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FACULTY INTENTIONS TO LEARN NEW TECHNOLOGY IN REGARDS TO EXISTING TEACHING, RESEARCH AND SERVICE COMMITMENTS: AN INTEGRATION OF PROSPECT THEORY AND THEORY OF PLANNED BEHAVIOR

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FACULTY INTENTIONS TO LEARN NEW TECHNOLOGY IN REGARDS TO EXISTING TEACHING, RESEARCH AND SERVICE COMMITMENTS: AN INTEGRATION OF PROSPECT THEORY AND THEORY OF PLANNED BEHAVIOR

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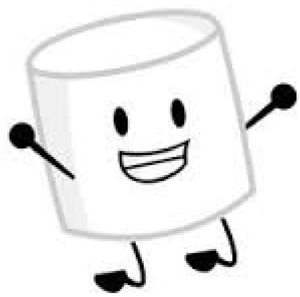
Dedication

To Kelly, my soulmate, *Ever*…

To Darby, Cullen, Samantha, Kayla, Antoinette, and Kendrick Jr. Here is my novel with a marshmallow on it.



Always follow your dreams!!

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Table of Contents

List of Tables ix

List of Figures x

Abstract xi

Chapter 1 1

Introduction 1

Chapter 2 7

Literature Review 7

Prospect theory and loss aversion 10

Theory of planned behavior 14

Perceived instrumentality 17

Perceived time pressure as a predictor of self-efficacy. 18

Self-efficacy as predictor of attitude and intention 18

Disposition to be loss averse as a moderator of self-efficacy and attitude. 20

Instrumentality as a predictor of attitude. 21

Attitude as a predictor of intention. 22

Research Questions and Hypotheses 22

Chapter 3 24

Methods 24

Participants 24

Sample size 24

Procedure 25

Measures 25

Loss aversion 26
Perceived instrumentality 27
Perceived time pressure 28
Self-efficacy toward learning new technology 28
Attitudes toward learning new technology 29
Intentions to learn new technology 29
Chapter 4 31
Results 31
Descriptive statistics and internal consistencies 31
Correlations 32
Path analysis 33
Test of indirect effects 38
Moderator analysis: Loss aversion X Self-efficacy 38
Chapter 5 41
Discussion 41
Limitations of the study 47
Implication and conclusion 50
References 52
Appendix A – Instrument 59

List of Tables

Table 1: Descriptive statistics of measured variable 31

Table 2: Correlation analysis of variables 33

Table 3: Fit Statistics for path models 35

Table 4: Unstandardized and standardized indirect effects 38

Table 5: Loss aversion "*Sure Gain*" 45

Table 6: Loss aversion "*Sure Loss*" 45

List of Figures

Figure 1: Proposed integrative model of intentions to learn new technology 10

Figure 2. Original theory of planned behavior model 14

Figure 3. Proposed integrative model of intentions to learn new technology 23

Figure 4. Integrative model 1 34

Figure 5. Re-specified Model 2 36

Figure 6. Re-specified Model 3 37

Figure 7. Re-specified Model 4 37

Figure 8. Plot of loss aversion regression lines 40

Abstract

This research used a revised theory of planned behavior model and incorporated perceptions of time pressure, perceived instrumentality and a modified loss aversion index, to examine relationships between these constructs in relation to faculty intentions to learn new technology. Faculty (N = 208) completed a survey created in Qualtrics presenting measures of time pressure, loss aversion, instrumentality, self-efficacy (perceived behavioral control), attitudes, and intentions. The loss aversion index was significantly correlated with perceived instrumentality, attitude, and intention to learn new technology. Significant correlations were also found among attitudes, perceived instrumentality and intentions. Path analysis (with 3 re-specified models) indicated perceptions of behavioral control, attitudes, and perceived instrumentality were significant predictors of intentions to learn new technology with direct and indirect effects. Moderator analysis suggests the presence of a statistical interaction between perceived behavioral control and the loss aversion index. These findings emphasize the need to consider perceptions of control (efficacy), dispositions to be loss averse, conflicts with re-prioritizing existing commitments, and perceived instrumentality as they may have an impact on faculty engaging in learning new technology.

Keywords: theory of planned behavior, faculty intentions, loss aversion, perceived instrumentality, predicting intentions

Chapter 1

> "We tend to make decisions as problems arise, even when we are specifically instructed to consider them jointly. We have neither the inclination nor the mental resources to enforce consistency on our preferences, and our preferences are not magically set to be coherent, as they are in the rational-agent model." – Daniel Kahneman, 2011

Introduction

In the 1986 film, "Field of Dreams," it was stated that "If you build it, they will come," referring to the instruction by a voice to Kevin Costner's character, Ray Kinsella, to build a baseball field in the middle of a cornfield. This instruction suggested that people will come to the field if Costner would just build it. In certain respects, this echoes the approach taken by colleges and universities with respect to the purchase of new technologies for instructional purposes: "If we buy it, faculty will use it." Perhaps it is more reasonable to assume that, "If we buy it, faculty *may* or *may not* use it." This study is formulated with the latter in mind. Rather, faculty may or may not use it if they view the time investment in learning a new technology will result in gambling with their existing obligations and goals.

Not only are colleges and universities spending considerable amounts of money on new technology initiatives, with many aimed at facilitating online/hybrid instruction, faculty's *work* hours at research and doctoral granting institutions are steadily increasing. Within this spending, enormous financial and time investments are dedicated to the acquisition of technology alone (Kuriloff, 2000; Massy & Zemsky, 1995). The reasoning associated with these efforts is that by purchasing new technologies and making them more accessible to faculty, they will be utilized in faculty's development of curricular materials and integrated into their instruction. This assumption ignores certain fundamental psychological and practical constraints, as perceived by instructional faculty, which may actually impede their adoption and integration of new technologies. Additionally, it ignores the demands of continuous change on faculty's existing teaching, research and service obligations. If those constraints are not effectively addressed by colleges and universities, it is quite conceivable that many technology resources will go under-used or unused.

Due to massive investing in technology infrastructures, investment and partnership opportunities with prominent hardware and software companies, and cost saving programs that attempt to guarantee academic pricing of hardware and software, the previous focus on academic technology support has been submersed by the notion of simple usability (Gillard, Bailey & Nolan, 2008; Kotter, 1996; Massy & Zemsky, 1995; Nworie & Haughton, 2008; Oblinger & Hawkins, 2007; Parker, Bianchi & Cheah, 2008; Wunsch, 1992). Every enterprise solution for higher education boasts seamless integration and ease of use in an effort to secure the likelihood that their products will be purchased. However, if it is simply a question of 'usability' then why aren't faculty using more technology? To that end, it becomes difficult to justify large expenditures on technologies by colleges and universities in those cases where faculty may perceive additional psychological and practical constraints is all that is gained through these purchases.

Many studies have examined faculty working and those that do through the conceptual lens of teaching, research, service are often most cited and considered seminal research (Gappa, Austin & Trice, 2007; Rosser & Tabata, 2010; Schuster & Finklestein, 2006). Across this literature, on faculty work, it is acknowledged that variation between allocating time resources across institutions and weekly work hours are highest at research universities. Division of time for principle activities includes: teaching (68%), research (12%), and service (11%), other (9%) (Rosser & Tabata, 2010). Over time, faculty 'work hours' has continuously and significantly increased since 1993 and based on 2004 NSOPF data, the average total hours worked by faculty is 55 hours per week (Townsend & Rosser, 2009). Taking into consideration the additional hours necessary to learn and become proficient with a new technology, faculty's work hours can conceivably exceed 55 hours a week. This increase has been experienced most dramatically by full-time faculty at research institutions (Rosser & Tabata, 2010). However, faculty who published more while teaching less were found to receive higher salaries regardless of the type of institution they work at (Bland, Center, Finstad, Risbey, Staples, 2005; Rosser & Tabata, 2010; Townsend & Rosser, 2007).

Bland et al. (2005), Fox (1992), Park (1996), and Townsend and Rosser (2009) assert that the more closely teaching activities are related to research, the more highly teaching will be valued by tenure and promotion governing boards. From this assertion it could be understood that if academic classroom technology could relate more closely to research, the more highly learning new technology will be valued by those same tenure and promotion governing boards. Research that assessed the influence of time commitments, research and teaching interests, and environmental orientation among social science faculty found that those publishing the most articles are not strongly invested in both research and teaching (Fox, 1992; Gappa, et al., 2007; Park, 1996) and explain this lack of shared interest as a "trade off of one set of investments (research time) against another (teaching time)" (Fox, 1992, p.301)

This study explores whether faculty perceive learning a new technology in terms of a gains/losses wager possibly conflicting with their existing (research, teaching, and service) priorities and how those conflicts in re-prioritizing may increase or decrease the likelihood that faculty will develop intentions to learn new technology tools. Because faculty at doctoral granting and research universities have teaching, service, and research commitments (as agreed by their contractual assignment) that consume their creative discretion it sometimes becomes less clear what the true advantage of learning a new technology may be. One of the side effects of *consumer-based* technology popularity is the voluntary inundation that just because technology is available and rapidly expanding across campuses it should also be rapidly incorporated via faculty and expanding across faculty roles with matched vigor. This popular thought does not take into consideration the lack of negotiating authority that faculty may have in regards to their existing commitments.

Further, research examining the faculty experience across research, teaching, and service obligations points out that “the road to teaching is not typically the road to tenure” (Rosser & Tabata, 2010). Implicitly, learning new academic technology requires faculty to consider foregoing the fulfillment of important criteria for promotion, tenure, and career advancement in order to reprioritize time for learning new technology. This would further exacerbate the gains/losses time trade-off perspective for faculty intending to learn new technology. Loss aversion may provide additional insight as an individual difference factor to explain slow adoption of technology and/or resistance to allocate time toward learning new technology.

The study proposes to examine intentions to learn new technology (based on the theory of planned behavior), perceived instrumentality, and briefly the technology acceptance model through a prospect theory based gains/losses lens. Learning new technology may be viewed as a threat to existing commitments because of the ‘learning’ component that is implicit. Reprioritizing commitments within a context that holds an uncertain outcome may be a wager that faculty do not intend to make.

Presented first is a brief account of the rapid influx of technology implementation on campuses while describing from the literature a variety of influences that shape faculty perceptions of technology use. This dissertation will describe a theoretical perspective of how the intention to learn new technology entails an element of uncertainty derived overtly from the ‘to learn’ (to gain knowledge previously unknown) expectation. Because this ‘uncertainty’ is inherent with learning technology, faculty may view it as a wagering/gambling agent vying for time within their existing commitments.

Presented next will be the operationalized factors that influence intentions to learn new technology in terms of two popular and well established models of technology use. Careful consideration will be paid to the theory of planned behavior model highlighting the complexities relevant to learning that are housed within the perceived behavioral control construct. The technology acceptance model has been replicated into various technology use contexts and offers a balanced and reliable practitioner’s approach to learning new technology that is relevant for the current study. Presented last is an explanation of the integrated model that aims to capture faculty perceptions of gains and losses, time pressure, instrumentality, behavioral control, and attitudes and the influence on intentions to learn new technology through empirical evaluation.

Chapter 2

Literature Review

The rapid development of academically focused technologies allows providers of higher education to move beyond the "brick and mortar" restrictions of place and time to serve a larger, broader, and more diverse population (Kosak, Manning, Dobson, Rogerson, Cotnam, Colaric, & McFadden, 2004; Schuster & Finkelstein, 2006). This perpetuates a domino effect across higher education leading to rapid development and haste to be competitive among institutions. As technology saturates higher education the demands on faculty to use it increases. Conversely, their available time to deal with technology decreases with each campus-wide implementation of new technology.

For faculty whose publication production is high, they (reportedly) are not invested in both research and teaching at the same time, but appear to have to use a trade-off system for their investments of time (Fox, 1992; Gappa, et al., 2007; Rosser & Tabata, 2010). This trade-off is exacerbated by faculty calculating their available time to learn new technology in regards to their available time for producing research (Gappa, et al., 2007; Rosser & Tabata, 2010). When an innovative or new technology is implemented on campus (or is perceived as new because the faculty has never used it before) faculty are being presented with a novel learning task. With the introduction of such novelty, it frames the faculty's choice of using (or not using) technology within an associated risk scenario that may be mediated by the types of support available. As the demand on faculty to learn to use technology increases, colleges and universities share immediate demands to create and design supportive programs.

On academic campuses, those technical support programs that include instructional objectives promoting technology skill development are likely to be more successful than those programs designed only to troubleshoot and provide limited desktop support. Many programs are driven by organizational objectives that target efficient problem-resolution and are generally known for offering support and workshops that are technically complex (Kyei-Blankson, Keengwe, & Blankston 2009; Metros, 2010), user unfriendly (Georgina & Olson, 2008; Metros, 2010), time intensive, and change too often (Ahadiat, 2005; Ertmer & Ottenbreit-Leftwich, 2010; Metros, 2010). To reiterate, in many cases, the goal of the problem-resolution support model is to fix a problem and provide an answer, not to teach (Ahadiat, 2005; Albright & Nworie, 2008; Ely, 2008; Kotter, 1996; Nworie, 2006, 2009).

Acknowledging that faculty perceive these offerings as such is insightful. Especially for those faculty who *intend* to learn to use new technology. In a study that examined the use, attitudes, and perception of barriers that increase or decrease faculty instructional technology use, findings indicated that faculty generally believe that the technologies had some potential in assisting with their teaching and learning process; however, many remained deeply suspicious of the way in which the change was being implemented and supported (Georgina & Olson, 2008; Kosak, et al., 2004; Kyei-Blankson et al., 2009; Schuster & Finkelstein, 2006).

Ultimately, the success of these technology tools is determined by the faculty who use them (or chose not to use them). There are clear indications that educational gaps exist in technology support that are based solely on business models and strategic outcomes (Ahadiat, 2005; Albright & Nworie, 2008; Bennett & Bennett, 2002; Ertmer

& Ottenbreit-Leftwich, 2010; Keengwe, Kidd, Kyei-Blankston, 2009; Kotter, 1996; Metros, 2010; Nworie & Haughton, 2008; Nworie, 2004, 2006, 2009). In the case where pre-requisite knowledge to use technology is limited and the user must develop proficient skills, those responsible for developing technology support programs should take this learning process and existing time constraints into consideration. What seems to be missing in most business models for technology service is an understanding of the psychological aspects the user will employ (in many cases faculty learners) when attempting tasks in which they are not experts (Albright & Nworie, 2008; Gillard, et al., 2008; Metros, 2010). If faculty feel the available technical support to be too complex and/or require too much time, then faculty may forgo seeking assistance given the existing amount of time pressures associated with their current obligations.

In this review, I discuss a model (see Figure 1) of faculty intentions to learn new technology, informed by the Theory of Planned Behavior, Prospect Theory, and research on perceptions of instrumentality. This model integrates important insights from these theories and suggests that faculty concerns about having insufficient time to learn new technology could "offset" any perceived gains they may feel from engaging in the learning process. Below, I will provide a global overview of each of the abovementioned theoretical frameworks. Following, I will discuss the predictive relationships laid out in my model.

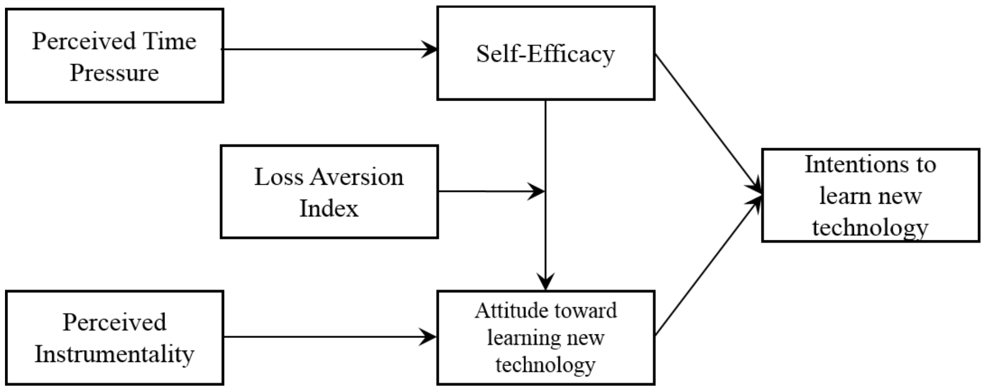

Figure 1: Proposed integrative model of intentions to learn new technology

Prospect theory and loss aversion

Bernoulli's eighteenth century theory of psychophysics (which later became utility theory) stated that people's choices, about one's own wealth, are not based on dollar values but on the psychological value of the outcome, or their perceived utility. With regard to choices about wealth, people almost always prefer a 'sure thing' over a favorable wager. However, Kahneman and Tversky (1979) further assert that this mode of thinking is flawed and the errors are rarely found in the explicit assertions of the experimental design. Instead, the evidence of these errors lies in the reference point that the choice maker is functioning from, not from the perspective of diminishing wealth (Kahneman, 1992, 2011; Tversky & Kahneman, 1981, 1991, 1992; Willemsen, Böckenholt & Johnson, 2011).

From this, prospect theory was formalized and brought focus to the concepts of gains and losses when faced with making a choice (forming an intention) in the presence of uncertainty. Kahneman and Tversky concluded that "losses loom larger than gains" and that, in general, people are loss averse (1979). Loss aversion can be conceptualized as a powerful force in preventing change whereas people have an intrinsic preference towards the current state of affairs (and existing commitments) over changes for a *possibly* better alternative (Kahneman, 1992, 2011; Tversky & Kahneman, 1981, 1991, 1992; Willemsen et al., 2011). In this light, many of the options faculty face in their academic careers are mixed and reflect a risk of loss and an opportunity for gains. They must decide among their options within their current circumstances whether to accept new challenges (run a risk) or reject new challenges (to preserve gains). When considering what the smallest gain that they would need in order to balance out a loss to existing commitments (e.g., teaching, service, and research), based on prospect theory it would need to be twice as much as the perceived psychological loss (Kahneman & Tversky, 1979; Kahneman, 2011; Tversky & Kahneman, 1992).

When a new technology is introduced on the campus, faculty may see the possible usefulness of the technology in their own courses, and they may feel they could ultimately learn it, but then they have to vet it against their already tightly booked schedule of teaching, serving on committees, and finalizing publications. If learning the new technology is perceived to be arduous and requires a large amount of time (with or without additional support) it will likely lose out during the vetting process. From this example, in order for the faculty to consider a loss (de-prioritizing an existing commitment in order to find time to learn the technology), the gain for choosing to learn the technology would need to be perceived as twice as large as the loss/cost. This is theoretically fitting given that in almost all professional endeavors, time is money. To further substantiate this position the relationship between the time faculty need to allocate to research productivity in order to achieve grants, promotions, and tenure is fitting.

Kahneman and Tversky's (1979) prospect theory posits that when making a decision under uncertainty a person does not process available information in a calculated and time intensive fashion (1979). Instead the decision maker relies on the available information about their situation and uses this as a reference point in which they will contemplate their options (Kahneman, 1992, 2011; Tversky & Kahneman, 1981, 1991, 1992; Willemsen, et al., 2011). Currently, consumer industry standards for technology use are the reference point that faculty technology usage across higher education is being evaluated from. As industry standards change so does that reference point. Additionally, as consumer based products drive technology use expectations the line between using technology because it exists versus using technology because of its instructional benefits is further blurred. As campuses become more technology enabled faculty may reach a point of saturation where so many tools have been introduced that it is a mere gamble to dedicate any time to learning them.

Consider the following examples below:

Problem 1: Which do you choose?

Get $900 for sure OR 90% chance to get $1000

Problem 1A: Which would faculty choose?

Get an additional 90 days extension on an upcoming publication deadline for sure OR 90% chance to learn a new technology in less than an hour

In Problem 1A faculty are likely to be risk averse, selecting the sure bet, as would a majority of people in Problem 1. To explain this further, the value of the sure bet of a 90 days extension on an upcoming publication deadline is certainly more than 90% of the value of reprioritizing ones set schedule to learning to use a new technology in less than an hour.

Next, consider the following different examples below:

Problem 2: Which do you choose?

Lose $900 for sure OR 90% chance to lose $1000

Problem 2A: Which would faculty choose?

Lose a week of scheduled research time that results in losing grant funding for sure OR 90% chance to learn a new technology in less than an hour

In problem 2 the sure loss of $900 is very averse and the decision maker is likely to speculate about this one (take the gamble on this one). Similarly in 2A faculty would not want to lose grant funding and would likely select the option with the technology. In this example, faculty only choose to engage in technology based on a need to reduce losses, ***not*** because they are contemplating the applicability of it in their courses, or because they feel efficacious to use technology, or finally, because others feel they *ought* to. It is merely a response to the context in which the choice was presented where previous experience and choosing to learn new technology is competing for gains within an existing set of ‘sure bet’ commitments (i.e., research, teaching, and service).

Importantly, research on loss aversion has tended to focus almost exclusively on the role of external conditions on perception of loss – reflecting the view that loss aversion is a generalized tendency across people (Kahneman, 2011; Tversky & Kahneman, 1991, 1992; Williamson, et al., 2011). To date, there has been very little discussion or research on the possibility that people may exhibit individual differences in loss aversion. The research that has addressed this possibility has focused on emotional (e.g., anxiety) and neuropsychological correlates of loss aversion (e.g., Bibby & Ferguson, 2011; Hartley & Phelps, 2012). Moreover, no research to date appears to have considered how individual differences in loss aversion might be related to behavioral intentions. In this regard, my study marks new territory, as I address the possibility that individual differences in faculty loss aversion may be related to their intentions to learn new technology. Next, I discuss the Theory of Planned Behavior.

Theory of planned behavior

The framework below (Figure 2) represents an amalgamation of theoretical concepts and relationships from self-efficacy theory (Bandura, 1997) and the theory of planned behavior (Ajzen, 1991; Fishbein & Ajzen, 2010). The key predictors of a person's behavioral engagement in the model are attitudes, perceived subjective norms, and perceived behavioral control. The effect of these predictors on behavior is assumed to be mediated through a person's formation of the intention to engage in that behavior.

Figure 2

Theory of Planned Behavior Model (Ajzen, 1991; Fishbein & Ajzen, 2010)

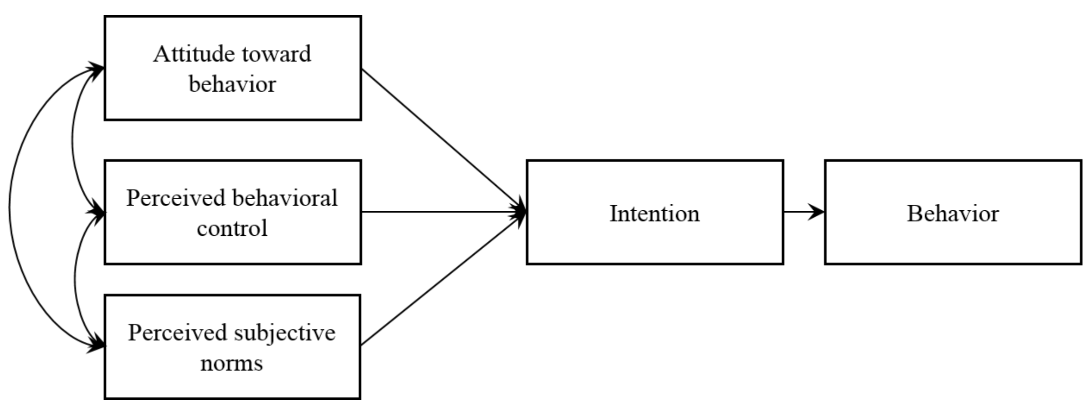

Figure 2. *Original theory of planned behavior model*

Attitudes are feelings of favorableness or un-favorableness towards performing an action (Ajzen, 1991; Ajzen, Czasch, & Flood, 2009; Smith, Manstead, Kotterman & Wolfs, 2007; Taylor & Todd, 1995). Perceived subjective norms refer to the perception that other people in one's social environment engage in a behavior (descriptive norm) or else expect the individual to engage in that behavior (injunctive norm)(Ajzen, 1991; Ajzen, Czasch, & Flood, 2009; Fishbein & Ajzen, 2010). Finally, perceived behavioral control refers to one's belief that he/she has the internal and external resources to be able to engage in a behavior (Ajzen, 1991; Fishbein & Ajzen, 2010).

Stepping back from the theory a bit, it is easy to see how these concepts might apply to understanding faculty intentions to learn new technology. The faculty member's evaluative response to the behavior of learning a new technology should influence his/her likelihood of engaging in the behavior. A faculty member who holds negative attitudes toward learning a new technology should be less inclined to formulate intentions and strategies for actually engaging in the learning process. Moreover, a faculty member who feels a sense of control over his/her own ability to engage in the learning process should be more likely to formulate an intention to learn.

Previous research on faculty technology use based on the theory of planned behavior (and the technology acceptance model (TAM); a modified version of the theory of planned behavior) provides support for its incorporation – at least in part – into my integrative framework on faculty intentions to learn new technology. Several studies have investigated the efficacy of each model in various contexts independently (TAM in information systems research Lee, Kozar, & Larson, 2003; TAM in faculty technology adoption research, Ahmad, Madarsha, Zainuddin, Ismail, & Nordin, 2010;

TAM in resistance to change research, Seigel, 2008; TAM in workplace interventions, Venkatesh, 2008; theory of planned behavior in faculty technology adoption, Lee, Cerreto, & Lee, 2010; theory of planned behavior in internet banking researching, Yousafzar, Foxall, Pallister, 2010; theory of planned behavior in entrepreneurial intent research, Gird & Bagraim, 2008) and many of those investigations prompted further studies examining the contribution of combining the models (Chau & Hu, 2002; Fusilier & Durlabhji, 2005; Shuie, 2007; Venkatesh, Morris, Davis, & Davis, 2003). Both the theory of planned behavior and TAM have yielded similar predictive efficacy in conditions in which technology use is the behavioral component (Fusiler & Durlabhji, 2005; Mathieson, 1991; Venkatesh et al., 2003).

In my integrative framework (Figure 1), the purpose of this study is to examine and identify contributing factors, not evaluate the actual performance of the behavior. In addition, the focus of this study is not to develop an intervention or strategy to increase or decrease the behavior of faculty. It is important to point out that numerous fields/domains have been attracted to the theory of planned behavior and TAM in an effort to increase a behavior (use more technology or use technology more often). I focus on identifying additional contributing factors that have not yet been brought to the forefront and are evident in the specific experience of faculty. Lastly, the integrative framework does not incorporate perceived subjective norms as a predictor to maintain a strict focus on *internal* faculty factors. Rather, it only incorporates the attitudes, self-efficacy (perceived behavioral control), and intentions components from the theory of planned behavior model.

Perceived instrumentality

Perceived instrumentality refers to one's belief that engaging in a more proximal behavior will allow one to achieve more distant, valued future goals (Husman & Lens, 1999; Husman, Pitt-Derryberry, Crowson, & Lomax, 2004; Miller & Brickman, 2004). This factor has been identified as an important predictor of learning-related processes and outcomes within education settings. Greene, Miller, Crowson, Duke, and Akey (2004) found that perceived instrumentality was a significant positive predictor of mastery goal orientation and cognitive strategy use in their test of an integrative model predicting academic achievement in a sample of 220 high school students. In another test of an integrative model that incorporated perceived instrumentality, Hardré, Sullivan, and Crowson (2009) found that perceived instrumentality again significantly predicted mastery goals (termed learning goals in that study). Moreover, calculating the indirect effects of perceived instrumentality on school engagement and effort from the standardized path coefficients in their development and cross-validation samples suggests that instrumentality predicts engagement and effort, with its impact on engagement perhaps being mediated by learning goals (development sample: standardized indirect effect = .275, moderate effect; cross-validation sample: .304, moderate effect).

Husman et al., (2004) and Miller, DeBacker, and Greene (1999) found that perceptions of task instrumentality predict the experience of intrinsic motivation and/or extrinsic motivation in students, while Tabachnick, Miller, and Relyea (2008) provided additional evidence that instrumentality perceptions predict use of task-oriented self-regulation strategies. Taken altogether, the research suggests that perceptions of instrumentality largely have a positive effect on an individual's orientation toward learning and engagement in learning. At this time, I turn to laying out the rationale behind the predicted relationships in my integrative model (Figure 1).

Perceived time pressure as a predictor of self-efficacy.

As noted earlier, perceived behavioral control is defined as one's perception of having the internal and external resources in which to execute a behavior. To date, most of the research based on the theory of planned behavior has focused on perceived behavioral control as an antecedent of behavioral intention and largely ignored questions concerning potential antecedents of this factor (see Elie-dit-Cosaque, Pallud & Kalika, 2011, for exception). In my study, I consider faculty's experience of time pressure, brought on by their numerous teaching, research and service commitments, to serve as an antecedent of internal self-efficacy as it relates to the learning of new technology. In my model I assume that the perception that one's time is already determined by competing demands limits one's perception of having control over the execution of a new behavior – in this case, faculty's self-efficacy over learning a new technology. Given this line of reasoning, I hypothesize that perceived time pressure will emerge as a significant negative predictor of self-efficacy in the test of my model.

Self-efficacy as predictor of attitude and intention toward learning new technology.

In the theory of planned behavior, attitude toward performing a behavior and perceived control over that behavior as correlated concepts while ignoring the possibility of a causal relationship between them (Figure 2). This is typically the way in which these variables have been incorporated into models predicting intention within the theory of planned behavior literature (Ajzen, 1991; Ajzen, 2006; Ajzen et al., 2009; Fishbein & Ajzen, 2010; Lee et al., 2010). Nevertheless, it seems reasonable to question whether a correlation best describes the relationship between these variables. I reason that the correlation observed in previous studies between these two factors could reflect an underlying causal association wherein a person's self-efficacy over engaging in a behavior serves as a cause of his/her evaluative response (i.e., positive or negative attitude) towards that behavior. Perceived behavioral control includes both ability (self-efficacy) and access control over engaging in a behavior (Ajzen, 1991; Ajzen, 2006; Ajzen et al., 2009; Fishbein & Ajzen, 2010). For the purpose of this study I focus on the self-efficacy component.

Although I was unable to identify any research that has directly tested the proposition that self-efficacy exerts a causal influence on attitudes, there is one finding within the literature that does appear consistent with the causal claim that I am making. Specifically, researchers have shown that self-efficacy (a construct that exhibits considerable overlap with perceived control) is a significant positive predictor of a mastery and performance approach goals (e.g., Greene et al., 2004; Hardré et al., 2009; Lau, Darmanegara, & Nie, 2008). Arguably, in order to adopt an approach orientation concerning a particular task, a person must first feel positively disposed toward the task itself. If that is the case, then the relationship between self-efficacy and approach goals could be explained by the positive attitude a person develops toward a behavior as a result of feeling efficacious about his/her ability to carry it out.

In my model, I reason that faculty members who perceive that they have greater control over engaging in learning about new technology should experience greater positive affect concerning the behavior. Those who experience less control should experience more negative affect. This affective consequence of low self-efficacy should, in turn, manifest itself in either greater intention or less intention to engage in learning about new technologies. In short, I hypothesize that self-efficacy should positively predict attitudes toward engaging in new learning in my model. Likewise, self-efficacy should have a positive predictive relationship on intentions.

Disposition to be loss averse as a moderator of self-efficacy and attitude relationship.

As noted above, according to prospect theory many decisions about an outcome boil down to “quick and dirty” assessments of the gains and losses associated with engaging a behavior (Kahneman, 2011; Tversky & Kahneman, 1974, 1992). Although prospect theory assumes a generalized tendency across people to be more loss averse, some researchers (Bibby & Ferguson, 2011; Hartley & Phelps, 2012; Kim, Rao, Kim, & Rao, 2011; Willemsen et al., 2011) suggested nonetheless that this tendency may be more pronounced in some individuals as opposed to others, suggesting that loss aversion may also be conceptualized as an individual’s difference factor. If it is the case that people vary in their level of loss aversion then it also stands to reason that in contexts where individuals are low in self-efficacy over engaging in a behavior they should be even less likely to perform the behavior.

Based on this line of reasoning I argue that faculty who perceive that they are less efficacious over learning new technologies and who are more loss averse should be particularly likely to experience negative affect when thinking about learning a new technology. Faculty who are low in self-efficacy but also are less loss averse may still be more likely to feel less negative about learning new technologies. The effects of efficacy on attitudes toward learning new technologies may be moderated by faculty members' dispositions to be loss averse, with faculty members who are more loss averse exhibiting more negative attitudes toward engaging in learning about new technologies than those who are less loss averse.

Instrumentality as a predictor of attitude.

As noted earlier, within the theory of planned behavior, the attitude variable is conceptualized as an affective evaluation of a target behavior. In my model, the attitude variable represents the faculty member's positive versus negative evaluation of engaging in learning new technologies. As with perceived behavioral control, it is notable that within the theory of planned behavior literature there has been little work done on identifying possible antecedents of individuals' evaluative responses to a behavior, or attitude (see Elie-dit-Cosaque, et al., 2012, for exception). Arguably, one's attitude toward a behavior should be impacted not only by the expectancies of being able to carry out the behavior, but also by the perceived instrumentality of that behavior.

To date, most of the research on instrumentality perceptions and engagement in learning processes has been limited to the study of student populations within classroom settings. To my knowledge, perceived instrumentality has neither been considered in relation to faculty technology use nor their intentions to learn about new technologies. Nevertheless, it seems reasonable to argue that if faculty members perceive learning new technologies as being instrumental to their future goals (e.g., as teachers), they are more likely to formulate positive evaluative responses toward that behavior. Faculty perception of instrumentality of learning new technology will positively predict their attitudes towards that behavior.

Attitude as a predictor of intention.

The last component of my model simply reiterates the theory of planned behavior's assumption that one's attitudes toward a behavior produce a behavioral intention (Ajzen, 1991; Ajzen, 2006; Fishbein & Ajzen, 2010; Lee, et al., 2010; Smith et al., 2007). In short, faculty members who feel more positive about learning a new technology should be more likely to develop an intention to engage in that behavior.

Research Questions and Hypotheses

Based on my review, I summarize my hypotheses as follows:

1. Faculty perceptions of time pressure directly influence feelings of control over learning new technology. Time pressure is negatively related to self-efficacy.
2. Faculty perceived instrumentality of learning new technology directly influences attitudes about learning new technology. Perceived instrumentality for learning new technology is positively related to attitudes toward learning new technology.
3. Self-efficacy will positively predict faculty attitudes toward learning new technology. Specifically, faculty who are more efficacious in learning new technologies will hold more positive attitudes toward learning. Faculty who are less efficacious will experience more negative attitudes toward learning.
4. Self-efficacy will positively and significantly predict intentions to learn new technology.

5. (Favorable) attitudes toward learning new technology will positively and significantly predict intentions to learn new technology.
6. Individual differences in loss aversion will moderate the effects of self-efficacy on attitudes toward learning. Specifically, faculty who experience low self-efficacy and are *more* loss averse will hold more negative attitudes toward learning new technologies as compared to faculty who experience low self-efficacy and are *less* loss averse.

Proposed Model

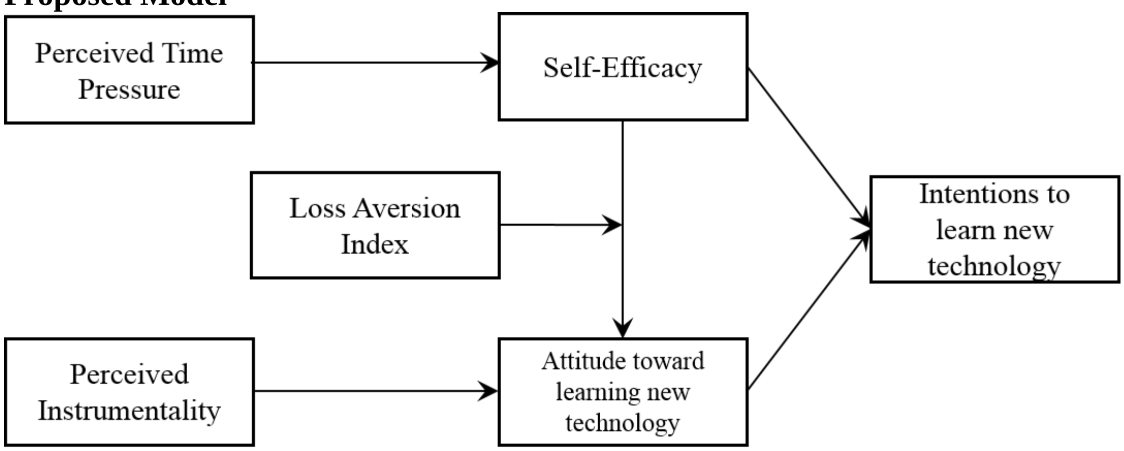

Figure 3. Proposed integrative model of intentions to learn new technology

Chapter 3

Methods

Participants

The focal group for this study was full-time faculty members who teach in higher education who have teaching, service, and research activities as part of fulfilling their appointment requirements. The existence of these requirements is essential to the theoretical model discussed and can (should) include faculty across numerous institutions. The sample are faculty at a mid-sized university in the Midwest, located within the United States. Characteristics to qualify as a participant included: full-time faculty, tenure and tenure track appointments, teaching in higher education at a research and teaching institution where teaching, service, and research commitments are part of their contractual agreement. Participants were recruited from the University of Oklahoma (OU), Norman campus, a Midwestern research university, to complete a 15-20 minute online survey (36 items) designed to address faculty perspectives on learning new technology. Of the faculty members that completed the study were 228 faculty, 173 tenured and 55 pre-tenure. Most of the pre-tenure faculty were in either their 1st (20%), 2nd (20%), 3rd (31%), or 5th (18.2%) year of tenure review. Sixty percent of the faculty sampled were male. Faculty member ages ranged from 28 to 79 (M = 49.19).

Sample size

A number of factors impact the sample size needed to carry out SEM models effectively. According to Kline (2011) and Schumacker (2004), more complex models in which more parameters are estimated generally require a greater sample size than models that involve the estimation of fewer parameters. The “N:q rule” (for maximum likelihood estimation) suggests a ratio of 20 subjects per estimated parameter in a model. Based on this rule, it was estimated that approximately 220 cases were necessary. This sample size is fairly typical of many SEM studies (Kline, 2011). This estimated sample size was initially achieved; however, due to some faculty not completing the survey in its entirety and using listwise deletion a sample of 208 was used for analysis.

Procedure

Faculty completed one electronic survey through Qualtrics (an online survey tool). Participants received an invitation email that included a brief description of the study and a link to the survey. Upon clicking on the link received via email, participants were routed to the beginning of the survey in which the first item was the informed consent and full description of the study. If participants selected "*I decline*" they were then shown a thank you message and instructed to close their browser. Participants who selected "*I agree to participate*" continued through the survey. Upon completing the survey, participants were given the option to provide their contact information, via electronically routing them to a separate survey, to be eligible for a drawing for one of 15 gift cards to local merchants. The survey required approximately 15-20 minutes to complete.

Measures

In this survey faculty responded to items examining a person's loss aversion (Kahneman, 1992, 2011; Tversky & Kahneman, 1981, 1991, 1992), perceived instrumentality (Miller et al., 1999), perceived time pressure (novel items created for this survey), self-efficacy (perceived behavioral control), attitudes, and intentions to perform a learning behavior (Ajzen, 2006; Fishbein & Ajzen, 2010; Ajzen, 1991; Lee et al., 2010; Venkatesh, et al., 2003). The full instrument used in this dissertation is provided in Appendix A. A description of each sub-scale is presented next.

Loss aversion

> "Loss aversion is a powerful conservative force that favors minimal changes from the status quo in the lives of both institutions and individuals."
> -- Daniel Kahneman, 2011

As fully described by two seminal papers of Amos Tversky and Daniel Kahneman (Kahneman and Tversky 1979; Tversky and Kahneman 1992), loss aversion is the psychological tendency that losses loom larger than equal-sized gains relative to a reference point. Fishbein and Ajzen (2010) acknowledge the complexity of this tendency within their theory of planned behavior and state that the beauty of prospect theory is the demonstration that the way the options are framed has a dramatic impact on the decision to be made (see also Lee et al., 2010; Smith et al., 2007). This tendency can occur in both riskless and in risky choices. Using dichotomous option sets presented the respondents with a choice between two options that both contained a gain, and an option set where both options contained a loss. In my study, faculty responded to each item (16 items total) by selecting the option that they would most prefer. The original option sets were borrowed directly from Daniel Kahnemen's examples and include:

(1) Get $900 for sure

(2) Take 90% chance to get $1000; 10% chance to get nothing.

The second option set contained scenarios in which a loss was part of either choice:

(1) Lose $900 for sure

(2) Take 90% chance to get $1000; 10% chance to lose nothing.

Kahneman states that a great majority of people are risk averse because the negative value of losing $900 is more than 90% of the negative value of losing $1000 (Kahneman, 1992, 2011; Tversky & Kahneman, 1981, 1991, 1992; Willemsen et al., 2011).

My study uses research, teaching, and service as the reference point a decision will be made about. Faculty were presented with 4 context-based scenarios that include the original loss aversion items from prospect theory, a research based option set, a teaching focused option set, and a service related option set. Given a pair of options, faculty are asked to choose one of the options they *most prefer* (even if both options include a loss of some kind). Determining this preferred choice would be based on their decision value, the contribution of an anticipated outcome to the overall attractiveness of the options presented and their experience value of the outcome (Kahneman 1992; 2011; Tversky & Kahneman, 1981, 1991, 1992; Willemsen, et al., 2011). Participants' loss aversive decisions were addressed by their responses to dichotomous option sets. The context of the option sets were designed to assess if a loss is more aversive than a gain. Faculty responses to each option set were coded either 0 (meaning more loss averse) or 1 (less loss averse). After summing across the 16 items, a composite index of the tendency to be loss averse was computed, which could range from 0 to 16. A higher score on this index reflects lower levels of loss aversion (i.e., more willing to take a chance).

Perceived instrumentality

Faculty were asked to respond to statements of importance that instructional technology may have on their teaching future. Three items borrowed from Miller et al.,

(1999) and Green et al., (2004) use a 6 point Likert-type scale (anchored “Strongly Disagree” to “Strongly Agree”) to assess faculty perceived instrumentality of learning to use new technology. Items have been reworded to provide an appropriate fit with the context of this study. Sample items include: *“I believe that learning about new instructional technologies will benefit me as a teacher in the classroom”, “I believe that learning about new instructional technologies will benefit my students in their learning”, “I do not believe that learning about new instructional technologies will enhance the instruction I provide to my students”*.

Perceived time pressure

Faculty were asked about the degree to which they agree or disagree with a given statement about time pressure and existing commitments. These items asked faculty to reflect on their own experience and respond to a statement about existing time pressure and the trade-offs they would consider in order to learn new technology. Participants responded to 5 items on 6-point Likert-type scale (anchored “Strongly Disagree” to “Strongly Agree”). Five new items were created for the purpose of this dissertation to measure faculty perceptions of being under time pressure. Sample items include: *“I feel like I am under constant time pressure in my role as a faculty member”, “I feel like there is not enough time in the day for me to get all of my work done”*.

Self-efficacy toward learning new technology

As discussed in the literature review faculty perceived behavioral control in the context of learning new technology closely resembles Bandura’s explanation of self-efficacy (1997). Faculty were asked to respond to 3 items on a 6-point Likert-type scale (anchored “Strongly Disagree” to “Strongly Agree”) and determine their level of agreement with a self-efficacy statement. Examples include: "*I feel confident in my ability to learn about new technology*", "*I have the ability to learn new technology even if I am experiencing a time crunch with my existing projects*", "*I do not have the ability to learn new technology without having additional time to learn it*".

Attitudes toward learning new technology

Faculty attitudes about learning new technology are expected to produce a behavioral intention to do so. Faculty were asked to respond to three attitude assessment items and rate their level of agreement with a given statement. It is predicted that positive attitudes for learning technology will produce a positive behavioral intention to commit to the action. Example items include: "*Using technology to enhance the delivery of instruction is a good idea*", "*It is unpleasant to think about using technology in my courses*", "*I believe that the delivery of instruction is improved with the use of technology*", and "*I feel positive about learning new instructional technology*".

Intentions to learn new technology

Faculty intentions to learn new technology are assumed to be mediated through formulation of the intention to engage in the behavior of learning. According to the theory of planned behavior before a behavior is performed a person quickly contemplates several complex influences within a range of considerations and the result is either an intention to engage in the behavior or the lack of intention to engage (Ajzen, 1991, 2006; Ajzen, et al., 2009; Fishbein & Ajzen, 2010). Faculty were asked to respond to three statements regarding the intention to learn new technology and rate their level of agreement on a 6-point Likert-type scale (anchored "Strongly Disagree" to

"Strongly Agree"). Example items include: "*I plan to reprioritize some existing commitments so that I can make time to learn new technology*", "*I do not intend to learn technology if I must rearrange my already busy schedule*", "*I intend to learn new technology so that I can use it in my class*".

Chapter 4

Results

Descriptive statistics and internal consistencies

All variables were analyzed in a descriptive manner first. Reliability coefficients and descriptive statistics including mean, standard deviation, and Cronbach's alpha reliability coefficient for each construct were computed and are presented in Table 1. Among the scaled items (6-point Likert anchored "Strongly Disagree" to "Strongly Agree"), those with higher scores will reflect higher levels of agreement with the statements provided for the represented constructs. The loss aversion index is a summed total of responses, in which lower scores reflect greater loss aversion.

Table 1

Descriptive statistics of measured variables

Sub-Scale	Description	*M*	*SD*	Cronbach's alpha
Perceived Time Pressure	Perceived pressure as a result of time constraints	4.327	1.048	.705
Perceived Instrumentality	Perceptions that a proximal behavior will allow one to achieve more distant, valued future goals	4.187	1.252	.867
Self- efficacy	Personal feeling of ability and control	4.671	1.068	.686
Attitudes	How someone feels toward learning new technology	4.308	1.022	.854
Intentions	Intention to learn new technology	3.395	1.124	.830
Loss Aversion Index[a]	Disposition to perceive that losses loom larger than gains	5.144	1.506	.417

Note. [a]Lower scores represent greater loss aversion and higher scores represent less loss aversion.

On average, faculty from the sample scored well above the scale midpoint for the belief that they experience time pressure when considering to learn new technology

(M = 4.327, SD = 1.048), the belief that learning new technology has instrumental value (M = 4.187, SD = 1.252), efficacy for learning new technology (M = 4.671, SD = 1.068), and positive attitude toward learning new technology (M = 4.308, SD = 1.022). They scored low, on average, to the loss aversion index (M = 5.144, SD = 1.506), indicating that they tended to be relatively high in loss aversion. Additionally, faculty scored just above the midpoint of the scale for positive intentions to learn new technology (M = 3.395, SD = 1.124). Reliability analysis indicated that all scales had reasonable internal consistency (values ranged from .64 to .87) except for the loss aversion index (α = .417).

Correlations

Pearson's product moment correlations (see Table 2) were calculated among perceived time pressure, perceived instrumentality, efficacy, attitude towards learning new technology and the loss aversion index to observe the zero-order relationships between the constructs of interest. Perceived instrumentality was found to be positively and significantly correlated with attitudes (r = .769, p < .01) and intention to learn new technology (r = .622, p < .01), but not with time pressure or efficacy. Attitude toward learning new technology correlated significantly and positively with efficacy (r = .268, p < .01). Attitude correlated positively (r = .341, p < .01) with the loss aversion index, meaning that participants who had higher loss aversion scores (i.e. more willing to take a chance) were less loss averse and had more positive attitudes toward learning new technology). Intentions were positively correlated with loss aversion (r = .324, p < .01), indicating that participants who were less loss averse had more intention to learn new technology. Time pressure and efficacy were negatively, though not significantly, correlated.

Table 2

Correlation analysis of variables

	1	2	3	4	5	6
1. Loss Aversion Index	1	-.101	.299**	.052	.341**	.324**
2. Time Pressure		--	.128	-.066	.039	-.023
3. Instrumentality			--	.053	.769**	.622**
4. Self-efficacy				--	.268**	.064
5. Attitude					--	.653**
6. Intention						--

Note. ** Correlation is significant at the 0.01 level (2-tailed).

Path analysis

AMOS™ 17.0 was used to carry out the path analysis in this study using the maximum-likelihood method to estimate model parameters. Prior to conducting the analysis, the AMOS 17.0 regression imputation function was used to generate imputed values for those variables with missing values. Model fit was judged using the Comparative Fit Index (CFI), the Root Mean Squared Error of Approximation (RMSEA), and the Tucker Lewis Index (TLI). RMSEA values at .05 or less are considered indicative of good model fit, whereas values up to .08 are considered “adequate”. RMSEA values greater than .10 are indicative of poor fit (Kline, 2011). CFI and TLI values greater than .90 or .95 are also consistent with a good fitting model (Kline, 2011; Schumacker & Lomax, 2004). The parameter summary of the variables in the initial path analysis indicated that the model was *over-identified,* meaning that it was appropriate to utilize fit statistics to examine the fit of the model. All exogenous variables in the model were treated as uncorrelated, as there was no theoretical reason to expect them to be correlated with each other.

Table 3 contains the fit statistics for the proposed integrative model. Figure 4 contains the standardized path coefficients for the proposed integrative model. Although CFI (.954) and TLI (.907) fell within acceptable limits, the RMSEA value was high (.125). Self-efficacy (b = .208, SE = .038, p < .001) and instrumentality (b = .631, SE = .032, p = .001) were both significant, positive predictors of attitudes in the model. Efficacy and attitude predicted intention were also statistically significant predictors in the model, with the former being negative (b = -.126, SE = .054, p < .05) and the latter being positive (b = .750, SE = .057, p < .001). Time pressure was a negative predictor (b = -.075, SE = .068, p = .271) of efficacy, but failed to achieve statistical significance.

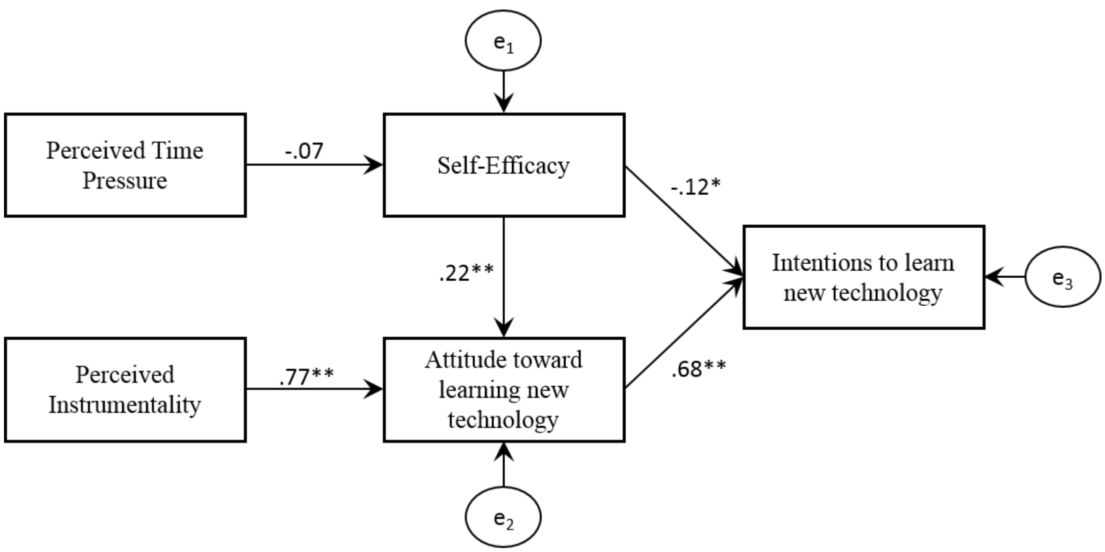

Figure 4. Integrative model 1. This figure illustrates the standardized path coefficients for the proposed integrative model with loss aversion removed. *Notes*. *p < .05, **p < .001

Table 3

Fit statistics for path models

Model	χ^2	CFI	RMSEA	TLI	AIC
Model 1 (proposed model without Loss Aversion)	χ^2 (5) = 22.476, p = .000	0.954	0.125	0.907	52.476
Model 2 (re-specified)	χ^2 (2) = 12.896, p = .002	0.971	0.156	0.912	36.896
Model 3 (re-specified)	χ^2 (1) = .082, p = .775	1.000	0.000	1.015	26.082
Model 4 (re-specified)	χ^2 (2) = 1.904, p = .386	1.001	0.000	1.001	25.904

Given the questionable fit of my hypothesized model to the data, I tested a series of re-specified models. Model 2 (Figure 5) involved one modification – that is, the removal of the perceived time pressure variable altogether from consideration. This was due to the fact that perceived time pressure exhibited only minimal zero-order relationships (see Table 2) with the other variables included in the model. For this re-specified model, the CFI and TLI values fell within acceptable limits, but the RMSEA value was high. The Akaike information criterion (AIC), - which allowed me to judge the quality of Model 2 relative to the quality of Model 1 - decreased, suggesting an improvement in fit over the initial hypothesized model (Leeuw, 2011; Schumaker & Lomax, 2004). Self- efficacy (b = .208, SE = .038, p < .001) and instrumentality (b = .631, SE = .032, p < .001) were again significant positive predictors of attitude. Efficacy emerged as a significant negative predictor (b = -.126, SE = .054, p < .05) of intention, whereas attitude was a significant positive predictor (b = .750, SE = .057, p < .001) of intention.

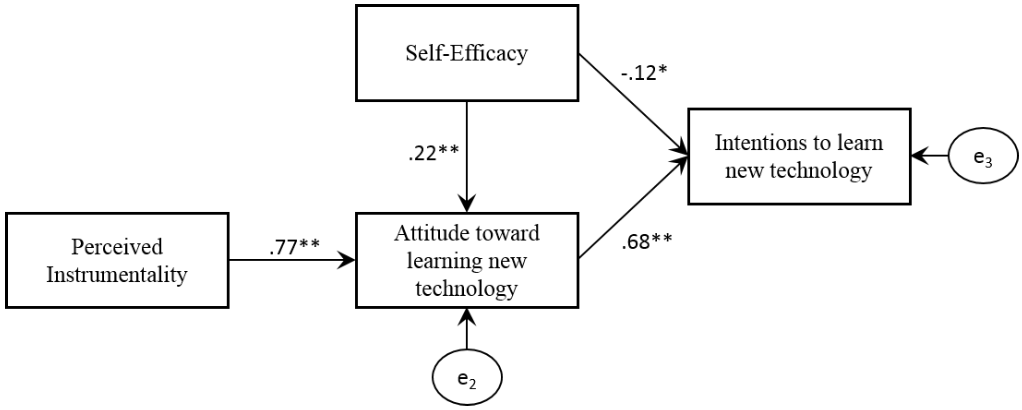

Figure 5. Re-specified Model 2. This figure illustrates the standardized coefficients for the re-specified model (Model 2). *Note.* *$p < .05$, **$p < .001$

Next, I re-specified Model 2 (see Figure 6 for Model 3) by adding a path from perceived instrumentality to intentions. Theoretically, this path makes sense in the context of learning a new technology whereas if faculty personally value using technology in the future this serves to increase the incentive value of proximal tasks such as learning new technology (Miller et al., 1999; Greene et al., 2004; Husman et al., 2004; Lau et al., 2008). Naturally, *learning* new technology is instrumental (and proximal) to achieving the skills to *utilize* technology. The fit indices for the re-specified Model 3 all fell within acceptable limits CFI (1.000), TLI (1.015), and RMSEA (0.000). Additionally, the AIC decreased from Model 2 to Model 3, suggesting that Model 3 was a better fitting model than Model 2. Efficacy (b = .208, SE = .038, p < .001) and instrumentality (b = .631, SE = .032, p < .001) emerged as significant positive predictors of attitudes in the model. Moreover, perceived instrumentality (b = .261, SE = .0072, p < .001) and attitude (b = .489, SE = .091, p < .001) were significant positive predictors of intention. With the inclusion of the direct effect of perceived instrumentality on intention, a change was noted in the path from self-efficacy to intention. Specifically, the path from efficacy to intention (b = -.074, SE = .055, p =

.176) dropped to non-significance. As such, I tested one final model (Model 4) after eliminating that path from consideration.

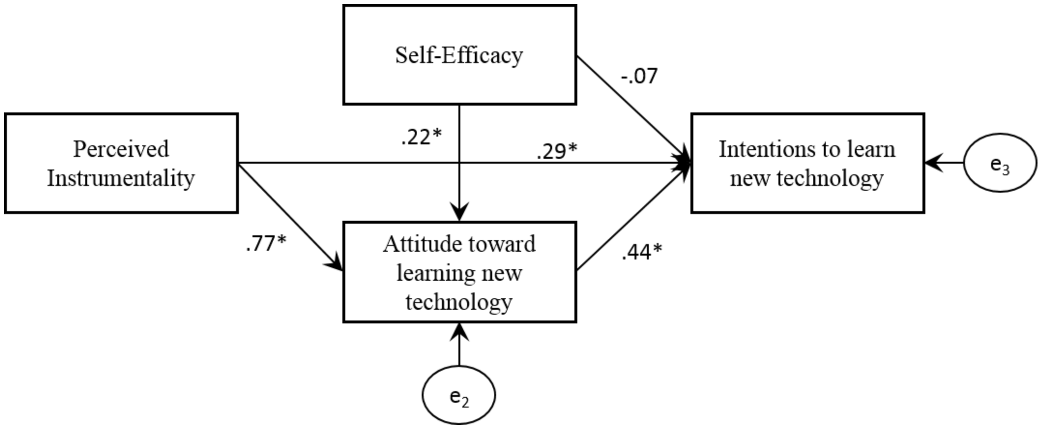

Figure 6. Re-specified Model 3. This figure illustrates the standardized coefficients for the re-specified model (Model 3). *Notes*. *$p < .001$

For Model 4 (Figure 7), the CFI (1.000), TLI (1.015), and RMSEA (0.000) were all indicative of a good fitting model. The AIC decreased from Model 3 to Model 4 suggesting that Model 4 is preferable. Efficacy ($b = .208$, $SE = .038$, $p < .001$) and instrumentality ($b = .631$, $SE = .032$, $p < .001$) emerged a significant positive predictors of attitude. Furthermore, perceived instrumentality ($b = .287$, $SE = .070$, $p < .001$) and attitude ($b = .447$, $SE = .085$, $p < .001$) were significant positive predictors of intentions.

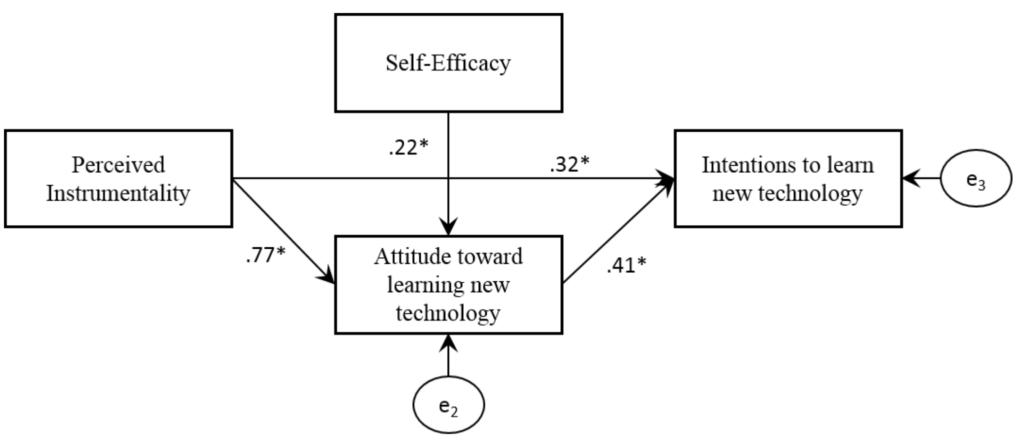

Figure 7. Re-specified Model 4. This figure illustrates the final best fit model based on the standardized coefficients of two exogenous and two endogenous paths with direct and indirect estimates. *Note*. **$p < .001$

Test of indirect effects

I utilized the AMOS 17.0 bootstrapping function (500 bootstrapped samples) to generate estimates of unstandardized and standardized indirect effects, as well as their standard errors, for Model 4. Table 4 contains the unstandardized and standardized indirect effects for Model 4. As the reader can see, the indirect effect of efficacy on intentions to learn via the mediator, attitudes, was statistically significant. Similarly, the indirect effect of perceived instrumentality on intention to learn via attitudes was statistically significant.

Table 4

Unstandardized and standardized indirect effects (Model 4)

Indirect Effect	Unstandardized	Standardized
Self Efficacy → Intentions to learn	.093	.088
Perceived instrumentality → Intentions to learn	.282	.313

All indirect effects in Model 4 are statistically significant at $p < .001$.

Moderator analysis: Loss aversion X Self-efficacy

In order to test whether dispositional loss aversion interacts with perceived behavioral control to influence attitudes, I carried out moderated multiple regression using Andrew Hayes' SPSS macro "Process" (http://www.processmacro.org/download.html). Self-efficacy and loss aversion were mean-centered prior to their inclusion into the regression model.

The regression model including both the main and interactive effects of efficacy and loss aversion on attitudes was statistically significant, $R^2 = .19$, $F(3, 209) = 16.255$,

$p < .001$. The main effect of loss aversion on attitude was positive and statistically significant ($b = .260$, $SE = .046$, $p < .001$), meaning that participants who were less loss averse (i.e. more willing to take a chance) had more positive attitudes toward learning new technology. The main effect of self-efficacy ($b = .216$, $SE = .060$, $p < .001$) was positive and significant, indicating that participants who were more efficacious also had more positive attitudes toward learning new technology. Importantly, the interaction term in the regression model was statistically significant ($b = .122$, $SE = .044$, $p = .005$), suggesting the presence of a statistical interaction between self-efficacy and loss aversion. Figure 8 contains a plot of regression lines depicting the predictive relationship between self-efficacy and attitude at the loss aversion index mean, as well as ±1 SD from the mean.

Simple slopes analysis was used to test whether the regression of attitudes onto efficacy differed significantly from zero at each of the abovementioned levels of the loss aversion index. Self-efficacy was a non-significant predictor ($b = .044$, $SE = .083$, $p = .594$) of attitudes among participants scoring -1SD from the mean on loss aversion (indicating higher levels of loss aversion). This means that self-efficacy was unrelated to attitudes among those participants who were high in loss aversion (i.e. less willing to take a chance). Self-efficacy was a significant positive predictor ($b = .216$, $SE = .060$, $p < .001$) of attitudes for participants scoring at the mean of the loss aversion index. Efficacy was also a significant positive predictor ($b = .388$, $SE = .089$, $p < .001$) for participants scoring at +1SD from the mean of the loss aversion index. This means that self-efficacy was a positive predictor of attitudes among participants who were less loss averse.

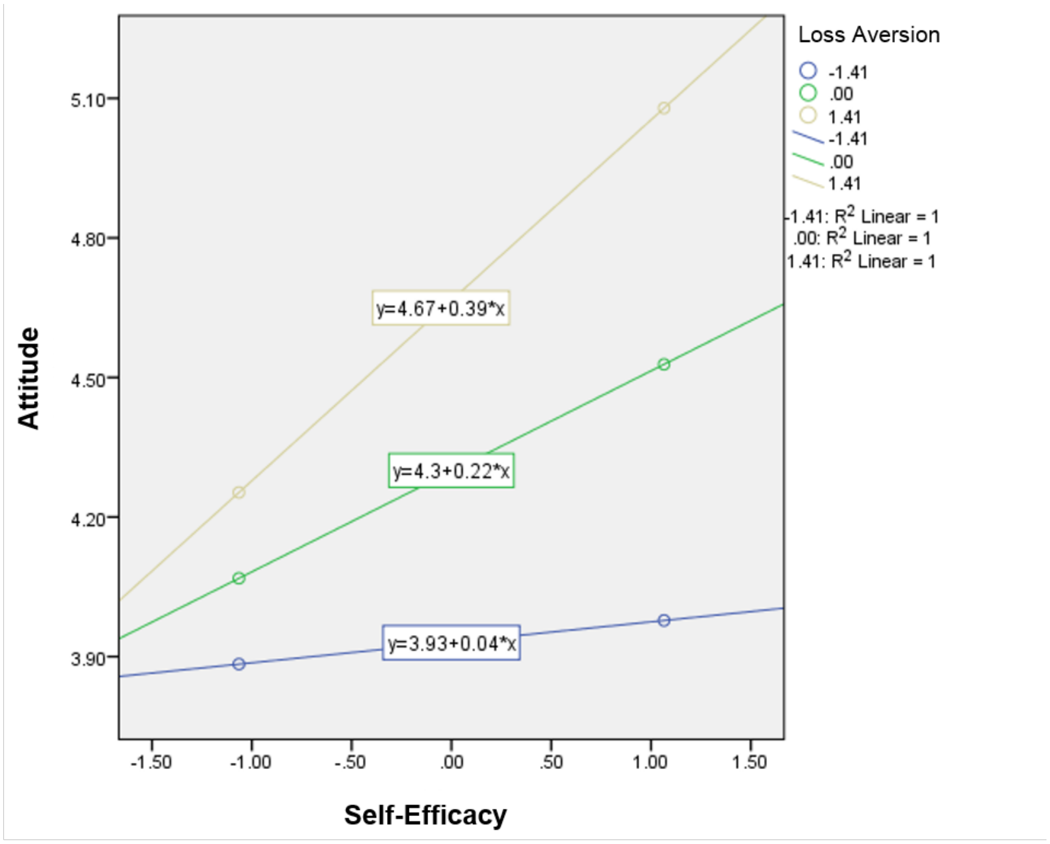

Figure 8. Plot of loss aversion regression lines. This figure depicts the predictive relationship between self-efficacy and attitude at the loss aversion mean, as well as ±1 SD from the mean.

Chapter 5

Discussion

In general, the results partially supported my hypotheses for this study. My first hypothesis was that faculty perceptions of time pressure would be a negative predictor of perceived behavioral control. Based on my data, the results indicated that there was no (correlational or predictive) relationship between time pressure and self-efficacy. One factor that may have contributed to the lack of apparent relationship may be that the operationalization of perceptions of time pressure. Upon reflection, the items in this sub-scale captured both general feelings of pressure, as well as feelings of pressure when juxtaposed against leaning new technologies. In hindsight, the sub-scale may not have been a valid indicator of generalized feelings of time pressure, as two of the items may have captured “trade-offs” that, ironically, are themes captured in the loss aversion measure. In future work addressing the relationship between perceived time pressure and self-efficacy it will be important to utilize better measures of the time pressure variable.

My second hypothesis was that perceived instrumentality would positively predict attitudes toward learning new technology. The zero-order correlation between these two variables was strong and positive, indicating that persons scoring high on perceived instrumentality also tended to score higher on (favorable) attitudes toward learning new technology. My path analysis results demonstrated that perceived instrumentality significantly predicted attitudes. Also as expected, perceived instrumentality exerted a significant indirect effect on intentions to learn new technology via the mediating factor, attitudes. Unexpectedly, the results of Model 4 suggest that perceived instrumentality may exert a direct effect on intentions to learn new technology. Considering that faculty (as teachers) would likely approach new technology with an incremental stance, it makes sense that perceived instrumentality result as a significant predictor of both attitudes and intentions to *'learn'* new technology. It is important to note that the framework of the proposed model operationalized the outcome behavior as "to learn" not "to use" new technology. This distinction was paramount in understanding the overall structure of the proposed model and may have influenced the effect of perceived instrumentality yielded in the path analysis.

My third hypothesis asserted that perceptions of efficacy toward learning new technology would positively predict faculty attitudes toward learning new technology to the extent that faculty who are more efficacious about their learning (new technology) will exhibit more positive attitudes. While the correlational association has been the typical approach for incorporating these variables into models predicting intention (Ajzen 1991, 2006; Ajzen et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Fishbein & Ajzen, 2010; Gird & Bahraim, 2008; Kyei-Blankson, et al., 2009), the current study examined the possibility of a causal association. The zero-order correlation between self-efficacy and attitudes was positive, indicating that faculty who felt greater internal control over learning new technology also had more positive attitudes concerning learning new technology. More importantly, the results from the path analysis indicate a significant positive predictive association between the two variables, where faculty who perceived that they have greater self-efficacy (internal control over) engaging in learning about new technology were predicted accurately by the model to have more positive attitudes.

My fourth hypothesis was that self-efficacy (perceived behavioral control) would positively predict intentions to learn new technology. The zero-order correlation between these variables indicated a complete absence of association between self-efficacy and intentions. For Model 1, a significant negative predictive relationship between efficacy and intention emerged; however, this appeared to represent a suppressor effect – that is largely uninterpretable. Its makes theoretical sense that faculty who are low in efficacy are more likely to learn new technology because of the understanding that before one can *use* technology they must develop skill (*learn it*). Examining the results in this way also makes practical sense. The best fitting path model was Model 4, which excluded the path from self-efficacy to intentions. As such, the data did not support the notion that a direct causal relationship between the two variables exists. Nevertheless, self-efficacy *did* appear to exert a significant positive indirect effect on intentions to learn, as reflected in the Model 4. Thus, my hypothesis that self-efficacy would predict intentions was partially supported (at least based on the results of the indirect effects test).

My fifth hypothesis was that attitudes toward learning new technology would positively and significantly predict intentions to learn new technology. The predictive relationship in my path models between these two variables was strong and positive; consistent with previous research using the theory of planned behavior (Ajzen, 1991; 2006; Ajzen et al., 2009; Fusiler & Durlabhji, 2005; Gird & Bagraim, 2008; Lee et al., 2010; Shuie, 2007; Smith et al., 2007; Venkatesh et al., 2003) indicating that those individuals more favorably disposed to a behavior are more likely to formulate the intention to engage in said behavior.

My sixth hypothesis was that an individual difference tendency to be loss averse would moderate the predictive relationship between self-efficacy and attitudes toward learning new technology. Specifically, it was expected that the relationship between self-efficacy and attitudes would be strongest among faculty members who were lowest in loss aversion. The results of my moderator analysis were consistent with my expectations. The relationship between self-efficacy and attitudes was essentially non-existent among those faculty who were highest in loss aversion (i.e., scored lowest on the loss aversion index). The relationship became increasingly positive for faculty at lower levels of loss aversion.

The findings were consistent with those laid out in the proposed causal relationship for the moderating effects of loss aversion on the predictive association between self-efficacy and attitudes. The main effects of both self-efficacy and loss aversion were significant confirming the predictors of attitudes. Importantly, the interaction term comprised of loss aversion and self-efficacy materialized as a significant interaction effect. The results are consistent with the principle of loss aversion where losses loom larger than gains regardless of the amount of the gain and a guaranteed gain is considered a ‘control’ or sure shot (Bibby & Ferguson, 2011; Hartley & Phelps, 2012; Kahneman, 1992, 2011; Kahneman & Tversky 1979; Tversky & Kahneman, 1981, 1991, 1992).

Faculty who feel efficacious about learning new technology and are willing to re-prioritize (e.g., being less loss averse and willing to take the chance that the technology will actually be instrumental in achieving their goals for using it) will hold more positive attitudes. The impact of loss aversion is clearly evident when faculty are high in perceived control (efficacious) about learning new technology for both the mean and least loss averse levels, but not when faculty are low in efficacy. This makes practical sense given that if faculty are low in efficacy for learning new technology the loss inherent in re-prioritizing an existing commitment looms larger than any known gain they may experience. When faculty are less loss averse (e.g. willing to re-prioritize existing commitments for an unknown technology based gain) and they are high in efficacy they have a more positive attitude.

To explore the findings further, the responses provided by faculty for the original gain and loss items designed by Kahneman & Tversky (1979, and Tversky & Kahneman, 1992) are provided in the tables below.

Table 5

Loss Aversion "Sure Gain"

		Frequency	Valid Percent
Get $900 for sure		201	91.8
Take 90% chance to get $1000; 10% to get nothing		18	8.2
	Total	219	100
	Missing	18	
	Total	237	

Table 6

Loss Aversion "Sure Loss"

		Frequency	Valid Percent
Lose $900 for sure		40	18.3
Take 90% chance to lose $1000; 10% chance to lose nothing		179	81.7
	Total	219	100
	Missing	18	
	Total	237	

In the tables above it is clear that 92% of the faculty that responded to the first set of options are representative of the control or confident decision utility reference point. In the second table the probabilities are flipped and a sure loss is compared to a larger loss that is merely probable, thus shrinking aversion associated with risk taking. With only a small probability (10%) lending to the possibility of experiencing zero loss, faculty participants were willing to view this option as attractive as opposed to a sure loss of $900. In this example the pain associated with losing $900 is more than 90% of the pain of losing $1000. Of the faculty responses, 82% resulted in a risk seeking decision in an effort to lose less.

One can explore for themselves what their level of loss aversion is for different situations. All readers of this dissertation are requested to ask themselves "what is the smallest gain I need to balance an equal chance to lose $100?" Kahneman offers several examples in his 2011 book *Think Fast and Slow*, and generally the estimated gain needs to be twice that of the possible loss presented. Many people may consider a win of at least $200 would be needed in order to override the loss aversion of speculating over a $100 loss. This 2:1 ratio of gain to loss is dependent upon many factors including how (predictively) they will respond emotionally and overall level of tolerating losses. When considering the context of professional risk takers in financial markets, it would be difficult to be emotionally responsive to every fluctuation and thus they are likely to be more tolerant of losses.

This is where loss aversion becomes distinctly relevant to the exploration of faculty intentions to learn new technology in higher education. Faculty, as professional scholars regardless of domain, identify with sound assessment (e.g. teaching/grading and/or research analysis) and opt to seek advancements in their career based on dedicated and consistent examples of gains that will ultimately lead to a final secure gain, career advancement (e.g., tenure, promotion, professional recognition). Many of their efforts are aimed at meticulously preparing and executing their examples of research, scholarship, scholarly creativity, professional practice, teaching, and service to assemble a dossier that may result in positive career advancement (i.e., personal gains). Such advancements may result in the exaltation of colleagues in the field, self-fulfilled scholarly achievement, and continued financial returns (be it wages or grants).

Limitations of the study

Several limitations should be considered with respect to this study. One limitation of this study is the structure and design of the loss aversion option sets which presumably resulted in poor internal consistency of that measure. Statements should be presented with scrupulous attention paid to the reference point presented in the statement. It is imperative that the statement present logically equivalent decision dilemmas. The items written for the loss aversion option sets were derived from Kahneman and Tversky's (1979) original examples and were tailored to anchor reference points in the context of an academic choice (e.g. gain/loss of research time, gain/loss assistance with grading, gain/loss related to service commitments). They were new to this study and possibly the lack of a track record with these items contributed to the low internal reliability observed in this study (Cronbach's alpha = .41). The poor reliability of the measure, in turn, may have negatively impacted the correlations observed between the loss aversion index and remaining measures, as well as the moderator analysis in this study. All this is to say that results that were presented that incorporated the loss aversion index should be considered cautiously. The option sets in this study could be improved by an appropriate instrumentation development process including item revision and analysis across multiple samples.

Similarly, the perception of time pressure subscale (though good internal consistency, $\alpha = .705$) was problematic and could be improved. As discussed, the intended operationalization of the perceived time pressure sub-scale may not be accurately reflected in the wording of the items. Two of the items represent general feelings, whereas, the other two incorporate a specific context.

Coding of the loss aversion items should be flipped to account for the counter intuitive nature of the measure. It may have been less confusing for readers if I would have framed the items as “more willing to take a chance” so that higher scores reflect more willingness. This became apparent during the write up of the results and discussion sections. Though I automatically frame the loss aversion index as “low means high”, possibly due to being familiar with the literature that examines it as such, it makes for a read that is very counter intuitive on paper. Several revisions targeted at clarifying the construct and its measurement direction were made to try and avoid confusion.

Faculty should also have been asked to assign a level of importance for each reference point so that data could be aggregated across self-prioritized reference points. I attempted to do something similar; however, it was with the time pressure variable in mind. Faculty were asked to assign a “percent of time to devote” to a specific existing obligation (see Appendix A, Q6). Specifically, faculty were asked to assign a percent from 1% - 100% to teaching, research, and service commitments (sum should total

100%). Overall the distribution across the three categories was balanced (40% to teaching, 40% to research, 20% to service commitments) and it was intended to be aggregated across levels of experienced time pressure. Due to the time pressure subscale failing to correlate with all 5 of the other measures there was no effect to examine with regard to priority of importance and level of time pressure experienced.

Consequently, it was the inability to extrapolate the level of priority devoted to time that brought up the need to perform a similar analysis with the loss aversion reference points used in the items presented to faculty (e.g. research, teaching and service commitments). For example, items that ask faculty to assign a “percent of importance when faced with re-prioritizing” or “percent of willingness to re-prioritize” when thinking about research, teaching and service commitment. Obtaining a level of rigidity against re-prioritizing across levels of reported loss aversion is necessary to make associations to a specific reference point. It would provide more information for the relevance of the specific reference points used in this study (research, teaching, service commitment gains and losses). Such that, faculty low in loss aversion (willing to re-prioritize) and high in self-efficacy may have more positive attitudes about and intend to learn new technology, but willing to re-prioritize ‘what’ remains unknown.

The assumption would be that faculty willing to re-prioritize the least important commitment would be less loss averse and faculty not willing to re-prioritize the most important commitment would be higher in loss aversion. Then it begs the question, do faculty perceptions of control over that commitment directly impact intentions, or indirectly via attitudes? Fishbein & Ajzen address the effect of framing similarly as a guide for formulating arguments or statements for participants to respond to (2010). It could be argued that faculty are willing to take a chance if it could help them avoid a bad outcome (specifically impacting research, teaching, or service commitments), but may be unwilling to take a chance if it results in risking a good outcome (specifically impacting research, teaching or service commitments). The measurement of loss aversion could be strengthened in future studies by including questions regarding the reference point context as it relates to the development of intention to perform a behavior (Ajzen, 1991, 2006; Ajzen et al., 2009; Smith et, al., 2007).

A final limitation concerns the convenience nature of the sample. The data for this study were collected at one research institution in the Midwestern U.S. As such, the results may not generalize beyond this context.

Implication and conclusion

Universities buying and implementing academic technology solutions should consider that self-efficacy and dispositions to be loss averse as they conflict with existing commitments. Also, perceived instrumentality may have an impact on whether faculty members actually engage in learning technologies. Facilitating those perceptions may increase the likelihood that faculty will actually use technologies.

The results also demonstrate a direct influence of perceived instrumentality which provides additional insight for identifying possible antecedents of faculty's evaluative responses about intentions to learn. Of these possible antecedents, it now seems logical to consider the threat of re-prioritizing existing commitments as a value factor (a loss) that influences perceptions of support, efficacy (control), attitude and intention to learn new technology. Learning new technology, specifically for faculty low on self-efficacy and attitude, was viewed as a loss (threat) to existing commitments because of the implicit uncertain outcome presenting a wager that faculty do not intend to make.

This study was not focused on increasing technology use behavior or mapping out an intervention to increase faculty technology use. The alternative focus of this study was to examine faculty intentions to *learn new technology* adds to the literature and offers a novel account for measuring faculty intentions. In doing so, I have incorporated a new type of behavior to model which is *engaging in learning new technology*, as opposed to, the often measured *using new technology*.

Lastly, the framework and combination of theories used in this study have not, to the best of my knowledge, been examined similarly in existing literature. The proposed model integrates important insights that suggest that faculty intentions to learn new technology could be "offset" by perceived losses they may anticipate regarding their existing professional commitments. Considering that I have found mixed evidence for my hypothesized model, this research needs to be refined, but does offer a novel approach for examining the faculty experience and learning new technology. The proposed integrative framework can be useful for a better understanding of the factors that influence faculty technology interactions and planning for higher education technology purchases and implementations.

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Appendix A – Instrument

Below is the survey instrument used to explore faculty intentions to learn new technology. The actual data collection tool is electronic and made possible using Qualtrics. Some formatting has been done to appropriately represent matrix style questions in print format.

In this survey you will be asked to evaluate statements that refer to your beliefs held about learning to use new technology. In statements referencing 'new technology' be thinking about technology that is new to you. New technology can include office productivity software, standardized classroom equipment, projectors, document scanners, or mobile devices as long as they are novel to your experience. Please reflect on your own experiences, beliefs and values and respond to the evaluative statements with those experiences in mind. First this survey begins with some basic descriptive items and a few questions regarding your current tenure expectations.

Q1 Please select one of the listed University of Oklahoma Colleges in which you perform a majority of your teaching and research tasks.

- Architecture (1)
- Arts & Sciences (2)
- Atmospheric & Geographic Sciences (3)
- Business (4)
- Continuing Education (5)
- Earth & Energy (6)
- Education (7)
- Engineering (8)
- Fine Arts (9)
- Graduate (10)
- Honors (11)
- International Studies (12)
- Journalism (13)
- Law (14)
- Liberal Studies (15)
- University College (16)

Q2 Please type your age in the following box. ________

Q3 Gender: (Select one)

- Male (1)
- Female (2)
- Choose not to designate among given options (3)

Q4 Please indicate your tenure status as of today (even if you are in review and expect your status to change)

- Tenured (1)
- Pre-Tenure (2)

Answer If Q4 is Pre-Tenure then Q4a is displayed
Q4a What year are you in your tenure review?

- 1st year (1)
- 2nd year (2)
- 3rd year (3)
- 4th year (4)
- 5th year (5)
- 6th year (6)

Q5 Which of the following examples best fits your teaching load?

- 1 Fall; 1 Spring (1)
- 2 Fall; 2 Spring (2)
- 3 Fall; 3 Spring (3)
- Other, please explain (4) ____________________

Q6 Please indicate the percentage of time you feel you should devote to each of the following aspects of your role as faculty. (should sum to 100%)
______ Teaching (1)
______ Service Commitments (2)
______ Research (3)

Q7 Please respond to the following two items in regard to your current level of skill with and interest in technology. What is your current level of skill with using technologies to teach?

- 1 Novice (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)
- 6 Advanced (6)

Q8 How interested are you in learning new technologies for use when you teach?
- 1 Not Interested (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)
- 6 Very Interested (6)

In the following sections you will be provided a pair of options that represent either a gain and/or a loss and asked to select one of the options that you *Most Prefer*. Some pairs present options in which a loss is represented in both cases. Given the options presented please select the one that you would *Most Prefer* over the other.

Below are two pair of options that present a situation with money, please indicate the option that you *Most Prefer* in each pair.

Q9 1st Pair of Options *(Kahneman, 2011)*
- Get $900 for sure (1)
- Take 90% chance to get $1000; 10% chance to get nothing (2)

Q10 2nd Pair of Options *(Kahneman, 2011)*
- Lose $900 for sure (1)
- Take 90% chance to lose $1000; 10% chance to lose nothing (2)

Below are two pairs of options that present a situation about *research time*, please indicate the option that you *Most Prefer* in each pair.

Q11 1st Pair of Options *(Research context)*
- Get a 90 day extension on an upcoming publication deadline for sure (1)
- Take 90% chance to learn a new technology (that will aid in your research efforts) in less than one hour; 10% chance to learn nothing (2)

Q12 2nd Pair of Options *(Research context)*
- Lose a week of scheduled research time that results in missing a publication deadline for sure (1)
- Take 90% chance to learn a new technology (that will aid in achieving grants) in less than one hour; 10% chance to learn nothing. (2)

Below are two pairs of options that present a situation about *service commitments*, please indicate the option that you *Most Prefer* in each pair.

Q13 1st Pair of Options *(Service related context)*

- Get four weeks of 'meeting amnesty' from committees, groups, and service commitments for sure (1)
- Take 90% chance of learning a new technology (that will assist with service commitments) in less than one hour; 10% chance to learn nothing. (2)

Q14 2nd Pair of Options *(Service related context)*

- Lose four weeks of productivity time to additional service commitments for sure (1)
- Take 90% change of learning a new technology (that will assist with service commitments) in less than one hour; 10% chance to learn nothing. (2)

Below are two pairs of options that present a situation about *grading time*, please indicate the option that you Most Prefer in each pair.

Q15 1st Pair of Options *(Teaching context)*

- Get 20 hours of grading assistance for large assignments/projects for sure (1)
- Take 90% chance to learn a new technology (that will assist with grading) in less than one hour (2)

Q16 2nd Pair of Options *(Teaching context)*

- Lose twenty hours of grading assistance for large assignments/projects for sure (1)
- Take 90% chance to learn a new technology (that will assist with grading) in less than one hour (2)

Q17 Please consider your experience as a faculty member and indicate below how strongly you agree or disagree with each of the following statements about the time pressures you experience in your role as faculty.

	Strongly Disagree 1	2	3	4	5	Strongly Agree 6
I feel stressed that I cannot get all of my work completed. (1)						
I feel like I am under constant time pressure in my role as a faculty member. (2)						
In order to have time for learning about using new technology, I would have to neglect other pressing commitments. (3)						
I see the benefit of learning new technologies for instruction as being outweighed by the reduction in time I will have to address more pressing obligations as a faculty member. (4)						

Q18 Considering your experience as a faculty member, indicate below how strongly you agree or disagree with each of the following statements about the benefit (or lack thereof) of new instructional technology.

	Strongly Disagree 1	2	3	4	5	Strongly Agree 6
I believe that learning about new instructional technologies will benefit me as a teacher in the classroom. (1)						
I believe that learning about new instructional technologies will benefit my students in their learning. (2)						
I do not believe that learning about new instructional technologies will enhance the instruction I provide to my students. (3)						

Q19 Considering your experience as a faculty member, indicate below how strongly you agree or disagree with each of the following statements about your ability to learn new instructional technology.

	Strongly Disagree 1	2	3	4	5	Strongly Agree 6
My ability to learn new technology for teaching is limited. (1)						
I feel confident in my ability to learn about new technologies for teaching. (2)						
I do not have the ability to learn how to use new technologies for teaching without the help of others. (3)						

Q20 Considering your experience as a faculty member, indicate below how strongly you agree or disagree with each of the following statements in regard to your attitude about learning new instructional technology.

	Strongly Disagree 1	2	3	4	5	Strongly Agree 6
Learning to use new technologies to enhance the delivery of instruction is a good idea. (1)						
It is unpleasant to think about learning to use new technologies in my courses. (2)						
I believe my instruction can be improved with the use of new technologies. (3)						
I feel positive about learning new instructional technologies. (4)						
I do not believe that technology enhances the delivery of instruction. (5)						

Q21 Considering your experience as a faculty member, indicate below how strongly you agree or disagree with each of the following statements about your intentions to learn new instructional technology.

	Strongly Disagree 1	2	3	4	5	Strongly Agree 6
I plan to re-prioritize some existing commitments so that I can make time to learn new technology. (1)						
I do not intend to learn technology if I have to rearrange my already busy schedule. (2)						
I intend to learn new technology so that I can use it in my class. (3)						

Q22 Considering your experience as a faculty member, indicate below how strongly you agree or disagree with each of the following statements about the social influences you notice about learning new instructional technology.

	Strongly Disagree 1	2	3	4	5	Strongly Agree 6
Colleagues in my department are currently learning to use new technologies for instruction. (1)						
Administrators in my department think our faculty ought to learn more about new technologies to support their teaching. (2)						