Does Technology Acceptance Affect E-learning in a Non-Technology-Intensive Course?

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Abstract

Prior research suggests that individuals' technology acceptance levels may affect their work and learning performance outcomes when activities are conducted through information technology usage. Most previous research investigating the relationship between individual attitudes towards technology and learning has been conducted in technology-intensive settings. In this study we investigate the relationship between individuals' technology acceptance factors and their performance in a non-technology intensive course – an introductory accounting course where technology is used as a learning tool but where knowledge of technology is ***not*** a primary learning objective. Results show that individuals with lower levels of academic proficiency are likely to perform worse if they are also less accepting of technology, compared to their relative peers with higher levels of technology acceptance.

Keywords: Technology acceptance model (TAM), Online education, Distance learning, Blended learning, Intention.

1. INTRODUCTION

Over the past decade, course support software (e.g., Blackboard®) and textbook supplemental material have provided university instructors with a variety of e-learning tools that may enhance their instructional and assessment activities. These tools are often used to create a blended learning environment – a learning environment that mixes face-to-face instruction with e-learning tools embedded in course support software such as course material repositories, online quizzing, discussion boards and assignment submission. However, the circumstances under which, and individuals for whom, these tools and techniques are effective are not well-understood. Prior studies have found that negative reactions to technology can adversely impact individuals' performance in technology-intensive courses (Buche et al., 2007; Vician and Davis, 2003; Maurer 1994; May 2008; Schneberger et al., 2007-2008; Weil et al., 1987) where the purpose of technology use is to "learn ***about*** technology". Little is known about the effects of individual reactions to technology upon performance in a non-technology-focused course – a course where the purpose of employing technology is to 'learn ***with*** technology'. The reduced emphasis on technology in such a course might mitigate the effects of individuals' reactions to technology. Or, individuals' reactions to technology might continue to affect their performance even when technology is less central to the course. The latter case would be troubling since tools that are intended to enhance learning may actually be impairing or impeding it.

Individual reactions to technology are part of the conceptual foundations of technology acceptance research in organizational studies of information technology adoption and diffusion (Davis, 1989; Davis et al., 1989, 1992; Hartwick and Barki, 1994; Venkatesh and Morris, 2000; Venkatesh et al., 2003). Although the current research stream is ultimately interested in performance as a key outcome of use, the antecedent technology acceptance factors (e.g., *reactions* and *intentions*) are relevant to understanding how individual reactions might affect performance. From a research perspective, the addition of performance to the Unified Theory of Acceptance and Use of Technology (UTAUT) model would extend existing knowledge on the effects of technology acceptance factors to include usage outcomes (Venkatesh, et al., 2003). For practitioners, a technology acceptance model that includes performance could be useful during the decision process when instructors are evaluating whether or not to utilize e-learning tools to supplement learning outcomes.

The objective of this paper is to investigate the extent to which individuals' performance may be affected by their levels of technology acceptance when using e-learning tools in a non-technology-intensive course. We contribute to the literature by providing evidence of an association between individual technology acceptance factors (*reactions* and *intention*), individual ability (*academic proficiency*), and *performance* in the context of an e-learning environment. This paper is organized into three additional sections. The next section provides the theoretical background and hypotheses for the study. The following sections provide the study's method, analysis, and results. The final sections provide the study limitations along with implications for practice and research.

2. THEORETICAL BACKGROUND AND HYPOTHESES

Acceptance of new technology is critical to the successful implementation of any information system, regardless of whether the intended users operate within a corporate or academic environment. Existing research streams do not directly address the key elements of our investigation and we integrate relevant research from two major areas: technology acceptance and learning performance within e-learning environments.

2.1 Technology Acceptance Research

Technology acceptance research grounded in the Technology Acceptance Model (Davis, 1989) and its successors (Venkatesh and Davis, 2000; Venkatesh et al., 2003) focuses on identifying the psychological and attitudinal antecedents to behavioral usage of information technologies. The conceptual foundation to this research stream argues that an individual's *reactions* to technology influence both an individual's *intention* to use technology along with an individual's *use* of technology, and that an individual's *use* of technology will continue to influence an individual's *reactions* to technology (Venkatesh et al., 2003), as depicted in Figure 1. *Reactions* to technology include performance expectancy, effort expectancy, social influence, and facilitating conditions; *intention* is driven by performance expectancy, effort expectancy, and social influence (cf. Venkatesh et al., 2003). The goal of technology acceptance research is to understand what technology acceptance factors influence the behavioral outcome of an individual's choice to use (or not use) the technology, and focuses largely on the decision to adopt a technology for subsequent usage.

In an academic setting where an instructor has decided to use e-learning tools to support learning *with* technology, an individual learner's choice to use the technology is mandated by course design, thus use of the technology is implied. Under these circumstances, one's performance in the e-learning environment becomes more salient to investigate, rather than the choice to use the e-learning tool. However, technology acceptance research based on the Technology Acceptance Model and its variants (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh et al., 2003) provides little guidance on how the outcomes of technology use (e.g., performance) are affected by key technology acceptance predictors. A complementary stream of technology acceptance research by Goodhue and Thompson (1995) argues for a technology-to-performance chain that integrates theories of attitudes and behavior with theories of fit, which

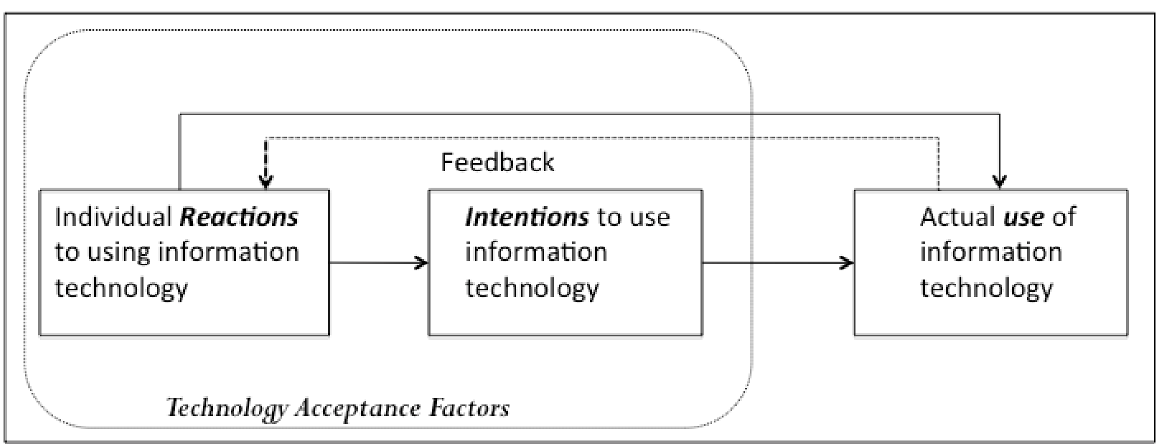

Figure 1: Conceptual Foundation to Technology Acceptance Research (adapted from Venkatesh et al, 2003)

lead to an influence upon performance outcomes. The original task-technology fit study utilized only *perceived* performance impacts due to the use of a field setting (Goodhue and Thompson, 1995). The current study uses an objective measure of performance: sum of the total quiz scores. A few studies have attempted to merge valuable constructs from the technology acceptance and task-technology fit research streams into a single model (Dishaw and Strong, 1999; Pagani, 2006; Tjahjono, 2009), although these studies have focused on the adoption decision rather than performance outcomes. Only recently have researchers begun to explore the linkages of technology acceptance factors with organizational performance outcomes (Ahearne et al., 2008), team performance outcomes (Fuller and Dennis, 2009), and individual performance outcomes (Abugabah et al., 2009; Kositanurit et al., 2006; Yu and Yu, 2010) within the context of extended IT usage (Limayem et al., 2007; Limayem and Cheung, 2011).

2.2 Learning Performance Research

Within higher education, research addressing performance outcomes in the context of technology use generally takes one of two forms: (1) a comparison of performance between individuals using technology in a learning situation versus individuals completing comparable work without technology usage; or (2) an investigation of the relationship between factors associated with individual learners and performance in a technology-mediated learning situation (Buche et al., 2007; Rossin et al., 2009). In distance learning research, there is some consensus that, on average, little to no significant difference exists in performance outcomes (e.g., learning) between those individuals utilizing technology to support learning outcomes versus those not using technology (Russell, 2001; Western Cooperative for Educational Telecommunications, 2009). In short, such research supports the conclusion that computer technology use for learning situations is, at its worst, a benign influence upon learning performance, and at its best, a positive outcome for certain kinds of learning scenarios such as disciplined, motivated adult learners who cannot avail themselves of co-located instruction (Russell, 2001). In other words, the benefits appear to outweigh any potential costs in performance.

Research addressing the relationship between individual differences and performance with technology has mixed outcomes. Within the technology acceptance research stream, computer anxiety is most often seen as a negative *reaction* to technology that has a dampening effect on an individual's choice to use technology. According to Venkatesh and his colleagues, effort expectancy fully mediates the relationship between computer anxiety and behavioral intent (Venkatesh, 2000; Venkatesh et al., 2003). Other studies indicate that there is a negative association between computer anxiety and performance (Buche et al., 2007; Keeler and Anson, 1995; Vician and Davis, 2003), and some suggest that there is no relation between computer anxiety and performance (Desai and Richards, 1998; Kernan and Howard, 1990; Webster et al., 1990). Further, Lee, Cheung and Chen (2005) provide mixed results with respect to the effects of technology acceptance factors on learning performance.

2.3 Research Model and Hypotheses

Figure 2 displays our initial conceptualization of the modified technology acceptance research model incorporating the influence of technology acceptance factors upon use outcomes (e.g., performance). We expect to see the effects of technology acceptance factors reflected in varying performance outcomes under situations of course mandated technology use.

Much prior work investigating the relationship between e-learning tools and academic performance fails to control for learners' natural ability (intelligence) and propensity to expend effort (work ethic). We hold that *academic proficiency* incorporates both intelligence and work ethic dimensions for an individual as manifested over time. In our conceptualization of the effect of technology acceptance factors on performance, we believe that an individual's academic proficiency will influence the degree of technology acceptance, which in turn will have an observable effect upon performance. Thus, our final conceptual research model is depicted in Figure 3.

For the purpose of this study we define *technology acceptance* as an individual's positive cognitive or emotional reaction to technology, resulting from technology acceptance factors of ***reactions*** and ***intentions*** (see Figure 3). An individual's acceptance of technology to achieve learning objectives is instrumental in attaining positive outcomes from using the technology. Learners who have less positive

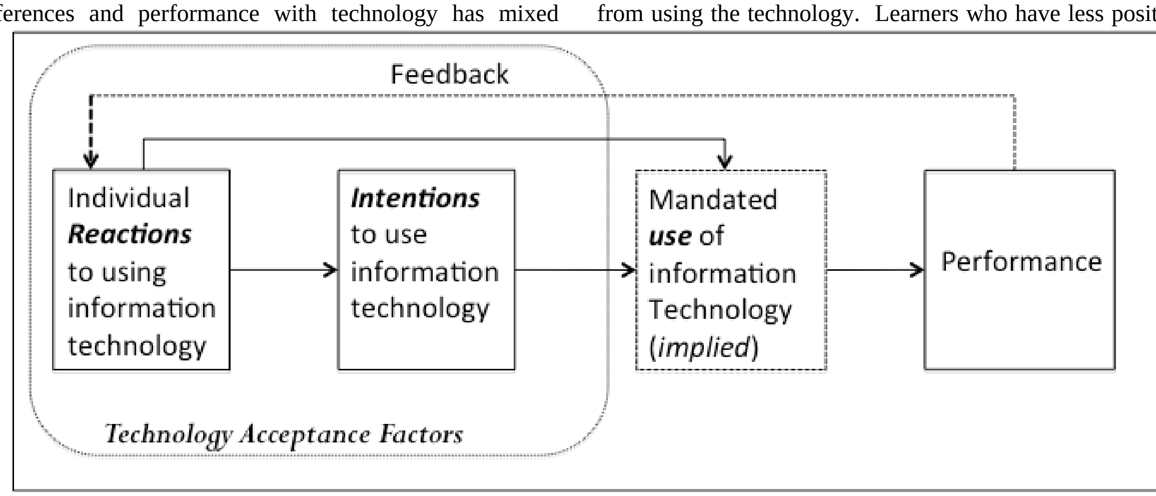

Figure 2: Modified Technology Acceptance Research Model

reactions to technology are more likely to engage in technology avoidance behavior (i.e. to avoid or minimize their use of the technology; see Igbaria and Parasuraman,

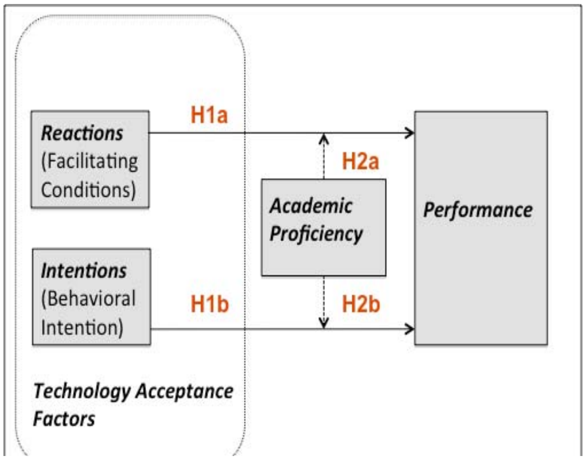

Figure 3: Research Model

1989). While research suggests there are multiple influences upon a user's acceptance of the technology, two critical factors are: (1) an individual's perception of how successfully the existing organizational and technical infrastructure will support use of the system (facilitating conditions) and (2) an individual's plan to act in a certain way (behavioral intention) (Venkatesh et al., 2003). Individual perceptions of the support structure (facilitating conditions) have a direct influence on actual system usage; an effect that is intensified for older and more experienced individuals (Venkatesh et al., 2003). Such direct effects on usage hold whether they are experienced in voluntary or mandatory system use settings. Research also indicates that an individual's behavioral intention to use a system may explain 35-40% of the variance in actual use of the system (Venkatesh et al., 2003), and may explain system usage outcomes such as performance (Goodhue and Thompson, 1995).

In the e-learning context, an individual's acceptance of course technology may have a measurable impact on performance in the course, particularly when technology use is mandated by the course design. Facilitating conditions, an individual's sense of how well the organization provides aid for technology use, could influence one's approach to using the technology. A perception that the organization provides a hospitable environment for technology use may encourage individuals to seek high performance outcomes; a sense of an alienating environment may frustrate individuals, thus causing them to settle for mediocre performance outcomes. An individual's strength of intention to use the course technology remains influenced by one's effort and performance expectancies for using the technology, and may affect one's commitment to do well in a course. The technology acceptance factors of *facilitating conditions* and *behavioral intention* are therefore important to research in this context. Most germane to the current study is that one would expect individuals with low levels of technology acceptance to avoid or lessen individual e-tools usage. Such behavior would normally result in less positive performance outcomes, such as lower grades, in comparison to individuals with higher levels of technology acceptance. A positive association between technology acceptance and performance would indicate that an individual with positive (negative) reactions to technology is more (less) likely to exhibit better performance than other individuals. Thus, we hypothesize:

H1: An individual with a higher level of technology acceptance will improve performance.

> **H1a**: An individual's positive perception of facilitating conditions will improve performance.
>
> **H1b**: An individual's positive level of behavioral intention will improve performance.

Research also indicates that performance outcomes with e-learning tool usage are not equally beneficial to all learners – in fact, performance benefits are a function of an individual's academic proficiency (Davis et al., 2005). Davis and colleagues (2005) found that individuals with lower academic proficiency benefited more from repeated, online quizzes than did individuals with higher academic proficiency. This evidence, taken together with research findings showing differential performance effects in the presence of computer anxiety when academic proficiency is controlled (Buche et al., 2007), suggests that academic proficiency can be expected to influence an individual's technology acceptance factors. One possible conclusion could be that an individual's academic proficiency may reduce negative effects of low technology acceptance for learners with higher academic proficiency levels, as more academically proficient learners may find coping strategies to overcome environmental challenges, such as technology acceptance. More troubling to find, however, would be that an individual's lower academic proficiency accentuates the negative effects of low technology acceptance. Hence, we hypothesize:

H2: Academic proficiency directly influences the effect of an individual's degree of technology acceptance upon performance.

> **H2a**: Academic proficiency directly influences the effect of an individual's perception of facilitating conditions upon performance.
>
> **H2b**: Academic proficiency directly influences the effect of an individual's level of behavioral intention upon performance.

3. METHOD

We adopted a field study with survey data collection methodology to test our research hypotheses. A class of 106 students from an introductory-level accounting course focusing primarily on managerial accounting topics participated in the study. The course was taught over a fifteen-week semester in the Business School at a small, Midwestern university. Participation in the study was voluntary and students did not receive grade or course credit for participating. Students were recruited during the second week of class and provided with class time to complete the questionnaire and other forms.

3.1 Sample Characteristics

Descriptive statistics for the initial sample are shown in Table 1. The subjects are primarily college sophomores. Over 70% were business majors, with the remaining students consisting primarily of engineering majors. Their average age was 21.1 years. About one-third of the subjects were male and two-thirds female, resulting in some over-representation of females in the sample (the business school where this study took place in 2008 was almost evenly split between male and female students). An overwhelming majority of the students indicated prior positive experience with computers. The subjects' average GPA prior to taking the class and their average final course grade were close to the cumulative average GPA on campus of about 2.9 out of a possible 4.0.

Table 1: Descriptive Statistics

Variable	Mean (Standard Deviation)
Final Course Grade (0 – 4)	2.85 (.96)
GPA (0 – 4)	2.76 (.75)
Behavioral Intent (1 – 7)	5.7 (.92)
Facilitating Conditions (1 – 7)	4.33 (1.42)
Age (in years)	21.1 (3.2)
Gender	37% male 63% female
Prior Experience with Computers as Positive	83%
N	106

3.2 Variables

Performance is measured in terms of students' total scores on seven, 5-question online quizzes administered during the semester using Blackboard® course management system. The maximum possible quiz score was 70 points (7 quizzes x 5 questions per quiz x 2 points per question). The total quiz score represents 70 out of 550 total possible points in the class. Students were required to complete each online, unproctored quiz on their own time before the in-class coverage of the related material began. Each quiz tested material covered in one chapter of an introductory accounting text, such as product costing, cost-volume-profit analysis or relevant costs. Quiz formats included multiple-choice and true/false questions that emphasized accounting concepts. The online quizzes were made available two days prior to the required completion date, with the goal of encouraging individual student preparation for class. Students were allowed to refer to the course textbook while taking the quizzes, but they were required to complete the quizzes without the assistance of other individuals. Students were permitted only one attempt at each quiz and had unlimited time for each attempt, until the course management system prevented access after the quiz due date (constraints set by the instructor). The quizzes were taken at a time and location of the student's own choosing, the only necessity being Internet access. Quiz scores were captured in electronic form by the Blackboard® course management system.

Behavioral Intent (BI) and **Facilitating Conditions** (FC) are measured using a survey instrument (see Table 2 below) that has been validated in prior research and has demonstrated reasonable reliability and validity (Venkatesh et al., 2003). Cronbach's alpha for BI is .93 and for FC is .91. All question responses are on a 7-point scale with the composite factor scores divided by the number of items in the factor loading so that they are also measured on a 7-point scale. ***Higher*** scores represent ***higher*** levels of technology acceptance with a positive correlation expected between performance and the technology acceptance measure; that is, the higher the level of technology acceptance, the higher the student's performance is expected to be.

Table 2. Measurement Items

Facilitating Conditions
• The University will be helpful in the use of the Blackboard system. • In general, the University will support the use of the Blackboard system. • I have the resources necessary to use the Blackboard system. • I have the knowledge necessary to use the Blackboard system. • The Blackboard system is not compatible with other systems I use. • A specific person (or group) is available for assistance with Blackboard system difficulties.
Behavioral Intention
• I intend to use the Blackboard system in the next 3 months. • I predict that I would use the Blackboard system in the next 3 months. • I plan to use the Blackboard system in the next 3 months.

Academic proficiency is measured by individuals' GPA values prior to the semester in which they take the course involved in this study. With the consent of the participants, GPAs were gathered by the researchers from official university records. The coefficient on academic proficiency is expected to be positive and significant. While prior research has shown that academic proficiency and e-learning tools may interact to affect performance (Davis et al., 2005), we have no *a priori* expectations regarding the interactions between academic proficiency and our measures of technology acceptance. The influence of academic proficiency upon the relationship between technology acceptance and performance is still of an exploratory nature, therefore two-tailed tests will be performed.

4. ANALYSIS AND RESULTS

This study represents, in part, an investigation of whether the Technology Acceptance Model can be applied to an e-learning environment. Currently, there is no well-developed and validated model of the relation between technology acceptance and e-learning performance, and little empirical evidence about which dimensions of technology acceptance do and do not affect e-learning. It is for these reasons that we use a regression rather than Structural Equation Modeling (SEM) for our analysis. SEM techniques such as LISREL require a strong theoretical basis (Gefen, et al. 2000); Partial Least Squares (PLS) "…is not usually appropriate for screening out factors that have a negligible effect…" (Tobias, 2010).

To test our hypotheses we estimate the following regression model:

Performance = AP + BI + FC + APBI + APFC

where:

Performance =	The student's total score on seven 10-point quizzes, measured on a scale of 0 to 70
AP =	Academic proficiency as measured by the student's grade point average as of the end of the semester prior to participating in this study, measured on a scale of 0 (F) to 4 (A)
BI =	A subject's Behavioral Intent, measured on a scale of 1 – 7, with scores indicating higher levels of technology acceptance
FC =	A subject's perception of the Facilitating Conditions for use of the Blackboard Software used to administer the online quizzes measured on a scale of 1 – 7, with higher scores indicating higher levels of technology acceptance
APBI =	The interaction between AP and BI
APFC =	The interaction between AP and FC

Regression results are presented in Table 3. The adjusted R-squared for the model is .40 (F = 14.58, $p < .001$), indicating a good linear fit. The coefficient on Academic Proficiency is positive and significant as expected ($p < .001$). With regard to the primary experimental variables of interest: the coefficient on BI (Behavioral Intent) is positive and significant ($p < .0001$, one-tailed) while the coefficient on the interaction between Behavioral Intent and Academic Proficiency (APBI) is negative and significant ($p < .001$, two-tailed). The coefficient on FC (Facilitating Conditions) is not significant ($p < .89$, one-tailed) as is the coefficient on APFC (the interaction between Academic Proficiency and Facilitating Conditions) ($p < .50$, two-tailed). Our results for facilitating conditions are consistent with Venkatesh et al. (2003) whose work suggests that facilitating conditions have no effect on use in a mandated use setting. The effect of facilitating conditions upon usage is also more salient for older workers with increasing levels of experience with the technology, rather than the predominantly younger-aged individuals found in our sample.

Table 3: Regression Results
Dependent Variable = Performance

Variable	**Coefficient (t-value)**
Intercept	-39.45 (-1.80)
AP	31.12 **(4.27)***
BI	12.61 **(3.69)***

AP **BI**	**Below Median**	**Above Median**
Below Median	3.86 (.74)	4.5 (1.19)
Above Median	6.4 (.2)	6.3 (.07)

FC	.35 (.14)
APBI	-3.93 **(-3.45) ****
APFC	-0.15 (-.17)
Adjusted $R^2 = .40$ (F = 14.58, p< .001) N = 106	

***significant at $p < .001$, one-tailed**
****significant at $p < .001$, two-tailed**

The results for BI and the interaction between BI and Academic Proficiency are consistent with an association between BI and performance, the nature of which is moderated by an individual's academic proficiency. The negative coefficient on the interaction term indicates that the effect of BI on performance is less positive for the high Academic Proficiency individuals than for the low Academic Proficiency individuals. This could be attributed to either a lower but still positive relationship between BI and performance, or a negative relationship between BI and performance, for the high Academic Proficiency individuals.

To further investigate these results the sample was partitioned along two dimensions: (1) whether the individual's Academic Proficiency was above or below the median, and (2) whether the BI score was above or below the median. Descriptive statistics for this partitioning are shown in Tables 4A and 4B. As illustrated in Table 5, a comparison of performance (in %) for high and low BI individuals indicates that for individuals with lower Academic Proficiency, those with higher BI levels also had higher performance; for individuals with higher Academic Proficiency, there was no difference in performance between individuals with high and low BI levels.

Our results are consistent with the following characterization of the relationship between individuals' levels of technology acceptance and academic performance: Individuals who are more accepting of technology exhibit stronger performance with technology-based instruction. However, this relationship is influenced by an individual's academic proficiency (natural abilities and predisposition for academic effort as measured by GPA). The performance of individuals who have exhibited weaker academic proficiency in the past are more likely to be affected by low levels of technology acceptance than are individuals who have exhibited stronger academic proficiency in the past.

Table 4A: Behavioral Intention (BI) Descriptive Statistics by Academic Proficiency (AP) Means (s.d.)
Table 4B: Academic Proficiency (AP) Descriptive Statistics by Behavioral Intention (BI) Means (s.d.)

AP BI	Below Median	Above Median
Below Median	2.29 (.74)	3.5 (.38)
Above Median	2.4 (.7)	3.3 (.36)

Table 5: Average Performance (%) Partitioned on Academic Proficiency (AP) and Behavioral Intention (BI)

AP BI	Below Median	Above Median
Below Median	74	87
Above Median	80	87

5. DISCUSSION

The key result from this research, supported by the data analysis, is that all individuals are not served equally by online education. There are individual differences that can impact the successful internalization of course content, contributing to varying levels of performance independent of the person's comprehension of course material. Additionally, the individuals most profoundly affected by the online learning environment are those individuals with lower overall academic proficiency. Better performing individuals show less sensitivity to the course medium employed. In other words, a "good student" will overcome low behavioral intention (i.e. low technology acceptance) and persevere whether in a traditional classroom setting or online environment. Introductory accounting is often taught at the sophomore level after students have demonstrated basic computer competency – either through course work or an exemption process – and have frequently been exposed to some form(s) of e-learning in their other coursework. However, in spite of this record of prior experience with e-learning tools, our results indicate that the adverse effects of low levels of technology acceptance persist over time. This finding appears to contradict the pervasive assumption that contemporary students embrace technology and are universally computer literate. Further, our results indicate some empirical support for Sun and Zhang's (2007) integrative model of user technology acceptance that includes a moderating factor of "individual intellectual capabilities".

An important implication for practice is that e-learning tools are not equally effective for all students. To the extent such tools are used to assess functional knowledge, skills, or abilities (e.g., accounting, finance, marketing, operations, information systems), assessment results may be confounded by individuals' level of technology acceptance. In those cases, it might be prudent for instructors to include a weighting factor associated with the use of e-learning tools, such that an individual's functional comprehension is captured independently from the use (or non-use) of the e-learning tools. For those situations where e-learning tools are used primarily as student supplemental learning aids, instructors may wish to assess levels of technology acceptance – using measurement devices such as the survey in this study – and design interventions to assist individuals exhibiting lower levels of technology acceptance. Although some individuals might experience lessened technology anxiety with continued exposure to the technology (Buche et al., 2007), other research suggests that the individual apprehensions experienced in computer-mediated environments are <u>not</u> mitigated by additional technology exposure and may indicate a more targeted response (Brown et al, 2004). Failure to implement interventions could impair individual achievement with e-learning tools and make the use of e-learning tools counter-productive. For instance, tailored demonstrations might be beneficial when introduced at the beginning of the term. Additionally, the judicious selection of e-learning tool features such as feedback (and instructor modeling of same) has been shown to have a positive affect on learner acceptance of the technologies (Tsai et al., 2011). As learner acceptance of e-learning tools increases, it is presumed that the negative influence on performance may diminish. However, this conclusion extends beyond the scope of this study and should be tested in future research.

The current research model extends the UTAUT model by including performance as an outcome of technology use (see Figure 3). In a mandatory use environment, usage is implied and is directly observable in an individual's performance. However, as our study demonstrates, the quality and impact of the usage will vary among individuals. Involuntariness can be viewed as a continuum, rather than as a dichotomous variable (Hebert and Benbasat, 1994). Although this study does not specifically address the continuous nature of the mandatory use variable, the results suggest that individuals not only differ in their acceptance of technology, but also in how they choose to use the online resources to meet their educational goals.

The use of a single university for participants is a limitation of the study. The research should be replicated in other educational environments, including distance learning courses and corporate online training classes to compare the findings and determine the robustness of the research model. In the current study the performance measure consisted of online quiz scores within a blended learning academic format. We extend our discussion of implications to include distance learning, but that extrapolation must be tested in appropriate course settings. Also, even though individuals were prohibited from collaborating on their online quizzes, there was no supervision imposed on the test takers. Therefore, it is possible that quiz scores are not accurate representations of individual effort. However, in this study, collaboration would most likely have led to a bias *against* finding significant results due to a reduction in the variance in quiz scores across levels of Behavioral Intent and Academic Proficiency. Further, violations of collaboration (i.e. working together when not permitted) and authentication of identity (i.e. impersonating someone else) are common concerns in all types of online instruction. In spite of these issues, the results proved significant and provide valuable insights for practitioners and academic researchers.

Future studies should recognize that the effectiveness of e-learning tools is not uniform across individuals. Researchers investigating performance with e-learning tools should attempt to identify and control relevant individual differences. The steady growth and pervasiveness of distance learning highlight the importance of these findings. As more individuals are attracted to the convenience and flexibility of online educational opportunities, participants demonstrating marginal academic proficiency (e.g. low grade point average) might experience unanticipated negative reactions to the technological resources, leading to even lower performance outcomes. Furthermore, online course assessments may lead instructors to misinterpret performance comparisons among students. Assessment results (i.e. grades) might be, at least partially, attenuated by the learner's reactions to the technology-mediated setting. Future research might address the relationship between technology acceptance and other forms or uses of e-learning tools. For example, future work might investigate the relationship between technology acceptance and learning that occurs through the use of online homework submission and grading. Another potential area of future research is to investigate the relationship between e-learning tools and other individual differences such as age, gender, locus of control and learning styles.

6. CONCLUSION

The objective of this study was to investigate the extent to which an individual's performance when using e-learning tools in a non-technology-intensive course may be a function of individuals' levels of technology acceptance, an individual difference. While computers and other information technology are ubiquitous in both business and educational environments, reports of erratic individual usage and inconsistent performance continue to surface (e.g, Angelocci et al., 2008; Cheng, 2011; Chou and Tsai, 2009; Davis et al., 2005; Ilias et al., 2009; Menkes, 2008; Muwanguzi and Lin, 2010; Sprague and Dahl, 2010; Vathanophas et al., 2008; Youngberg et al., 2009). Results showed that individuals with lower levels of academic proficiency are likely to perform worse if they are also less accepting of technology, compared to their relative peers with higher levels of technology acceptance. These findings have implications for both practice and research, and highlight the need to be aware that the effectiveness of e-learning tools is not uniform across individuals. In particular, our findings suggest that educators may need to take practical actions to allow for differing level of technology acceptance in the student audience when e-learning tools are used for learning outcomes.

Some educators might balk at these implications, stating that it is not their responsibility to provide remedial instruction on electronic tools but rather to teach course content. This added remedial instruction responsibility could, in fact, lead educators to avoid use of electronic learning resources that are already available at the organization (e.g., educational institution or corporate training environment). The underutilization of course support tools by instructors on many university campuses provides an important complementary area of investigation. It might be that educational institutions need to proactively address these issues, rather than leaving such concerns to individual instructor decisions. Further, the common assumption that contemporary students universally embrace new technology and possess advanced computer literacy skills might be called into question (McDonald, 2004). Our study suggests that participation in social networking and use of Internet search engines do not adequately prepare students for the attitudes and competencies required to be successful in blended and online educational environments. Awareness of these limitations is only the first step in addressing such issues in our current academic environment.

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