Experience Richness: Effects of Training Method on Individual Technology Acceptance

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Abstract

The nature of the training experience a person is exposed to is an important contextual element influencing technology acceptance, but little research has explored the differences in technology acceptance for different types of training experiences. This research investigates the difference in technology acceptance for individuals experiencing different types of training. Our work builds on prior research by Venkatesh, Bandura, and others examining the technology acceptance model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and self-efficacy and this paper is focused on addressing several remaining questions raised by this research stream. Specifically, our research addresses the nature of training and user acceptance and our findings show that individuals who are exposed to vicarious experience training differ on many dimensions with regard to technology acceptance when compared to individuals experiencing direct, hands-on training.

1. Introduction

Research addressing individual adoption of technology has had an extensive history within the IS discipline [1, 2]. The technology acceptance model (TAM), and its derivatives, predicts individual technology adoption and use with a high degree of accuracy and reliability [2-5]. Further, TAM and related theories have been extended to include various contextual variables that help to explain individual technology acceptance in specific settings [1]. One important contextual variable is experience, with research showing that the nature of subjects’ interactions with a technology affects the relationship among model constructs [2]. Experience adds a needed dimension to technology acceptance, but the nature of the experience construct has yet to be adequately explored. Previous research has focused on usage time as a measure of experience [2]; however, while the amount of time utilizing a product is an important dimension of experience, duration remains a non-specific measure of the experience construct. Training is one specific type of experience and scholars have called for additional research examining the different types of experience-based training and their relationship with IT adoption. Specifically, Venkatesh and Bala [1] state, “…there is still a need for more granular understanding of the effects of different training modes on the determinants of IT adoption” [1]. Our research builds on this call by examining how the nature of training experience influences user technology acceptance.

2. Background

2.1. Training and Experience

Traditionally, the level of experience with a technology has been measured using temporal metrics, with more time using a product equating to greater experience. Differences in the amount of time of experience have been shown to have an impact on technology acceptance. For example, studies applying the Theory of Reasoned Action found that attitude became more influential with increasing experience (i.e., usage time) while the role of subjective norms diminished in importance [2, 6]. Additionally, research shows that the ease-of-use construct in the TAM model becomes insignificant with increasing experience [7, 8]. Variables such as complexity, affect toward use, social factors, and facilitating conditions were all less significant with more experience [9]. Differences were also found in adoption versus usage behavior with regard to the impact of innovation characteristics under different experience conditions [6]. Venkatesh and colleagues [2] show that the significance of the effect of some constructs decreases or sometimes disappears with increasing experience under a range of theories (i.e., Theory of Reasoned Action, Technology Acceptance Model, Theory of Planned Behavior, Model of PC Utilization, and Innovation and Diffusion Theory). Also, the Unified Theory of Acceptance and Use of Technology (UTAUT) model showed that experience influenced the effect of both Effort Expectancy and Social Influence on Behavioral Intent, where having less experience strengthened the effect of both Effort Expectancy and Social Influence on Behavioral Intent [2].

Training and experience have similar characteristics with regard to attitudes toward a new...
technology; therefore, training can be conceptualized as one influential type of experience. In fact, Sharma and Yetton [10] suggest that training may be one of the most important interventions that lead to greater user acceptance of technology. Training can be conducted both before and after the implementation of a new system [11] and training experience is influential in both technology adoption and ongoing use [11-13].

2.2. Research Model and Hypotheses

To conceptualize training’s role as a form of experience, it is important to frame a discussion of training using a theoretical lens. Specifically, Bandura argues that experience is not merely time-based, but that there can be varying effects of experience within the same allotment of time based on the nature of the experience. His social cognitive theory distinguishes between two types of active experiential conditions, vicarious experience (VE) and enactive mastery (EM) [14]. Enactive mastery involves actively performing a specific task during experiential training while vicarious experience involves viewing another person actively performing the task. Bandura asserts that enactive mastery provides the greatest increase in self-efficacy, although some situations mandate the use of vicarious experience. Our goal in the present research is to examine the differing impact on adoption decision-making when experience is garnered through either enactive mastery training or vicarious training.

We use UTAUT (adapted to operationalize our research) to test for these training effects on adoption decisions. Our adaptations to UTAUT are as follows: first, consistent with earlier non-longitudinal research [2], Behavioral Intent (BI) was used as the dependent measure rather than a measure of actual adoption. Further, we added two mediating paths, positioning Performance Expectancy (PE) as a partial mediator between both Effort Expectancy (EE) and Social Influence (SI) on Behavioral Intent (EE>PE>BI and SI>PE>BI), to conform our hypothesized paths with other TAM models (while UTAUT and TAM include slightly different measurement constructs, we suggest that the theoretical relationships expressed in TAM have application relative to the UTAUT constructs). The moderating variable of experience from the UTAUT model is operationalized using VE and EM as described above. Voluntariness of use and age were not explored as moderators given the lack of variance in age and the perceived non-optional nature of the research activity. Gender was also not explored in this research, but offers fodder for future research.

Previous studies have shown that experience can have a substantial impact on users’ perceptions about the effort necessary to learn and use a product [11-13]. EE in UTAUT is built upon Bandura’s self-efficacy theory [15, 16], which posits that both efficacy and outcome expectations determine behavior. EE is said to be related to these efficacy beliefs as a process expectancy, in that it influences the determination of an outcome expectancy (PE) [17]. Individual motivation differs based on the effect of the training context, with greater motivation influencing perceptions and behavior related to the training environment [18], leading to beneficial outcomes [19]. As noted above, Bandura [14] asserts that enactive mastery increases the subjects’ sense of self-efficacy, which in turn should positively influence perceived EE. We hypothesize:

H1: Effort Expectancy will be higher among users in an enactive mastery training context as compared to users in a vicarious experience training context.

Research suggests that PE is an outcome belief [15]. Perceived Usefulness (a related measure from TAM) is not directly influenced by training type, but is determined by a match between the technology’s capabilities and the person’s job needs [4]. Research shows that PE remains stable when measured over an extended period of time [4] and is minimally impacted by intrinsic motivation [20]. Given this information,

H2: Performance Expectancy will be equivalent among users in an enactive mastery training session as compared to users in a vicarious experience training session.

SI was added to TAM as a construct to measure the effect that other people have on an individual’s technology acceptance or, put another way, to examine the perceived influence of other social actors on the focal individual [2, 4]. Social Influence mechanisms, including compliance, internalization, and identification, play a role in the Social Influence process [21-23]. In an enactive mastery context, individuals are apt to perceive themselves as attaining a greater degree of compliance, because compliance involves performing a behavior to attain rewards or avoid punishment [24]. Also, by actually performing a task, the individual gains a greater degree of identification because they can better understand whether the behavior will elevate their social status with a particular reference group [4]. Furthermore, actively performing a task will allow for greater internalization of the perceived referent beliefs into the subjects’ own belief structures [25]. Given this,

H3: Social Influence will be higher among users in an enactive mastery training session as compared to users in a vicarious experience training session.

UTAUT posits that BI is a combination of EE, PE, and SI. The preceding hypotheses state

• EE will be greater in the enactive mastery group.
• PE will remain the same between the groups.
• SI will be greater in the enactive mastery group.

Taken together, subjects that are exposed to the enactive mastery training will ultimately report a
higher Behavioral Intent than subjects in the vicarious experience sessions. Given this, we offer the following hypothesis related to Behavioral Intent.

H4: Behavioral Intent will be higher among users in an enactive mastery training session as compared to users in a vicarious experience training session.

BI within the UTAUT model has been shown to be influenced by a combination of EE, PE, and SI [2]. Traditionally, training methods emphasizing knowledge transfer have shown that PE is a much stronger determinant of BI compared to the other exogenous constructs in the model [11]. Previous research has also shown that by providing an appropriate framing effect [26] through the use of an intrinsic motivator, EE and SI can have a more significant impact on BI [11].

Cognitive evaluation theory posits that intrinsic motivation will lead to higher levels of effort [27]. This locus of causality is the basic cognitive mechanism driving performance of a behavior. When intrinsic motivation is high, the locus of causality is internal and driven by intrinsic needs and rewards. Enactive mastery shifts the locus of causality to internal drivers leading to greater emphasis being placed on EE [11]. Behavioral decision theory suggests that the greater compatibility there is between the stimulus attribute and the response mode, the more heavily the attribute will be weighted in judgment and choice [28, 29]. Enactive mastery would be expected to cause a greater degree of compatibility with a process expectancy (i.e., EE) due to enhanced intrinsic motivation causing greater weight to be placed on EE in determining BI [11]. Other research has shown that positive priming can have an effect in shifting user judgments [30]. Given that users will have hands-on use of the product, we expect enactive mastery to have a positive priming effect that will cause EE to have a positive impact on BI. Given this, we hypothesize the following:

H5: The influence of Effort Expectancy on Behavioral Intent will be positive and greater for users who receive training using enactive mastery as compared to users who receive training using vicarious experience.

Research suggests that traditional vicarious training methods typically emphasize extrinsic value when using a technology. This tends to accentuate “what a technology can do,” which causes the locus of causality to be external and more focused on the outcome expectancy (i.e., PE) of interacting with the technology [11]. Given that users are held accountable for their performance, typical work activities incorporate PE as a key factor influencing BI. Because the underlying formation of PE will evaluate the match between product features and job tasks, training method will have little impact on this relationship [4]. Therefore we hypothesize

H6: The influence of Performance Expectancy on Behavioral Intent will not be significantly different for users who receive training using enactive mastery when compared to users who receive vicarious training.

These arguments state that by providing an appropriate framing effect that raises intrinsic motivation, both EE and SI will have a more significant impact on BI. Hands-on training through enactive mastery provides this appropriate framing effect and, hence, a higher level of intrinsic motivation. Finally, previous research has asserted that SI affects compliance (with regard to technology acceptance) more significantly in mandatory settings [2, 4] in the early stages of actual experience [4, 6, 9, 31-33]. While the voluntariness/involuntariness of the activity in our research sessions could not be absolutely enforced, individuals should perceive the instruction to use a product (i.e. the enactive mastery group) as more compulsory than an instruction to passively observe a demonstration (i.e. the vicarious experience group). Given this information,

H7: The effect of Social Influence on Behavioral Intent will be positive and higher for users who receive training using enactive mastery as compared to users who receive training using vicarious experience.

Previous technology acceptance research has shown that Perceived Ease-of-Use has both a direct impact on BI as well as an indirect effect through Perceived Usefulness [4, 7]. While the UTAUT model does not theorize a relationship from EE to PE, the argument can be made that such a relationship should exist since these two constructs correspond to Perceived Ease-of-Use and Perceived Usefulness from the original TAM model. Also, EE is a process expectancy, and should be expected to have an effect on an outcome expectancy such as PE [14]. Research has shown that this indirect relationship is much smaller and only becomes significant with greater experience [3, 8]. The present study examines the effects of training method on technology acceptance, with the training coming before users have had significant experience with the technology [1]. Given this, we hypothesize the following,

H8: The influence of Effort Expectancy on Performance Expectancy will not be significantly different for users who receive training using enactive mastery as compared to users who receive vicarious training.

SI represents the importance of perceived referent beliefs regarding the actual benefits of using a particular technology [4]. For this reason, both TAM2 [4] and TAM3 [1] posit that subjective norm will have a significant impact on Perceived Usefulness because an individual’s beliefs about referent attitudes toward a particular technology will calibrate the actual benefits they perceive they will garner from using the technology. While UTAUT does not hypothesize a direct effect of SI on PE, Venkatesh, et. al. [2]
specifically derived the PE construct from the Perceived Usefulness construct. Similarly, they note that the Social Influence construct is derivative of the Subjective Norm construct, stating that “Social Influence as a direct determinant of BI is represented as subjective norm in TRA, TAM2…” [2]. As a result, while UTAUT does not specifically hypothesize this relationship, we believe a direct effect of SI on PE is warranted. The influence of social referents on individual perceptions of system usefulness comes from hands-on experience with the system [34]. Also, given the perceived mandatory nature of actual system use (i.e. the enactive mastery group), previous research has shown that the effects of SI on other constructs is greater in “mandatory” settings as opposed to “voluntary” [2, 4]. Given this, we hypothesize...

H9: The influence of Social Influence on Performance Expectancy will be positive and higher for users who receive training using enactive mastery as compared to users who receive training using vicarious experience.

UTAUT posits that the variance of BI explained (squared multiple correlation, or pseudo-R2) is a combination of the effects of PE, EE, and SI on BI. Thus, the effect of EE on BI will be greater in the enactive mastery group, the effect of PE on BI will remain the same between the groups, and the effect of SI on BI will be greater in the enactive mastery group. Taken together, the model will explain more variance in BI among subjects in enactive mastery training than subjects in the vicarious sessions. Given this:

3. DATA COLLECTION

Subjects were asked to learn to use a virtual world, Second Life, because it provided users with an intrinsically motivating environment and all subjects had not previously used the environment (prior users were eliminated from the study). Further, while Second Life is sophisticated and, at times, challenging, many of the more basic functions can be mastered quickly.

H10: The variance of Behavioral Intent explained by Performance Expectancy, Effort Expectancy, and Social Influence will be higher in a group using an enactive mastery training session as compared to a group using a vicarious experience training session.

This fits well with Venkatesh’s suggestion that training on complex or disruptive systems can mitigate against negative reactions to a new system [1]. Subjects were told that virtual worlds are used in a number of business applications and that they would benefit from learning about how to use these tools because of their future use of these environments. Subjects for this study were students from an introductory MIS course at a Midwestern university and were incented with extra credit.

The general procedures for the research sessions are summarized as follows. First, the facilitator introduced himself and gave a brief introduction to the research session. This was followed by a pretreatment questionnaire consisting of questions designed to measure prior subject experience with 3D virtual world technologies. Next, the presentation was given, after which the subjects filled out a second questionnaire designed to measure the subjects technology acceptance with regard to Second Life (see http://bit.ly/PITPIh for a copy of the questions used).

The research presentation consisted of a video demonstrating Second Life and consisted of captured video of a user in the Second Life virtual environment. In the video a narrator described how to accomplish various tasks in Second Life using an avatar. These included both simple tasks such as walking and turning, as well as how to manipulate objects. The stated objective was to show users how to manipulate a number of virtual objects so that the room arrangement was more functional.

To test for the treatment effect of mode of training, the sessions were randomly assigned to one of two treatment conditions. The subjects in the vicarious experience group viewed the video. The enactive mastery group viewed the video but was also instructed to follow along, using their own avatar to accomplish each task in the demonstration. Each user’s avatar was preconfigured in the environment with its own individual “room” and furniture. Each subject’s virtual room was configured exactly the same (i.e., the rooms were copies of one another) and each avatar was positioned in the same relative starting position. To insure consistent delivery of the training in each session and treatment, videos were used to present the training for each treatment and each used the same script, processes, and instructions, with the only difference being occasional interjections during the process where the subjects were reminded to follow along in the enactive mastery treatment. While there was a “vicarious” component in both treatment conditions in that the subjects watched a video, the training manipulation was established by varying whether the subjects were allowed to “follow along” versus merely passively watching the facilitator. This is consistent with Bandura’s definition of the two training modes, vicarious experience and enactive
mastery, that are modeled after two common modes of learning used in classroom settings [14]. The trainer’s avatar was presented in the two videos performing the same tasks within the same environment as the subjects were asked to utilize.

4. Results

4.1. Measurement Model

The psychometric properties of the latent measures were evaluated using a confirmatory factor analysis (CFA). The measurement model was evaluated using multiple fit criteria, specifically the comparative fit index (CFI), the non-normed fit index (NNFI), the root mean square error of approximation (RMSEA), the standardized root mean square residual (SRMR), the goodness-of-fit index (GFI), and the adjusted goodness of fit index (AGFI). Acceptable levels for each included CFI ≥ 0.95, NNFI ≥ 0.95, RMSEA ≤ 0.06, SRMR ≤ 0.08, GFI ≥ 0.90, and AGFI ≥ 0.80 [35-38].

The measurement model included the four factors from the UTAUT model with their corresponding 15 indicators. The first run of the measurement model indicated that the model did not fit the data well: \( \chi^2 (81)=265.02, p < 0.001, \) CFI=0.95, NNFI=0.935, RMSEA=0.094, SRMR=0.108, GFI=0.883, AGFI=0.827. Upon further investigation, we found that two of the measures for SI loaded poorly on the latent SI construct at 0.227 and 0.287 respectively. Also, one item from the EE measure was found to load lower than normal at 0.584. As these items were well below the recommended cutoffs of both 0.7 [39] and 0.6 [40], the individual items were investigated. The second two items of SI were found to deal with the facilitator of the session as opposed to those who would have greater influence on the subject’s life. Also, the first EE item was found to deal with the clarity of use regarding the system as opposed to the ease of use. Due to these further analyses, the items were dropped and the measurement model was rerun. The revised measurement model fit the data well in terms of the fit indices: \( \chi^2 (45)=70.03, p=0.010, \) CFI=0.99, NNFI=0.99, RMSEA=0.047, SRMR=0.026, GFI=0.96, AGFI=0.93. The means, standard deviations, Cronbach’s alpha, composite reliability, average variance extracted (AVE) and correlations of the measures are shown in Table 1.

<table>
<thead>
<tr>
<th>Mean</th>
<th>Std. Dev</th>
<th>Alpha</th>
<th>CR</th>
<th>AVE</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE</td>
<td>3.41</td>
<td>1.53</td>
<td>0.92</td>
<td>0.02</td>
<td>0.75</td>
</tr>
<tr>
<td>EE</td>
<td>5.33</td>
<td>1.11</td>
<td>0.91</td>
<td>0.09</td>
<td>0.77</td>
</tr>
<tr>
<td>SI</td>
<td>2.68</td>
<td>1.35</td>
<td>0.94</td>
<td>0.04</td>
<td>0.80</td>
</tr>
<tr>
<td>BI</td>
<td>2.25</td>
<td>1.47</td>
<td>0.98</td>
<td>0.04</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Validity and reliability of the scales was performed to further ensure the psychometric properties of the measures [41, 42]. As stated above, convergent validity is established if all the standardized factor loadings for an item are above 0.7 [39]. After dropping the above three items, the lowest standardized loading was found to be 0.73, indicating acceptable convergent validity of the scale measures. Next, discriminant validity was shown to be satisfactory as the square root of the AVE of each measure is larger than its correlation coefficients with the other measures [42, 43]. Three types of reliability were also examined in relation to this measurement model. We examined Cronbach’s alpha, composite reliability, and average variance extracted, which are recommended to be greater than 0.7, 0.7, and 0.5, respectively [35, 41, 42]. The lowest value for Cronbach’s alpha is 0.91, the lowest for composite reliability is 0.91, and the average variance explained is 0.75; all of these measures are above the recommended values; therefore, the measurement model shows acceptable fit, validity, and reliability, allowing for further tests of the research model.

4.2. Research Model

Covariance-based structural equation modeling (SEM) was used to test the proposed model. The model was first tested across both groups to assess the overall fit of the model. The results suggest that the model fit the data well \( \chi^2 (46)=76.88, p=0.003, \) CFI=0.99, NNFI=0.99, RMSEA=0.051, SRMR=0.069, GFI=0.95, AGFI=0.92. The model also explained a significant amount of the variance in the endogenous variable BI \( R^2=0.42 \). Furthermore, the overall model showed significant paths from PE to BI, SI to BI, and SI to PE. Insignificant paths were found from EE to PE and from EE to BI. Figure 2 shows the research model with the associated standardized weights listed for the paths.

4.3. Multigroup Analysis

To test for differences between groups (VE vs. EM), a multigroup SEM analysis was performed as outlined in Hair et al. [44]. Table 2 shows the fit indices for the factor structure equivalence model.
[χ²(90)=147.52, p < 0.000] and the factor loading equivalence model [χ²(99)=155.85, p < 0.000]. Both suggest that the model fits the data for both groups well. Also, the change in χ² analysis indicates that the factor loading equivalence model fits the data as well as the factor structure equivalence model [Δχ²(8)=4.96, p=0.762]. Because both factor structure equivalence and factor loading equivalence have been satisfied and two loadings were constrained for all of the factors, partial metric equivalence has been satisfied. This allows for further multigroup analysis of means and also the structural parameters.

Table 2: Multigroup Statistics, the Measurement Model

<table>
<thead>
<tr>
<th>Model Description</th>
<th>χ²</th>
<th>CFI</th>
<th>NNFI</th>
<th>RMSEA</th>
<th>SRMR</th>
<th>GFI</th>
<th>AGFI</th>
<th>Δχ²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Combined Model</td>
<td>155.85</td>
<td>0.90</td>
<td>0.90</td>
<td>0.049</td>
<td>0.04</td>
<td>0.96</td>
<td>0.96</td>
<td>7.18 (1), p = 0.007</td>
</tr>
<tr>
<td>Factor Structure Equivalence</td>
<td>147.52</td>
<td>0.98</td>
<td>0.98</td>
<td>0.048</td>
<td>0.04</td>
<td>0.92</td>
<td>0.86</td>
<td>---</td>
</tr>
<tr>
<td>Factor Loading Equivalence</td>
<td>152.48</td>
<td>0.98</td>
<td>0.98</td>
<td>0.047</td>
<td>0.04</td>
<td>0.92</td>
<td>0.86</td>
<td>3.58 (2), p = 0.167</td>
</tr>
<tr>
<td>Intercept Equivalence EE</td>
<td>173.04</td>
<td>0.98</td>
<td>0.97</td>
<td>0.046</td>
<td>0.04</td>
<td>0.92</td>
<td>0.86</td>
<td>4.35 (1), p = 0.037</td>
</tr>
<tr>
<td>Intercept Equivalence PE</td>
<td>161.82</td>
<td>0.98</td>
<td>0.98</td>
<td>0.046</td>
<td>0.04</td>
<td>0.92</td>
<td>0.86</td>
<td>9.34 (3), p = 0.025</td>
</tr>
<tr>
<td>Intercept Equivalence BI</td>
<td>156.05</td>
<td>0.98</td>
<td>0.98</td>
<td>0.046</td>
<td>0.04</td>
<td>0.92</td>
<td>0.86</td>
<td>3.58 (2), p = 0.167</td>
</tr>
<tr>
<td>Mean Equivalence EE</td>
<td>163.23</td>
<td>0.98</td>
<td>0.98</td>
<td>0.046</td>
<td>0.04</td>
<td>0.92</td>
<td>0.86</td>
<td>19.56 (2), p &lt; 0.001</td>
</tr>
<tr>
<td>Mean Equivalence PE</td>
<td>163.23</td>
<td>0.98</td>
<td>0.98</td>
<td>0.046</td>
<td>0.04</td>
<td>0.92</td>
<td>0.86</td>
<td>20.56 (2), p &lt; 0.001</td>
</tr>
</tbody>
</table>

To provide an initial test for H1 – H4, a test of partial scalar invariance was utilized on the measurement model [44]. For our analysis, we ran four separate intercept equivalence models to check for equivalence of the four latent factors individually. To accomplish this we constrained the intercepts to be equal for the variables corresponding to the PE, EE, SI, and BI factors respectively in each of the four models beyond the factor loading equivalence model. Table 2 shows the results for the four models where the intercepts were constrained to be equal across groups. The model testing for equal intercepts across groups for EE is significantly different from the model with the factor loadings constrained [Δχ²(1)=19.56, p<0.001]. This provides evidence that the intercepts for the items in the EE factor are significantly different across groups. Given that scalar equivalence for the EE factor has not been met, we can conclude that the means for EE are significantly different between the VE and EM groups. The model testing for equal intercepts across groups for PE is significantly different from the model with the intercepts constrained [Δχ²(2)=9.34, p=0.025]. This provides evidence that the intercepts for the items in the PE factor are significantly different across groups. Given that scalar equivalence for the PE factor has not been met, we can conclude that the means for PE are significantly different between the VE and EM groups.

The two tests for intercept invariance for SI and BI both were not significantly different from the model with the factor loadings constrained [Δχ²(1)=1.93, p=0.165 and Δχ²(2)=3.58, p=0.167 respectively].

This indicates that the intercepts of the factors are not significantly different across groups, but to achieve full scalar invariance, the means must also be significantly different across groups. Table 2 shows the results for the two models where the means were constrained to be equal across groups for both SI and BI, individually. The model testing for equal means across groups for SI is significantly different from the model with the intercepts constrained [Δχ²(2)=4.35, p=0.037]. This provides evidence that the means for SI are significantly different across groups. Given that scalar equivalence for the SI factor has not been met, we can conclude that the means for SI are significantly different between the VE and EM groups. The model testing for equal means across groups for BI is significantly different from the model with the intercepts constrained [Δχ²(2)=7.18, p=0.007]. This provides evidence that the means for BI are significantly different across groups. Given that scalar equivalence for the BI factor has not been met, we can conclude that the means for BI are significantly different between the VE and EM groups.

To provide greater insight into the differences in the mean values for the latent constructs between groups, the mean values from the models for the two groups are given in Table 3. As shown in the previous analysis, all factor means are significantly different across groups. Upon further analysis provided by Table 3, EE, SI, and BI are each significantly higher in the EM group as compared to the VE group, providing support for H1, H3, and H4. PE is also found to be significantly higher in the EM group as compared to the VE group, which is contrary to H2.

To test for differences in path loadings between groups, we started with the measurement model with partial metric equivalence [44]. Next, five structural models were constructed and the gamma/beta loadings between latent constructs were constrained between groups for each relationship separately; therefore, the loadings from EE to BI, PE to BI, SI to BI, EE to PE, and SI to PE were constrained to be equal between groups.

Table 3: Comparison of construct means across training groups (all differences are significant).

<table>
<thead>
<tr>
<th>Latent Construct</th>
<th>Vicarious Experience</th>
<th>Enactive Mastery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effort Expectancy</td>
<td>4.3</td>
<td>6.7</td>
</tr>
<tr>
<td>Performance Expectancy</td>
<td>2.5</td>
<td>3.0</td>
</tr>
<tr>
<td>Social Influence</td>
<td>1.9</td>
<td>2.2</td>
</tr>
<tr>
<td>Behavioral Intent</td>
<td>2.0</td>
<td>2.5</td>
</tr>
</tbody>
</table>

Table 4 shows the comparison of these models. The model testing for an equal gamma loading across groups for the EE→BI relationship is significantly different from the model with factor loadings constrained [Δχ²(1)=19.56, p<0.001]. This indicates that the intercepts of the factors are not significantly different across groups, but to achieve full scalar invariance, the means must also be significantly different across groups. Table 2 shows the results for the two models where the means were constrained to be equal across groups for both SI and BI, individually. The model testing for equal means across groups for SI is significantly different from the model with the intercepts constrained [Δχ²(2)=4.35, p=0.037]. This provides evidence that the means for SI are significantly different across groups. Given that scalar equivalence for the SI factor has not been met, we can conclude that the means for SI are significantly different between the VE and EM groups. The model testing for equal means across groups for BI is significantly different from the model with the intercepts constrained [Δχ²(2)=7.18, p=0.007]. This provides evidence that the means for BI are significantly different across groups. Given that scalar equivalence for the BI factor has not been met, we can conclude that the means for BI are significantly different between the VE and EM groups.

To provide greater insight into the differences in the mean values for the latent constructs between groups, the mean values from the models for the two groups are given in Table 3. As shown in the previous analysis, all factor means are significantly different across groups. Upon further analysis provided by Table 3, EE, SI, and BI are each significantly higher in the EM group as compared to the VE group, providing support for H1, H3, and H4. PE is also found to be significantly higher in the EM group as compared to the VE group, which is contrary to H2.
constrained \[ \Delta \chi^2(1)=6.98, p=0.008 \] providing evidence that this gamma loading is significantly different across groups. Because structural parameter equivalence for the EE→BI relationship has not been met, we can conclude that the influence of EE on BI is significantly different between the VE and EM groups. The model testing for an equal gamma loading across groups for the PE→BI relationship is not significantly different from the model with factor loadings constrained \[ \Delta \chi^2(1)=0.42, p=0.516 \], which indicates that this beta loading is not significantly different across groups. Given that structural parameter equivalence for the EE→BI relationship has been met, we can conclude that the influence of PE on BI is not significantly different between the VE and EM groups, supporting H6. The model testing for an equal gamma loading across groups for the SI→BI relationship is not significantly different from the model with factor loadings constrained \[ \Delta \chi^2(1)=0.46, p=0.498 \], suggesting that this gamma loading is not significantly different across groups. Given that structural parameter equivalence for the SI→BI relationship has been met, we find that the influence of SI on BI is not significantly different between the VE and EM groups; contrary to H7. The model testing for an equal gamma loading across groups for the EE→PE relationship is not significantly different from the model with factor loadings constrained \[ \Delta \chi^2(1)=0.41, p=0.520 \], which suggests that the gamma loading is not significantly different across groups. Given that structural parameter equivalence for the EE→PE relationship has been met, we can conclude that the influence of EE on PE is not significantly different between the VE and EM groups, supporting H8. The model testing for an equal gamma loading across groups for the SI→PE relationship is not significantly different from the model with factor loadings constrained \[ \Delta \chi^2(1)=1.35, p=0.246 \], which indicates that this beta loading is not significantly different across groups. Given that structural parameter equivalence for the SI→BI relationship has been met, we can conclude that the influence of SI on BI is not significantly different between the VE and EM groups, contrary to H9.

A final model was utilized to test for differences in the proportions of variance in BI explained between the VE and EM groups (or R2 of BI). The R2 value of BI consists of the combined effects of EE, PE, and SI on BI; therefore, to test for differences in R2, a model was constructed which constrained the gamma loadings of EE and SI on BI and the beta loading of PE on BI to be equal across groups. The model testing for equal loadings across groups for the EE→BI, PE→BI, and SI→BI relationships is significantly different from the model with factor loadings constrained \[ \Delta \chi^2(3)=8.34, p=0.040 \]. This provides evidence that the R2 value is significantly different across groups. Given that structural parameter equivalence for the EE→BI, PE→BI, and SI→BI relationships has not been met, we can conclude that the proportion of variance explained in BI is significantly different between the VE and EM groups.

To provide greater insight into the differences in the structural relationships across models, blocking was utilized to generate results for each of the groups individually. The two separate models with their respective loadings can be viewed in Table 5. Also, a table summarizing the direct, indirect, and total effects of the relationships in the model for the two groups is provided in Table 5. As can be seen, the relationship between EE and BI becomes significant in the EM group, but this relationship changes from positive to negative, opposite to H5. Also, the relationship between SI and BI becomes significant in the EM group, but given the analysis above, the increase in significance is not significantly different between the two models. Both the relationship of PE on BI and of EE on PE remains fairly similar. Also, the relationship between SI and PE decreases for the EM group, but again this change is not significant given the analysis above. Finally, the R2 of BI in the EM group is greater than in the VE group, and given the analysis above, this difference is significant, supporting H10.

**Table 4: Multigroup Statistics for the Structural Model**

<table>
<thead>
<tr>
<th>Model Description</th>
<th>( \Delta^2 )</th>
<th>CFI</th>
<th>NNFI</th>
<th>RMSEA</th>
<th>SRMR</th>
<th>GFI</th>
<th>AGFI</th>
<th>AGFI vs. Original Combined Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Combined Model</td>
<td>7.69 (40)</td>
<td>0.90</td>
<td>0.94</td>
<td>0.03</td>
<td>0.05</td>
<td>0.89</td>
<td>0.88</td>
<td></td>
</tr>
<tr>
<td>Factor Structure Equivalence</td>
<td>6.61 (52)</td>
<td>0.90</td>
<td>0.97</td>
<td>0.05</td>
<td>0.04</td>
<td>0.89</td>
<td>0.92</td>
<td></td>
</tr>
<tr>
<td>Factor Loading Equivalence</td>
<td>0.038 (10)</td>
<td>0.90</td>
<td>0.90</td>
<td>0.04</td>
<td>0.05</td>
<td>0.90</td>
<td>0.90</td>
<td>0.40 (1), p=0.711</td>
</tr>
<tr>
<td>Structural Equivalence EE+BI</td>
<td>0.78 (101)</td>
<td>0.90</td>
<td>0.97</td>
<td>0.05</td>
<td>0.04</td>
<td>0.89</td>
<td>0.90</td>
<td>0.40 (1), p=0.004</td>
</tr>
<tr>
<td>Structural Equivalence PE+BI</td>
<td>0.22 (101)</td>
<td>0.90</td>
<td>0.90</td>
<td>0.04</td>
<td>0.05</td>
<td>0.90</td>
<td>0.90</td>
<td>0.40 (1), p=0.571</td>
</tr>
<tr>
<td>Structural Equivalence SF+BE</td>
<td>0.16 (101)</td>
<td>0.90</td>
<td>0.90</td>
<td>0.04</td>
<td>0.05</td>
<td>0.90</td>
<td>0.90</td>
<td>0.40 (1), p=0.499</td>
</tr>
<tr>
<td>Structural Equivalence EE+PE</td>
<td>0.21 (101)</td>
<td>0.90</td>
<td>0.90</td>
<td>0.04</td>
<td>0.05</td>
<td>0.90</td>
<td>0.90</td>
<td>0.40 (1), p=0.572</td>
</tr>
<tr>
<td>Structural Equivalence SF+PE</td>
<td>0.15 (101)</td>
<td>0.90</td>
<td>0.90</td>
<td>0.04</td>
<td>0.05</td>
<td>0.90</td>
<td>0.90</td>
<td>0.40 (1), p=0.248</td>
</tr>
<tr>
<td>Structural Equivalence EE,PE,SI+BI</td>
<td>0.13 (101)</td>
<td>0.90</td>
<td>0.90</td>
<td>0.04</td>
<td>0.05</td>
<td>0.90</td>
<td>0.90</td>
<td>0.40 (1), p=0.644</td>
</tr>
</tbody>
</table>

**Figure 3: Results separated by training experience**
5. Discussion

Training experience has been recognized as an important variable in the individual adoption of technology [1, 11]. Traditionally, researchers have measured individual experience with a technology by the amount of time spent with the product [2, 7, 8], ignoring the type of experiential richness of the interaction with the technology. Recently, Venkatesh & Bala [1] specifically called for research into the effectiveness of different training methods for enhancing the effect of determinants of variables inherent in technology acceptance. Our research offers a concrete example of the effect of training type on technology acceptance, and addresses the Venkatesh and Bala [1] call. Using a framework from research on learning methods and self-efficacy, we train users on a new technology using either vicarious experience or an enactive mastery method, grounded in Bandura’s social cognitive theory [14]. Previous research has looked at the effect of auxiliary activities during training on technology acceptance, specifically with regard to TAM [11], but that research did not examine a specific direct training difference. Second, we show that the type of training can have a significant impact on the relationship of variables within our modified UTAUT model. Specifically, we show that within an enactive mastery training experience, Performance Expectancy, Effort Expectancy, and Social Influence have a direct and significant impact on Behavioral Intent, and Social Influence also indirectly affects Behavioral Intent through Performance Expectancy. Conversely, within a vicarious training context, Performance Expectancy alone has a direct significant impact on Behavioral Intent, while Social Influence has only an indirect relationship through Performance Expectancy. Third, this research also demonstrates the viability of a fully specified adaptation of UTAUT; by adding the indirect effects of Social Influence and Effort Expectancy through Performance Expectancy (consistent with Bandura [14] as well as TAM [7], TAM2 [4], and TAM3 [1]) we provide a more robust articulation of the relationship among the UTAUT constructs.

Table 5: Comparison of model across training groups.

<table>
<thead>
<tr>
<th></th>
<th>Vicarious Experience</th>
<th>Enactive Mastery</th>
<th>Effect on Behavioral Intention</th>
<th>Effect on Behavioral Intention</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct</td>
<td>Indirect</td>
<td>Total</td>
<td>Direct</td>
</tr>
<tr>
<td>Effort Expectancy</td>
<td>0.12</td>
<td>-</td>
<td>0.13</td>
<td>-0.13</td>
</tr>
<tr>
<td>Performance Expectancy</td>
<td>0.50</td>
<td>-</td>
<td>0.50</td>
<td>-0.47</td>
</tr>
<tr>
<td>Social Influence</td>
<td>0.18</td>
<td>-0.05</td>
<td>0.55</td>
<td>0.24</td>
</tr>
<tr>
<td>Variance explained</td>
<td>0.42</td>
<td>-</td>
<td>0.43</td>
<td>-</td>
</tr>
</tbody>
</table>

One unexpected result was the difference in the effect of Effort Expectancy on Behavioral Intent between the two training types. In the vicarious experience group, Effort Expectancy had a non-significant impact on Behavioral Intent, while in the enactive mastery experience group this effect became negative and significant. This finding contrasts previous research on technology acceptance [1, 2, 5, 7, 11]. One possible explanation relates to the nature of the target software; subjects are exposed to a variety of virtual worlds in true video games, and they may have found the Second Life environment to be somewhat primitive (albeit easy to use). Consequently, there may have been a negative association among subjects between Effort Expectancy and perceptions of desire to use the product; with no significant relationship between Effort Expectancy and Performance Expectancy, this perception does not seem to affect subjects’ overall beliefs in the capabilities of the product, but it clearly has a direct effect on Behavioral Intent. Alternatively, in a more general sense, there may be a threshold where exceptionally easy to use programs seem “too easy” and are not regarded as seriously as more complex applications, and, therefore don’t foster enthusiasm for use.

Methodologically, this research provides a rigorous example of a multi-group analysis within a SEM framework. Specifically, we use an invariance, hierarchical methodology for investigating differences between groups. While this technique is not new per se [44-46], this research provides a useful template for future IS research to use an SEM framework for investigating differences in groups within the context of a complete structural model.

This research represents a step forward in the study of technology acceptance within different training experience contexts, but there are limitations and opportunities for future research. First, this research analyzes training context based on delineations of self-efficacy-based learning types provided by Bandura [14]. While these two experience types have been utilized extensively in research, there are other methods of training that could be used. Future research should look at other types of training experiences, which may affect technology acceptance. Another limitation of this research is the measure of technology acceptance used. While the UTAUT model – and its predecessor, TAM – have been utilized extensively in research, there are other models of technology acceptance. Future research should explore the effects of training experience on technology acceptance utilizing other models. Finally, the research context, specifically Second Life, is another limitation of this study. Second Life was utilized because most users did not have previous experience with the technology, it offers a degree of intrinsic motivation, and it has been utilized in certain business contexts. While students might find the product fun to learn.
about and use and they were told it was useful in the context of business, their preconceptions as business students about what makes for a useful business tool might not align with this environment's features. Future research should investigate other technologies and how they are impacted by training experience.

6. Conclusion

This research started with a call to action [1] and aimed to answer this call by investigating technology acceptance within differing training experience contexts. Our findings indicate that differences exist both in the levels of predictors of Behavioral Intent to utilize a technology as well as among the relationships among UTAUT predictors. These differences hold importance for researchers and practitioners wishing to better understand the effects of training type on technology acceptance. We also believe that the theoretical analysis presented in this paper offers a starting point for future research into this area.

7. References