay brand.

The two trials were identical with the only appreciable difference attributable to brand recognition and perhaps color of interface (green vs. blue). Between groups *t*-tests indicated no significant difference in-group mean risk levels for any risk facet, or TAM variable and therefore the results were pooled. Subjects once again evaluated the e-service trial software and reported perceived levels of each risk facet.

To further develop the risk facet scales additional items were added. While Cronbach's alpha scores listed in Table 4 indicate that the variables were strengthened in comparison to sample 1, the higher number of indicants unfortunately accentuated the small sample to indicant ratio which contributed to a reduction in SEM model fit indices. The GFI measure for each individual risk facet is provided below as an additional measure of internal consistency. Once again due to the limited number of items in order to provide this measure the psychological and social risk facets, were combined into one psychosocial facet as theorized by Cunningham (1967). Once again, the group means for each risk facet remained low for this sample however; the importance measures indicated that they were deemed essential. Group mean privacy risk concerns were again the highest and rated as second most important behind financial risk.

Table 5 provides strong support for convergent and discriminant validity however the performance-related risk facets remained collinear which likely reduced overall SEM model fit. High AVE and Cronbach's alpha scores provided support for convergent validity. Support for discriminant validity was also provided as in all but one case each variable's AVE (within factor shared variance) was larger than the squared correlation coefficients (r^2) between variables.

The first-order CFA model was however excellent with ML estimated fit indices recorded as X^2/df = 1.64, GFI = 0.92, AGFI = 0.877, NFI = 0.938, CFI = 0.975 and RMSEA = 0.06. Due to the small subject to indicant ratio the model was reestimated using general least-squares (GLS) estimation and the fit indices improved to X^2/df = 1.40, GFI = 0.93 and RMSEA = 0.05. This again indicated the research model fit the data very well as only five percent of the variance in the indicants was unexplained by the CFA model.

Table 4
Psychometric properties and descriptive measures of research variables

Variables	Alpha	GFI	# Items	$\bar{X}$	Importance
Time risk	0.845	0.999	4	2.82	4.83
Psychological risk	0.791	0.901[a]	2	2.37	3.42
Privacy risk	0.872	[b]	3	3.89	5.79
Financial risk	0.887	0.932	4	3.37	5.94
Performance risk	0.890	0.964	5	3.34	5.58
Social risk	0.914	0.901[a]	2	1.82	3.01
Overall risk	0.906	0.932	5	3.43	5.74
Ease of use	0.886	0.969	4	5.51	
Usefulness	0.901	0.971	4	5.29	
Adoption intention	0.937	0.914	4	4.39	

[a] GFI result from combined psychosocial risk facet.
[b] AMOS-based CFA not possible with 3-item variables.

Table 5
Sample #2 correlation matrix

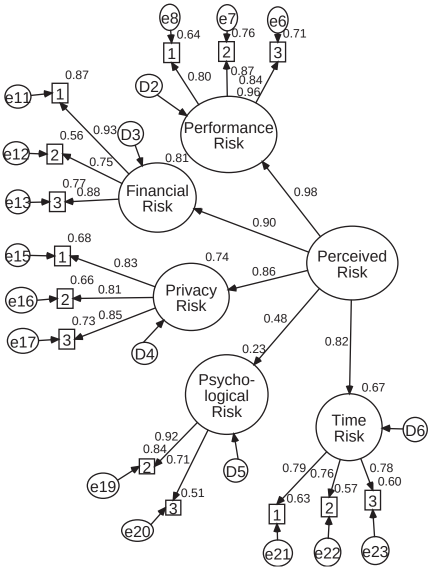
	1	2	3	4	5	6	7	8	9	10
1. Overall PR	**0.812**									
2. Performance risk	0.763	**0.787**								
3. Financial risk	0.798	0.791	**0.815**							
4. Privacy risk	0.774	0.713	0.730	**0.834**						
5. Psychological risk	0.392	0.400	0.358	0.267	**0.909**					
6. Social risk	0.229	0.225	0.183	0.116 (ns)	0.654	**0.959**				
7. Time risk	0.650	0.679	0.566	0.573	0.463	0.357	**0.762**			
8. Ease of use	−0.321	−0.383	−0.219	−0.273	−0.283	−0.054 (ns)	−0.505	**0.814**		
9. Usefulness	−0.346	−0.368	−0.242	−0.277	−0.253	−0.072 (ns)	−0.527	0.718	**0.846**	
10. Adoption intension	−0.304	−0.345	−0.248	−0.317	−0.142 (0.06)	0.0680 (ns)	−0.465	0.530	0.590	**0.886**

All correlations significant at $p < 0.01$ except where noted. Average Variance Extracted (AVE) displayed in the diagonal.

The second-order CFA model was again estimated to identify the relative importance of each risk facet. The research model was again estimated without the overall risk measure and results are shown in Fig. 5. Results supported H1 and again suggested the removal of social risk, as the model explained only 7% of its variance. The first-order CFA estimates reported in Fig. 5 below therefore were reported after removing the social risk variable.

The fit indices report very good model fit for the small sample with all indices except the AGFI above the desirable >0.90 threshold. The fit indices are considered very good considering the precariously small sample. All risk facet path loadings were strong except for psychological risk, which was not as important of a concern as the performance-related risk facets for this sample and context. The risk facets while divergent exhibited moderate collinearity and cross-loadings that reduced overall model fit. For example, several of the performance and privacy items shown in Appendix A tap the theorized facets but also suggest financial problems because of them. The minor cross loadings reduced the model fit indices from excellent to very good and point towards needed refinement in operational definitions. As with sample #1 the risk facets proved valid and reliable and therefore the research model could again be tested with the second sample.

Research model path weights, percentage of variance explained, and fit indices are shown in Fig. 6. The research model contained stronger measures of each variable, but suffered from a smaller sample to indicant ratio (12.1:1). Results suggested that the research model's nomological pattern was confirmed for this second sample. All relationships amongst the variables exhibited similar significance and directionality. The fit indices confirmed the research model as all but 7.3% of the variance in the data was accounted for.

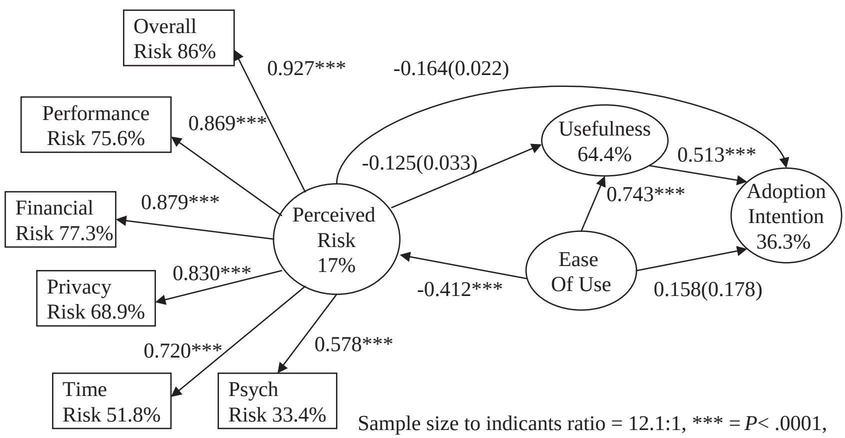


Sample size to indicant ratio = 12.1:1
ML fit indices after removing Social Risk
X^2/df = 1.95, GFI = 0.90, AGFI = 0.852,
NFI = 0.922, CFI = 0.96, RMSEA= 0.073

GLS fit indices X^2/df = 1.60, GFI = 0.909,
AGFI = 0.867, RMSEA= 0.057

Risk Facet	Std Path weights Sig <0.001	Square Mult Correl
Performance risk	0.982	0.964
Financial Risk	0.899	0.808
Privacy Risk	0.861	0.742
Time Risk	0.817	0.667
Psychological Risk	0.483	0.233

Fig. 5. Sample #2 second-order CFA perceived risk facets model.



Sample size to indicants ratio = 12.1:1, *** = $P< .0001$,
ML fit indices X^2/df = 2.59, GFI = 0.868,
NFI = 0.911, CFI = 0.944, RMSEA = 0.091
GLS fit indices X^2/df = 1.95, GFI = 0.877, RMSEA = 0.073

Fig. 6. Sample #2 research model results.

Support for H2 was provided by sample #2, as consumer concerns for the perceived risks of e-service adoption inhibited both USF and AI. Support for H3 was again provided, as privacy risk both indirectly reduced system evaluations and adoption intention when modeled as a facet of the second-order latent perceived risk variable. Testing a simplified SEM, which included only privacy risk, USF and AI, again provided further support for H3. The path from the privacy risk exogenous

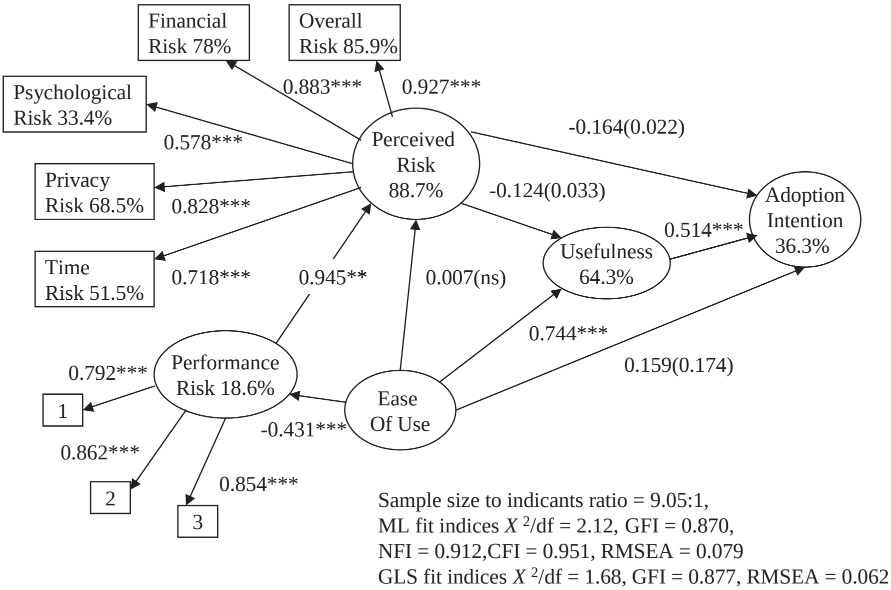


Fig. 7. Sample #2 final structural model.

variable to the USF was −0.356 and explained 12.6% of its variance. The direct effect of privacy risk on AI was −0.362, explained 13.1% of its variance, and exhibited a GFI = 0.90, NFI = 0.92, and CFI = 0.94. Each maximum likelihood estimated path was significant at $p<0.001$. Results again suggested that privacy concerns related to Internet-based e-payments are salient and a significant inhibitor to system evaluation and adoption.

Finally, H4 was again supported as perceptions of the e-service's likely ease of use gleaned from the shopping trial significantly reduced consumer's expected performance uncertainty and therefore risk perceptions. For the e-services research context ease of use was not a direct antecedent to AI and rather functioned indirectly through USF, consistent with previous TAM empirical validations. In both samples however the indirect effect of EOU on USF and AI was indicated by its reduction of perceived risk. Subject's perceptions that the software service functions smoothly are a very important risk-reducing factor.

The expanded model employing two PR variables is presented in Fig. 7. The model is insightful as it confirms that the e-service's EOU primarily reduces performance risk concerns and only indirectly reduces the remaining perceived risk facets. The fit indices are very good considering the sample size to indicant ratio is half of the typically suggested 20:1 ratio. The GLS estimated RMSEA index was again strong as only 6.2% of the variance in the data set was not accounted for, which was lower than the composite model shown in Fig. 6.

The two models were again compared using the Akaike Information Criterion (AIC) measure. The AIC for the final saturated model was again 306 as compared with 240 for the composite variable model shown in Fig. 6. Analysis of model fit indices indicate that the two latent PR variable model was measured as having similar or slightly better fit to the data which is significant given the smaller sample to indicant ratio. The single composite risk variable model performed better on the AIC measure, however suggesting that it is the higher quality model.

Structural equation model results again supported all hypotheses and provided insight into the research questions. Privacy risk emerged as an important performance-based inhibitor to e-service evaluation and adoption. Privacy, time, financial and performance were for a second time the strongest facets of perceived risk for the e-service adoption context.

6. Discussion

Previous consumer behavior and information system research has highlighted the importance of perceived risk as an inhibitor to purchasing on the web and adoption of an e-service. The majority of information systems research has focused on the importance of trust and trust building as a prerequisite to e-commerce transactions and development of business relationships. This research looked at perhaps the other side of the trust construct, perceived risk and attempted to dive deeper into the construct and provide insight into its facets.

The e-services context was chosen as the importance of this class of information system is growing. Self-service consumer software-based services delivered on-demand via the Internet can provide consumers utility gains measured in convenience and efficiency. Little was known however how consumers perceive the risks of using these e-services that are delivered to their homes.

Using the e-billpay service context, strong empirical evidence was provided for the perceived risk facet measures and support for a privacy risk variable was provided. Evidence for a second-order composite perceived risk variable was found enabling its testing within TAM. Perceived risk was found to exert a strong inhibiting influence on TAM's criterion variables. This finding encouraged the decomposition of the perceived risk variable into its theorized facets. Performance-related risk facets (time risk, privacy risk, financial risk) proved to be the most salient concerns for this sample and context. Evidence for a risk facet hierarchy was provided, as performance risk concerns appear to be the foundation for all other risk facets. For this sample and context social risk concerns—the chance of losing status by using the e-service were not salient.

The further definition of risk facets is seen as a major contribution to MIS focused human–computer interaction research. Rather than speaking in general terms of potential inherent risks in computer systems, the focus can shift to a more granular level of analysis. As these specific beliefs are understood risk-reducing system interfaces and mediums can be developed and communicated that counter each specific risk facet.

Research limitations include the usage of small sample sizes for SEM-based theory building. While the theorized expected patterns were displayed by the datasets, the overall model fit would have benefited from larger sample sizes. Many of the risk facets were moderately collinear contributing to indicant cross-loadings, which also reduced overall model fit. Further scale development work to identify increasingly divergent risk facet operationalizations is warranted. The research is deemed somewhat rudimentary, as the 2000 version of TAM (Venkatesh and Davis, 2000) was not utilized. Perceived risk is likely to affect other TAM variables such as subjective norm. This research therefore needs to be extended to include the expanded Technology Acceptance Model.

Results suggested that many of the important risk facets for the e-services context have been identified. Future research is needed however to discern whether these risk concerns are attributable to the Internet medium or to the e-service provider. Focus can now be applied to the identification and testing of risk-reducing user interface designs using the delineated risk facet operational definitions as the criterion variables. This research model should be re-confirmed with different samples, e-services and user interface designs. In summary, this research suggests the inclusion of a performance-based perceived risk variable in human–computer interface focused adoption research.

7. Practical implications

This research indicated that while the segment of consumers surveyed in general did not perceive the e-billpay service as having a high level of usage risk, the risks perceived were very important to them suggesting the criticality of controlling them. The sample studied had higher computing skills, were younger, and more highly educated than the general populace. It is highly likely that consumers that are older, less-educated, or possess reduced computing skills would perceive higher inherent e-service usage risks.

Perceptions of specific risk facets together inhibited system evaluation and adoption, and service providers must develop improved computer interfaces and portals to counter these concerns. The user interface did not include any information suggesting that users were interacting with a secured information system. Suggested changes to the e-service trial software might include graphics and/or notes to the user indicating (1) successful construction of a secure tunnel from the consumer's home to the secure server, (2) usage of session or private key encryption, (3) entry past the service provider's firewall or (4) access granted to the service provider's secure transaction processing server. The perceived security of the trial experience can be greatly strengthened and should be considered an important precursor to transaction efficiency. E-service trials typically explain likely transaction performance, but fall short on promoting system security.

Additional effective risk-reducing strategies may include money back guarantees and prominently displayed consumer satisfaction guarantees to counter financial and performance based risk concerns. Consumers may be willing to absorb the perceived risk if they're confident that the service provider stands behind their service. Simple statements and graphics stating that transactions are guaranteed may calm risk concerns. Additionally a succinct and well-presented privacy policy such as "we will never sell your personal information period" may reduce privacy concerns. As mentioned clear graphical presentation of security systems in place in layman's terms may also allay risk perceptions.

The trial software functioned well for the majority of the sample; however, occasionally JavaScript errors crashed the demonstration software. Results here suggested that the e-service's ease of use was able to reduce risk concerns; therefore, it is imperative to ensure that all consumers can experience the trial software without system-generated errors.

Results suggested that for this sample and context the performance, financial, privacy and time risk facets were the most salient causes for concern, leading to reduced system evaluation and adoption. With the most important risk facets identified, attention can now be turned to identification of maximum acceptable risk thresholds for each perceived risk facet. These thresholds can provide a target to indicate to what level risk perceptions must be lowered to encourage adoption for each target market. Many easy to implement risk-reducing strategies can be incorporated into the user interface to counteract consumer fears.

While this study identified performance-based risk facets as most salient for the e-service context, more applied research is needed to determine the optimal e-service interface and embedded level of assurances necessary to allay consumer's service usage concerns for each of the perceived risk facets. As the number of e-services directed at the consumer market grows, the user evaluation experience must be better understood and managed more carefully.

Appendix

The individual items and factor loadings are given in Table 6.

Table 6
Item factor loadings

		Sample 1 First-order CFA		Sample 2 First-order CFA	
		b	*SMC*	*b*	*SMC*
Financial risk					
1. What are the chances that you stand to lose money if you use the XXXX?	Low/high chance of losing $$	0.651	0.423	0.797	0.635
2. Using an Internet-bill-payment service subjects your checking account to potential fraud.	Strongly disagree/agree	0.891	0.794	0.835	0.697
3. My signing up for and using an XXXX would lead to a financial loss for me.	Improbable/probable	0.630	0.397	0.726	0.527
4. Using an Internet bill-payment service subjects your checking account to financial risk.	Strongly disagree/agree	0.870	0.757	0.894	0.800

Table 6 (*continued*)

		Sample 1 First-order CFA		Sample 2 First-order CFA	
		b	*SMC*	*b*	*SMC*
Performance risk					
1. The XXXX might not perform well and create problems with my credit.	Strongly disagree/ agree	0.781	0.610	0.838	0.702
2. The security systems built into the XXXX are not strong enough to protect my checking account.	Strongly disagree/ agree	0.583	0.340	0.809	0.654
3. What is the likelihood that there will be something wrong with the performance of the XXXX or that it will not work properly?	Low/high functional risk	0.718	0.516	0.735	0.540
4. Considering the expected level of service performance of the XXXX, for you to sign up for and use it would be.	Not risky at all/ risky	0.739	0.547	0.778	0.605
5. XXXX servers may not perform well and process payments incorrectly.	Strongly disagree/ agree			0.771	0.594
Privacy risk[a]					
1. What are the chances that using an XXXX will cause you to lose control over the privacy of your payment information?	Improbable/ probable	0.882	0.779	0.827	0.684
2. My signing up for and using an XXXX would lead to a loss of privacy for me because my personal information would be used without my knowledge.	Improbable/ probable	0.850	0.722	0.866	0.750
3. Internet hackers (criminals) might take control of my checking account if I used an XXXX.	Strongly disagree/ agree			0.807	0.651
Psychological risk[b]					
1. The XXXX will not fit in well with my self-image or self-concept.	Low/high psychological risk	0.867	0.752	0.903	0.815
2. The usage of an XXXX would lead to a psychological loss for me because it would not fit in well with my self-image or self-concept.	Improbable/ probable	0.927	0.860	0.773	0.598
Social risk[b]					
1. What are the chances that using the XXXX will negatively affect the way others think of you?	Low/high social risk	0.588	0.346	0.907	0.882
2. My signing up for and using an XXXX would lead to a social loss for me because my friends and relatives would think less highly of me.	Improbable/ probable	0.644	0.415	0.904	0.836

Table 6 (*continued*)

		Sample 1 First-order CFA		Sample 2 First-order CFA	
		b	*SMC*	*b*	*SMC*
Time risk[a]					
1. If you had begun to use an XXXX, what are the chances that you will lose time due to having to switch to a different payment method?	Low/high loss of time risk	0.759	0.576	0.733	0.537
2. My signing up for and using an XXXX would lead to a loss of convenience of me because I would have to waste a lot of time fixing payments errors.	Improbable/ probable	0.791	0.626	0.727	0.528
3. Considering the investment of my time involved to switch to (and set up) an XXXX makes them.	Not risky at all/ very Risky	0.705	0.497	0.720	0.519
4. The possible time loss from having to set-up and learn how to use e-billpay makes them.	Not risky at all/ very risky			0.859	0.738
Overall risk					
1. On the whole, considering all sorts of factors combined, about how risky would you say it would be to sign up for and use XXXX?	Not risky at all/ very risky	0.777	0.603	0.896	0.802
2. Using XXXX to pay my bills would be risky.	Strongly disagree/ agree	0.885	0.783	0.782	0.611
3. XXXX are dangerous to use.	Strongly disagree/ agree	0.869	0.754	0.821	0.674
4. Using XXXX would add great uncertainty to my bill paying.	Strongly disagree/ agree	0.536	0.287	0.716	0.512
5. Using XXXX exposes you to an overall risk.	Improbable/ probable			0.837	0.700

b = standardized regression weights (factor loadings); SMC = Squared multiple correlations.

[a] EFA-based maximum likelihood estimated factor loadings are reported for sample 1 as only 3 indicants were utilized.

[b] Psychological and social facets combined per Cunningham (1967) to enable CFA factor loading estimation.

References

Bandura, A., 1986. Social Foundations of Thought and Action: A Social Cognitive Theory. Prentice-Hall, Englewood Cliffs, NJ.

Bauer, R., 1967. Consumer behavior as risk taking. In: Cox, D. (Ed.), Risk Taking and Information Handling in Consumer Behavior. Harvard University Press, Cambridge, MA.

Beard, J., Peterson, T., 1988. A taxonomy for the study of human factors in management information systems. In: Carey, J. (Ed.), Human Factors in Management Information Systems. Ablex Publishing Corporation, Greenwich, CT, pp. 7–26.

Bellman, S., Lohse, G., Johnson, E., 1999. Predictors of online buying behavior. Communications of the ACM 42 (12), 32–38.

Bettman, J., 1973. Perceived risk and its components: a model and empirical test. Journal of Marketing Research 10, 184–190.

Cohen, J., Cohen, P., West, S., Aiken, L., 2003. Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences. Lawrence Erlbaum, NJ.

Compeau, D., Higgins, C., Huff, S., 1999. Social cognitive theory and individual reactions to computer technology: a longitudunal study. MIS Quarterly 23 (2), 145–158.

Cunningham, S., 1967. The major dimensions of perceived risk. In: D. Cox (Ed.), Risk Taking and Information Handling in Consumer Behavior. Harvard University Press, Cambridge, MA.

Davis, F., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 13, 319–340.

Davis, F., 2002. Human computer interaction research in the MIS discipline. Panel Presentation at AMCIS'02, http://melody.syr.edu/hci/amcis02_panel.cgi.

Davis, F., Bagozzi, R., Warshaw, P., 1989. User acceptance of user technology: a comparison of two theoretical models. Management Science 35, 982–1002.

Diamantopoulos, A., Siguaw, J., 2000. Introducing LISREL. Sage Publications, London.

Dowling, G., Staelin, R., 1994. A model of perceived risk and intended risk-handling activity. Journal of Consumer Research, 21, 119–134.

Engel, J., Blackwell, R., Miniard, P., 1986. Consumer Behavior. CBS College Publishing, New York.

Featherman, M., 2001. Is perceived risk germane to technology acceptance research? AMCIS Proceedings, Boston, MA.

Festinger, L., 1957. A Theory of Cognitive Dissonance. Stanford University Press, Stanford, CA.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research 18, 39–50.

Gefen, D., Straub, D., 2000. The relative importance of perceived ease-of-use in IS adoption: a study of e-commerce adoption. JAIS 1 (8), 1–20.

Germunden, H.G., 1985. Perceived risk and information search: a systematic meta-analysis of empirical evidence. International Journal of Research in Marketing 2, 79–100.

Grewal, D., Gotlieb, J., Marmorstein, H., 1994. The moderating effects of message framing and source credibility on the price-perceived risk relationship. Journal of Consumer Research 21, 145–153.

Hoffman, D., Novak, T., Peralta, M., 1999. Building consumer trust online. Communications of the ACM 42 (4), 80–85.

Hu, L., Bentler, P., 1995. Evaluating model fit. In: Hoyle, R. (Ed.), Structural Equation Modeling Concepts, Issues, and Applications. Sage Publications, Thousand Oaks, CA.

Igbaria, M., 1993. User acceptance of microcomputer technology: an emprirical test. Omega International Journal of Management Science 21 (1), 73–90.

Jacoby, J., Kaplan, L.B., 1972. The components of perceived risk. Proceedings of the Third Annual Conference, Ann Arbour, MI, Association for Consumer Research.

Jarvenpaa, S., Tractinsky, N., 1999. Consumer trust in an internet store: a cross-cultural validation. Journal of Computer Mediated Communication 5 (2), 1–35.

Koller, M., 1988. Risk as a determinant of trust. Basic and Applied Social Psychology 9 (4), 265–276.

Mitchell, V.-W., 1992. Understanding consumers' behavior: can perceived risk theory help? Management Decision 30 (2), 26–31.

Moon, J., Kim, Y., 2001. Extending the TAM for a world-wide-web context. Information and Management 28, 217–230.

Moore, G., Benbasat, I., 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research 2 (3), 192–222.

Pavlou, P., 2001. Integrating trust in electronic commerce with the technology acceptance model: model development and validation. AMCIS Proceedings, Boston, MA.

Peter, J., Ryan, M., 1976. An investigation of perceived risk at the brand level. Journal of Marketing Research 13, 184–188.

Ping, R., 1996. Latent variable interaction and quadratic effect estimation: a two-step technique using structural equation analysis. The Psychological Bulletin 119, 166–175.
Roselius, T., 1971. Consumer rankings of risk reduction methods. Journal of Marketing 35, 56–61.
Ruyter, Ko de, Wetzels, M., Kleijnen, M., 2001. Customer adoption of e-service: an experimental study. International Journal of Service Industry Management 12 (2), 184–207.
Taylor, J., 1974. The role of risk in consumer behavior. Journal of Marketing 38, 54–60.
Teo, S., Lim, V., Lai, R., 1999. Intrinsic and extrinsic motivation in internet usage. Omega International Journal of Management Studies 27, 25–37.
Venkatesh, V., Davis, F., 2000. A theoretical extention of the technology acceptance model: four longitudinal field studies. Management Science 46 (2), 186–204.
Zaltman, G., Wallendorf, M., 1983. Consumer Behavior. Wiley, New York.
Zhang, P., Benbasat, I., Carey, J., Davis, F., Galletta, D., Strong, D., 2002. Human computer interaction research in the MIS discipline. Communications of the AIS 9, 334–355.