Tax software acceptance: how do professional users differ from novices?

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Abstract: This paper explores how performance expectations, anticipated learning curve, social influences, privacy concerns, and risk perceptions affect taxpayers' intention to use tax preparation software. We contribute to the extensive technology acceptance literature in three ways. First, we investigate whether perception and acceptance of tax software is different for professional accountants ('experts') compared to the general public ('novices'). Second, we assess the unified theory of acceptance and use of technology (UTAUT) model in the novel context of individual tax preparation and confirm the theory's ability to explain technology use outside the 'traditional' environment of business organisations. Third, we include constructs related to privacy and risk and test this extension of the technology acceptance model. Results indicate dissimilarities between the two subject groups and suggest the technology acceptance model may not be equally applicable to experts and novices.

Keywords: technology acceptance model; tax software; privacy; risk; novices; tax professionals; unified theory of acceptance and use of technology; UTAUT.

Reference to this paper should be made as follows: McLeod, A. and Pippin, S. (xxxx) 'Tax software acceptance: how do professional users differ from novices?', *Int. J. Business Information Systems*, Vol. X, No. Y, pp.000–000.

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1 Introduction

The purpose of this research is to explore user acceptance of tax software and to investigate if individual differences in domain knowledge and expertise affect tax software use. We apply the relatively new Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) in the context of individual intention to use tax preparation software. Further, we test whether technology acceptance of tax software varies for different user groups. Specifically, we investigate how users who are tax professionals and mostly certified public accountants (CPAs) view tax software compared to non-expert or novice users. Lastly, we incorporate elements of privacy and risk and assess the effects of these constructs on technology acceptance. We believe that the highly complex domain of tax law provides an ideal environment to test whether different subject groups, such as domain experts and novices place different emphasis on the various constructs within UTAUT.

One aim of academic research is to develop and assess new theories and models (Creswell, 2003; Wacker, 2008). Prior studies have shown that the UTAUT model works well in organisational settings. However, in order to advance user acceptance theory it must be applied and tested in various environments using diverse subject groups. Individual tax preparation provides a different context compared to the typical application of the UTAUT model for several reasons. In earlier technology acceptance studies, the individual decision to accept a certain technology generally related to job performance. Tax preparation software use is different because it is an individual private decision not directly related to job performance. Thus, other factors, such as individual perception of privacy and risk may be significant determinants of acceptance whereas social influence from superiors or peers may be less important. While some research has looked at technology acceptance and e-filing or e-government (Chang et al., 2005; Fu et al., 2006; Wang, 2003; Ilias et al., 2009; Mouakket, 2010) none of these studies employed the UTAUT model or contributed to the extension of acceptance theory by integrating privacy and risk.

Studying the difference between expert and non-expert users is interesting and relevant for several reasons. The UTAUT model measures the correlation of different constructs to individual acceptance of technology. However, the importance of these constructs is likely to vary across different user groups (Devolder et al., 2008). A significant difference has implications for researchers, software producers, and practitioners. Academic researchers using technology acceptance models need to explore the possibility that the relationships between constructs may depend on the user characteristics. Similarly, practitioners wanting to improve technology acceptance across various user groups must understand which factors influence technology acceptance most. For example, the Internal Revenue Service (IRS) promotes electronic filing by emphasising certain benefits such as speed of receiving a refund, speed of filling out the tax forms, accuracy of the output, and ease of preparation. This implies the IRS is under the impression that taxpayers consider these factors most important. Studies like ours can provide insight as to whether the IRS's assumption is accurate.

We investigate these issues surveying a group of professional tax preparers, mostly CPAs, and a group of undergraduate students who served as a proxy for the novice group. Our results indicate significant differences between the two groups which we attribute to the differences in knowledge and experience.

The remainder of the paper is structured as follows. The next section provides the theoretical background. Section 3 introduces the research methodology. Section 4 lists and discusses the results as well as the limitations of this study and Section 5 concludes.

2 Theoretical background

The complex environment of individual tax preparation provides an interesting and novel research setting. Technology use in this context involves individual choice of software versus manual methods when completing and electronically filing a tax return. Note that the choice to file electronically is only available to taxpayers who elect to use tax preparation software. Electronic filing (e-filing), and to a lesser extent the use of tax preparation software, has been subject to recent academic studies because it provides a rich research setting for the following reasons. Most of the households in the USA have to file tax returns; thus, while individuals may not be too familiar with the tax law and the country's tax policy, they are familiar with filing and paying taxes. Furthermore, the tax domain is different from other situations where individuals may choose electronic over traditional services, such as electronic shopping or online banking because the domain is fairly complex, rapidly changing and most taxpayers are not experts. In addition, e-filing introduces the issues of risk, security and privacy protection. Last but not least, e-filing research provides an intersection of various academic disciplines, namely information systems, public finance, public administration, and accounting. Because tax laws are complex and frequently change, many individuals rely on software to complete their tax returns. Most tax software users are not tax experts and therefore lack the knowledge to verify the output of tax preparation software.

Human behaviour is highly variable and modelling intentions is fraught with potential for limited success. Still, many researchers have created models and representations of technology acceptance in an effort to understand the factors affecting technology use. The most recent model is based on a consolidation of technology acceptance research by Venkatesh et al. (2003) termed the unified theory of acceptance and use of technology (UTAUT). According to this theory, perceived performance of the technology, anticipated learning curve, influence of superiors and peers, and facilitating conditions determine intention to use technology. This paper starts with the fundamental tenet that technology acceptance is substantially formed by user perception of performance, ease of use, and social influence. Relevant studies include those involving the application of technology acceptance and UTAUT outside the organisational context or business environment. For example, Chiu and Wang (2008) use UTAUT to examine web-based learning. AbuShanab and Pearson (2007) looked at internet banking adoption of individual users. Other works have addressed 'non-organisational' cultural effects – such as the applicability of UTAUT in different countries (AbuShanab and Pearson, 2007; Bandyopadhyah and Fraccastoro, 2007; Im et al., 2011). These studies support the three main constructs of UTAUT: performance expectancy, effort expectancy and social influence. Given this premise, UTAUT appears to be an excellent tool for evaluating individual intention to use tax preparation software and its antecedents. Aside from testing the applicability of UTAUT outside its original business organisation setting, this paper examines the question whether individual expertise and knowledge characteristics affect technology acceptance. Specifically, we focus on user differences in knowledge and expertise, which we believe lead to very different perceptions regarding the implications of using tax software because of the highly complex domain.

One more recent aspect examined in the technology acceptance literature is the triangular relationship between risk, trust, and use intention (Chellappa and Pavlou, 2002; Chellappa and Sin, 2005; Nicolaou and McKnight, 2006; Kim and Tadisina, 2010). Since individual tax information is highly sensitive we believe that risk perceptions will also be relevant determinants of use. In summary, we viewed the following questions as important to our study:

- Do the determinants of user acceptance differ between domain experts and the general public?
- How does user acceptance apply outside the traditional business organisation environment?
- Is individual intention to use tax preparation software affected by privacy or risk concerns?

3 Research model

Based on the above research questions, we employ an extension of the UTAUT model developed by Venkatesh et al. (2003). We exclude constructs related to voluntariness and facilitating conditions because these constructs are not relevant for individuals choosing to use tax preparation software. Thus, our model includes what the literature identifies as major determinants of use: 'performance expectancy', 'effort expectancy' and 'social influence' as indicators (Davis, 1989; Davis and Venkatesh, 1996; Venkatesh et al., 2003). Based on cited literature and our research questions, we add additional constructs and relationships as shown in Figure 1 and described below.

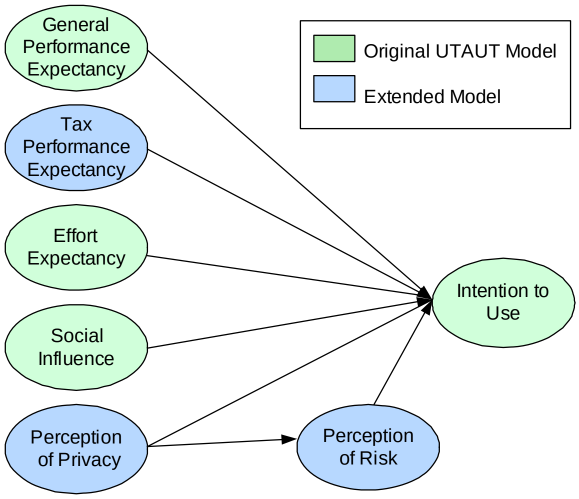
We define the constructs as follows:

- *General performance expectancy (PEG).* This construct measures the degree to which the individual believes that using tax software will help to improve performance. One important distinction from other studies is that tax preparation takes place outside of the traditional organisational setting but, nonetheless, in a highly complex domain. Individuals making the choice to use tax preparation software do not focus on job performance but rather on the system's performance in preparing personal tax returns. Thus, for purposes of this study, performance relates to what individuals ultimately desire in tax software.

- *Tax performance expectancy (PET).* While the general performance expectancy items have been shown to predict use in other contexts, we wanted to explore how specific performance expectancy in the tax realm might be different. We included questions about specific desires related to the potential for an IRS audit and greater refunds. For example, if a person's priority is to receive a high refund, they will rate the software's performance based on how successful the software is in getting that refund. On the other hand, if a person wants to avoid a tax audit, they will rate software performance based on the probability of avoiding a tax audit. Because different users may employ tax software for different reasons, we believed that measuring specific and general performance expectancy will provide insight into what particular aspects of tax preparation software users consider most important.
- *Effort expectancy (EE).* This construct measures an individual's perception of how easy it is to use the technology. In this particular case, the individual will compare how much effort it takes to complete a tax return with or without tax software. Interestingly, there are two alternatives for individuals who opt not to use tax preparation software: either they can complete their tax return on paper themselves or they can have a tax return professional prepare their tax filing. Depending on the taxpayer's individual situation, both alternatives may require more or less effort than using tax preparation software.
- *Social influence (SI).* This construct is designed to measure the extent to which individuals believe 'important others' think they should be using tax software. One significant difference compared to prior studies is that in this study there are no supervisory influences. Rather, 'important others' are spouses, partners, parents, friends, co-workers, etc. We believe that this construct is less important in measuring technology acceptance in this setting because the organisational context and therefore influence is not present. According to prior studies employing the UTAUT model, the relationship between social influence and behavioural intention (defined below) is influenced by individual differences such as age or gender.
- *Intention to use (ITU).* This construct measures individual intention to use tax software for preparing and filing a tax return. Prior studies have shown that performance expectancy, effort expectancy, and social influence affect intention to use. Behavioural intention has been shown to have an attenuated effect on actual usage.
- *Perception of privacy (PP).* This construct is defined as the belief that personal information entered into a system will remain private. For example concerning tax preparation software, a user who trusts the system's privacy controls, expects that personal information will be remain confidential.
- *Perception of risk (PR).* We also introduced a variable related to individual perceived risk. The studies cited above found that trusting beliefs inversely affect perceived risk which in turn is negatively correlated with intention to use new technology. While we measure an individual's general risk perception, we do not measure in what regard the user considers the tax software program risky/non-risky.

For example, an individual may believe it is risky because he or she does not have any means to verify output.

Figure 1 Extended UTAUT model (see online version for colours)



3.1 Partial least squares analysis (PLS)

To measure the effects of the defined factors on individual intention to use this specialised software, we developed and administered a survey (Appendix A) to a professional organisation of individuals using tax software and to accounting students at a major public university in the western USA. A total of 153 respondents completed the survey. Responses with missing values were removed yielding 136 valid respondents comprised of 72 professionals and 64 novices. Fifty eight respondents were male and 78 were female. The mean age of novice participants was 22 years with a standard deviation of 6.05 years. For professionals, the average age was 49 years with a standard deviation of 15.05 years. Between group t-tests indicate that the age difference between the two groups is significant. Table 1 reports the demographics of the study participants.

Table 1 Demographic information for both subject groups

	Novices	*Professionals*
Respondents	71	77
Average age	22	49
Females	37	47
Average years of filing	2.7	24.8
Average years of using tax software	1.1	14.6
Accounting degree	2	52
Tax professional	3	65
CPA licence	0	41

Note: Numbers for individual categories do not add up due to missing values.

We used SmartPLS (Ringle et al., 2005) to model our constructs and their relationships following structural equation modelling techniques (Chin et al., 2003; Gefen and Straub, 2005). There were several reasons for this choice. PLS makes fewer demands on the underlying data distribution and sample size, and it is also capable of analysing both reflective and formative indicators (Chin, 1998b). Probably because of these advantages, PLS analysis is now commonly used in information systems research and provides a robust way of analysing survey data (Chin, 1998a; Chin et al., 2003; Gefen and Straub, 2005; Gefen et al., 2000). To analyse the psychometric properties of the measures, we calculated the average variance extracted (AVE), composite reliability (ρ_c), Cronbach's alpha (CA), latent variable correlations and cross loadings. Table 2 reports these measures for both subject groups.

Table 2 Partial least squares results: overview for both subject groups

	Novices				*Professionals*			
	Ave	*Composite reliability*	*R Square*	*Cronbach's alpha*	*Ave*	*Composite reliability*	*R Square*	*Cronbach's alpha*
EE	0.80	0.94		0.91	0.74	0.92		0.88
ITU	0.80	0.93	0.59	0.88	0.68	0.85	0.71	0.74
PEG	0.76	0.93		0.89	0.83	0.95		0.93
PP	0.77	0.93		0.90	0.83	0.95		0.93
PR	0.78	0.94	0.03	0.93	0.75	0.92	0.02	0.91
SI	0.81	0.95		0.92	0.81	0.95		0.92

Although there is no standard method for calculating statistically acceptable composites, the generally accepted rule is for composite reliability to be greater than 0.7 (Yi and Davis, 2003). In this study, the lowest composite reliability was for tax performance expectancy in the novice group at 0.62. All other construct composite reliabilities were greater than 0.9.The latent variable factor loadings were derived following Gefen and Straub (2005) using SmartPLS and are provided in Appendices B and C. Discriminant validity of individual items were examined by verifying 'on factor' loadings greater than 0.7. Convergent validity was assessed by comparing 'on factor' loadings with 'cross factor' loadings. Not surprisingly, two novice loadings, PET2 and PET4 demonstrated inadequate discriminant validity. One item, ITU3 'on factor' loaded low at 0.47 for professionals. Since it loaded well for novices, we chose to retain it. However all other items loaded well. Overall, we argue that – with the exception of the PET construct – these results demonstrated good discriminant and convergent validity.

The PET construct had very low loadings for the novice group for PET2 and PET4. Further, the PLS results also indicate a poor model fit for this construct with AVE of 0.4, composite reliability of 0.62 and Cronbach's alpha of 0.45. In order to determine the cause of this poor fit for the PET construct, we reevaluated the model with two instead of one PET construct (each with two items). The results (not tabulated) show a much better fit. However, generally the lowest accepted number of items per construct is three; we therefore decided to remove PET completely instead of splitting it into two. We tested whether removing the PET construct impacted the overall results by running the PLS analysis without PET (tabulated), with PET and with two separate PET constructs. The relationships between other constructs remained the same.

4 Survey analysis and results

In order to test for between group differences, we performed t-tests on the average value per construct. The results show that the construct measures for general performance expectancy, social influence, and intention to use differ significantly across the two user groups. We split the dataset into two groups and analysed each set independently using the same structural model. In a second step, we compared the results to see what individual differences existed. We formulated our structural path model to test the UTAUT framework and applied our structural model.

Then we calculated the partial least squares path values and followed with a bootstrap resampling method. Five hundred samples were generated in order to determine fit. We used t-tests to calculate statistical significance for each path. Figure 2 shows the β coefficients and p-values extracted via PLS for the professional group. The UTAUT model accounted for a significant portion of variance in individual intention to use (R^2 = 0.71). General performance expectancy was significant, while all other constructs did not significantly impact intention to use. Next, we calculated the PLS path values for the novice group and followed with a bootstrap resampling method. Again, 500 samples were generated in order to determine fit. Statistical significance was then calculated for each path using t-tests.

Figure 2 Professionals – β, p val, R^2 (see online version for colours)

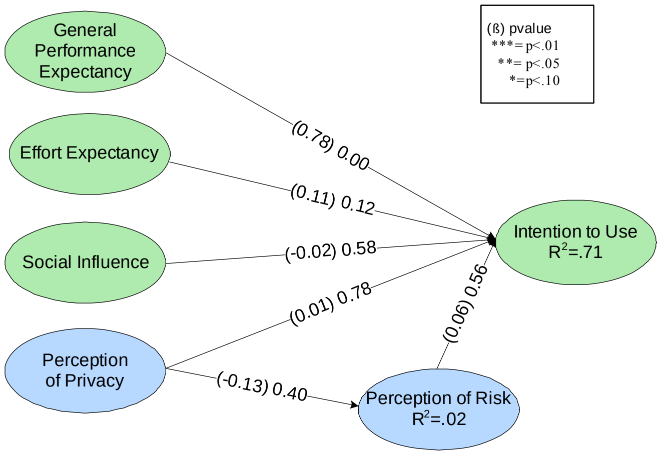


Figure 3 shows the β coefficients and p-values extracted via PLS for the novice group. In this case, the model also accounted for a significant amount of variance (R^2 = 0.59). Further, the privacy construct significantly relates to the novice attitude toward risk and explains 3% of its variance. Table 3 compares the results from both use groups (Figures 2 and 3). As expected, the importance of the relationships within the model varies significantly between the two groups. For professionals, only the general performance expectancy matters; for novices it is effort and performance expectancy as well as social influence that are important.

Figure 3 Novices – β, p val, r^2 (see online version for colours)

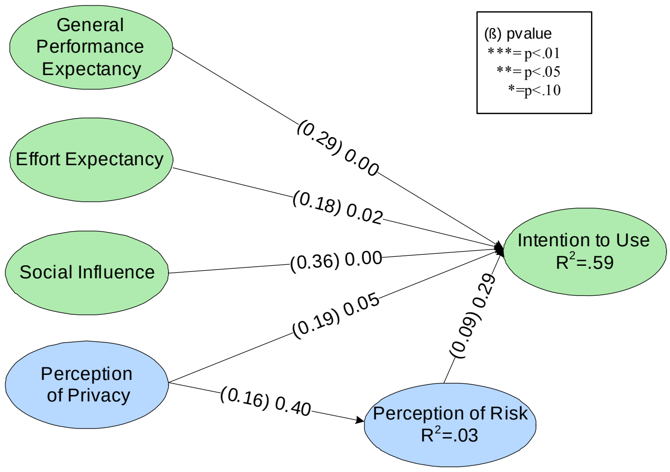


Table 3 Partial least square results: model relationships for both subject groups

Path	*Novices*				*Professionals*			
	Sample mean	*Standard dev*	*T Statistics*	*p-value*	*Sample mean*	*Standard dev*	*T Statistics*	*p-value*
EE → ITU	0.18	0.07	2.48	0.02	0.11	0.07	1.56	0.12
PEG → ITU	0.28	0.10	2.91	0.00	0.78	0.10	8.00	0.00
PP → ITU	0.19	0.09	2.03	0.05	0.01	0.07	0.28	0.78
PP → PR	–0.15	0.21	0.85	0.40	0.13	0.17	0.85	0.40
PR → ITU	0.09	0.08	1.07	0.29	–0.06	0.07	0.58	0.56
SI → ITU	0.36	0.08	4.41	0.00	–0.02	0.06	0.56	0.58

In general, a non-significant relationship offers two explanations: either there is insufficient power to reject the null or the null hypothesis is true. PLS does not allow testing for power. We therefore performed a power analysis using ‘traditional’ OLS regression methodology for each of the model relationships. We found high power for all but two relationships (privacy → risk; and risk → intention to use), suggesting that only the risk construct may require a larger sample.

4.1 *Robustness tests*

The sample size in this study is relatively small. We therefore believe that PLS regression methodology is the most appropriate approach given the limitations of other methods, such as factor analysis or OLS and other regression methods. However, one disadvantage is that we cannot test for the interaction of the main constructs (performance expectancy, effort expectancy, and social influence) with subject group dummy variables. Given the apparent differences between the two subject groups (see Figures 2 and 3) it is very likely that such an interaction would be significant. To assess this, we analysed our model using traditional OLS regression methods including a dummy variable equalling one if the participant was a novice and zero otherwise. Generally, the results from this analysis (untabulated) support our findings.

We were surprised how little influence privacy and risk perceptions seem to have on individuals' intention to use tax software. In particular, we expected to find strong correlations between privacy and risk as well as risk and intention to use and privacy and intention to use. Because of the possibility of multicollinearity the privacy → risk → intention to use 'triangle' was examined separately using PLS and OLS regression methods. As shown in Tables 4 and 5, when examining the three constructs separately, privacy perception impacts intention to use for both subject groups. However, the privacy → risk relationship remains insignificant suggesting domain expertise is not relevant. However, it appears that just like in the full model the privacy → risk relationship is significant only for novices but not for tax professionals.

Table 4 PLS results perceptions of risk and privacy and intention to use for both subject groups

Path	*Novices*				*Professionals*			
	Sample mean	*Standard dev*	*T Statistics*	*p-value*	*Sample mean*	*Standard dev*	*T Statistics*	*p-value*
PP → ITU	0.53	0.09	6.10	0.00	0.34	0.13	2.52	0.01
PP → PR	0.30	0.15	2.01	0.05	–0.14	0.17	0.85	0.40
PR → ITU	0.05	0.12	0.33	0.75	0.02	0.16	0.00	1.00

Table 5 OLS regression results

	Parameter estimate	*Standard error*	*p-value*
Intercept	5.11	0.61	<.0001
Novice dummy	–2.63	0.87	0.00
PR (Perception of risk)	0.01	0.07	0.91
PP (Perception of privacy)	0.23	0.10	0.02
PR * Novice dummy	–0.01	0.12	0.94
PP * Novice dummy	0.33	0.15	0.03

4.2 Limitations

As is common with survey research this study is not devoid of limitations. Our sample size is rather small which may impact the significance of our findings. Further, the novice group consists primarily of lower division business students. Compared to the general population students represent a very homogeneous group with a young average age and a relatively high education level. Thus, our subjects may not be representative of the general population. An extension of this study could therefore include subjects from different population segments. Further, one may argue that the strong relationship between e-filing and tax preparation may have lead to some confusion especially with regard to the privacy and risk items. However, we believe that the survey questions were sufficiently clear in stating that the focus of research was tax preparation software and not electronic tax filing.

5 Conclusions and outlooks

In this paper, we advance the technology acceptance literature in three ways. Firstly, we compare the perceptions of experts and novices with regard to tax software and how the different perceptions affect individual acceptance of the technology. Secondly, we test whether the relatively new UTAUT model works outside the traditional business and organisational environment. Lastly, we introduce privacy and risk constructs and compare results of both groups. Our results show that, generally, the three main constructs of the UTAUT model explain a significant amount of individuals' use intentions with R-square measures of 0.59 and 0.71 for novices and experts respectively. This indicates that the UTAUT factors do apply in the context of individual use of tax software. However, we also demonstrate that not all relationships between the major constructs and use intentions are significant and that different factors matter for different user groups. We differentiate between highly experienced users – professional tax preparers and novices.

For professionals the only significant factor is general performance expectancy. In other words, users who are very familiar with the tax domain only care about how well they think the technology will function. They are not concerned about the expected effort to use the system nor are they influenced by the opinion of others. Novices, on the other hand, are not only concerned with the performance of the technology. For users without any background in tax law, important aspects are also the perceived effort it will require to use the software and what their peers believe they should do. This indicates that alternative technology acceptance models may need to be created and tested to account for expertise-related individual differences.

Our findings have academic and practice-oriented implications. Academics should realise that the importance of the relationships within technology acceptance models, such as the UTAUT model, might depend on individual characteristics. We use an example of very strong individual differences – mostly related to experience and expertise – to illustrate that in cases when the subject matter is highly complex, these differences impact the factors affecting technology acceptance. Interestingly, we find between group differences with regard to the individual factors as well as the relationships between the factors. Namely, tax professionals have higher expectations with regard to tax software performance. They also are more likely to believe that their family, friends and peers thinks they should use software and have higher intentions of using software for their next personal tax return. Practitioners promoting new technology should be aware of individual differences because they may indicate that different aspects of the technology must be emphasised in order to achieve high acceptance.

Acknowledgements

We would like to thank the reviewers for their assistance in revising this paper. An earlier version of this was presented at the American Conference on Information Systems (AMCIS) in August 2009.

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Appendix A

Survey

1. Tax preparation software lets me prepare my taxes more quickly (PEG1).
2. My tax return will have less errors if use tax preparation software (PEG2).
3. I find tax preparation software useful for doing my taxes (PEG3).
4. Tax preparation software is helpful in completing my taxes (PEG4).
5. If I use tax preparation software, I increase my chances of getting a larger refund (PET1).
6. By using tax preparation software, I decrease my chances of being audited (PET2).
7. Tax preparation software will make my tax return more accurate (PET3).
8. If I use tax preparation software, my tax return is less likely to contain errors (PET4).
9. It would be easy for me to become skillful at using tax preparation software (EE1).
10. I would find tax preparation software easy to use (EE2).
11. Learning to operate tax preparation software is easy for me (EE3).
12. It would require little effort for me to use tax preparation software (EE4).
13. People who are important to me think that I should use tax preparation software (SI1).
14. People who influence my behaviour believe I should use tax preparation software (SI2).

15 In general, people around me have supported me using tax preparation software (SI3).

16 Most of the people I know think I should use tax preparation software (SI4).

17 The use of tax preparation software can be dangerous (PR1).

18 It would be risky to use tax preparation software (PR2).

19 I think it is unsafe to use tax preparation software (PR3).

20 By using tax preparation software I am taking a chance (PR4).

21 Tax preparation software will not divulge my personal information to unauthorized persons (PP1).

22 I believe that when using tax preparation software my personal information will be held private (PP2).

23 I do not worry about my personal information when using tax preparation software (PP3).

24 I can rely on tax preparation software to keep my personal information private (PP4).

25 I intend to use tax preparation software for my income tax return next year (ITU1).

26 In choosing preparation methods for my income tax return, my first choice would be to use tax preparation software (ITU2).

27 I would recommend tax preparation software to my relatives and friends (ITU3).

Demographic information

- age
- gender [f/m]
- education
- degree [some college/bachelors/graduate/other]

Education in Accounting

- Do you have a degree in accounting? [YES/NO]
- How many college accounting courses have you taken?
- How many college tax courses have you taken?

Education in IS

- Do you have a degree in information systems? [YES/NO]
- How many college information systems courses have you taken?

Experience

- Years of personally filing tax returns

- Years of using tax preparation software
- Are you a professional tax return preparer? [YES/NO]
- Are you a CPA? [YES/NO]
- Years of using computers
- List the computer software programs you use regularly
- Do you have any special recognition such as professional certifications in your field of study/work? [YES/NO/N/A]
  - If so, please list them:
- Are you currently full-time employed in the IS field? [YES/NO]
- Are you currently full-time employed in the accounting field? [YES/NO]

Appendix B

Novice cross loadings

	EE	*ITU*	*PEG*	*PET*	*PP*	*PR*	*SI*
EE1	0.91	0.43	0.46	0.24	0.29	0.14	0.27
EE2	0.91	0.51	0.54	0.37	0.35	0.23	0.38
EE3	0.95	0.47	0.50	0.34	0.37	0.24	0.30
EE4	0.79	0.38	0.31	0.17	0.31	0.10	0.18
ITU1	0.43	0.91	0.48	0.41	0.41	0.14	0.50
ITU2	0.43	0.94	0.52	0.46	0.39	0.14	0.54
ITU3	0.51	0.89	0.68	0.50	0.58	0.24	0.65
PEG1	0.46	0.55	0.87	0.41	0.44	0.27	0.45
PEG2	0.48	0.50	0.76	0.68	0.36	0.22	0.54
PEG3	0.43	0.56	0.95	0.56	0.45	0.18	0.48
PEG4	0.44	0.60	0.95	0.61	0.47	0.21	0.48
PP1	0.38	0.37	0.46	0.49	0.85	0.42	0.33
PP2	0.38	0.55	0.48	0.54	0.95	0.25	0.44
PP3	0.25	0.44	0.37	0.41	0.88	0.19	0.22
PP4	0.30	0.49	0.43	0.45	0.91	0.24	0.38
PR1	0.21	0.24	0.34	0.34	0.31	0.94	0.41
PR2	0.17	0.15	0.16	0.17	0.25	0.96	0.33
PR3	0.23	0.19	0.22	0.21	0.31	0.93	0.33
PR4	0.15	0.13	0.18	0.16	0.28	0.94	0.34
SI1	0.31	0.51	0.44	0.39	0.27	0.31	0.90
SI2	0.21	0.52	0.48	0.47	0.36	0.41	0.90
SI3	0.34	0.60	0.59	0.49	0.43	0.33	0.88
SI4	0.30	0.62	0.46	0.45	0.32	0.33	0.93

Appendix C

Professional cross loadings

	EE	*ITU*	*PEG*	*PET*	*PP*	*PR*	*SI*
EE1	0.86	0.36	0.40	0.14	0.30	0.03	0.21
EE2	0.90	0.43	0.41	0.21	0.38	–0.13	0.29
EE3	0.87	0.51	0.50	0.25	0.43	–0.11	0.36
EE4	0.81	0.38	0.39	0.21	0.48	0.11	0.25
ITU1	0.50	0.95	0.86	0.24	0.23	0.02	0.43
ITU2	0.40	0.95	0.79	0.32	0.24	–0.04	0.42
ITU3	0.33	0.47	0.28	0.28	0.30	–0.07	0.25
PEG1	0.48	0.83	0.94	0.27	0.29	–0.07	0.49
PEG2	0.35	0.59	0.79	0.54	0.18	–0.05	0.50
PEG3	0.51	0.83	0.96	0.28	0.27	–0.02	0.49
PEG4	0.47	0.80	0.95	0.31	0.28	–0.04	0.60
PP1	0.20	0.11	0.13	0.05	0.84	–0.10	0.11
PP2	0.42	0.31	0.30	0.08	0.95	–0.19	0.20
PP3	0.50	0.27	0.28	0.11	0.91	–0.11	0.30
PP4	0.48	0.25	0.27	0.14	0.93	–0.09	0.15
PR1	–0.05	0.07	0.10	0.05	–0.15	0.85	0.20
PR2	–0.07	–0.01	–0.10	0.13	–0.03	0.86	–0.10
PR3	0.05	0.03	–0.06	0.18	–0.03	0.83	–0.19
PR4	–0.04	–0.10	–0.15	0.15	–0.14	0.91	–0.12
SI1	0.29	0.39	0.53	0.25	0.25	0.05	0.89
SI2	0.29	0.38	0.46	0.24	0.15	0.01	0.93
SI3	0.38	0.46	0.54	0.25	0.19	–0.01	0.90
SI4	0.21	0.38	0.49	0.19	0.20	–0.03	0.88