RELATIVE UTILITY OF THREE MODELS FOR USER EVALUATIONS OF LEARNING MANAGEMENT SYSTEMS: A HIGHER-ED INSTITUTION DECISION CONTEXT

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Dedicated to my beloved wife Melissa,

and my children, Ruth, Nicholas, and Andrew

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Learning management systems (LMSs) have broad adoption in higher education. Many institutions are re-evaluating their LMS strategy, comparing the relative advantage of alternative systems to the institution's current LMS. As part of a selection/decision process, most institutions gather instructor and student user evaluation after a level of "hands-on" user experience. Gathering users' input underscores their importance and relevance to the institution's technology decision process. Reviewing publically available LMS evaluation reports, one finds no mention of any framework or model used to guide the user evaluations, though common concepts occur frequently across the various reports. Conversely, there is a rich tradition of technology acceptance and success research, with several competing information system (IS) models having been developed over the past couple decades. This paper explicates the three most frequently used IS models used in LMS academic studies – the Technology Acceptance Model, the IS Success Model, and the Task-Performance Chain Model. This study examined the relative utility of the three models to begin to build a bridge between the academic literature and the LMS selection/decision processes underway at many institutions. Utilizing existing data from an LMS selection/decision process at a large, public higher education institution, a qualitative analysis was conducted by coding student user responses to open-ended survey question using the respective models' constructs. Quantitative analysis was conducted by first mapping closed-ended survey questions to the models' constructs and then analyzing the data with each model using partial least squares structural equation modeling (PLS-SEM).

Results indicated that technology acceptance and success models have considerable potential utility for understanding user input in the LMS selection/decision context in higher education. All three models exhibited utility in analyzing the student user-evaluations from an LMS pilot and contributed to the foundation for building a proposed Learning Management System – Pilot Model (LMS-PM) that could provide for practitioners common nomenclature and a framework for understanding and sharing LMS pilot evaluation results.

Keywords: learning management system, LMS, selection process, user evaluation, IS Success Model, Technology Acceptance Model, TAM, Task-Technology Fit, TTF, Task-Performance Chain, TPC, higher education

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CHAPTER 1: INTRODUCTION

Background of the Study

Learning Management Systems in Higher Education

Learning Management Systems (LMSs) attempt to provide a multitude of capabilities to support a variety of approaches to teaching and learning across multiple course settings. The importance of LMSs at higher-ed institutions is widely recognized (Means, Johnson, & Graff, 2013) and considered to have significant effects on teaching and learning at the university level (Coates, James, & Baldwin, 2005). Serving as a resource hub for classes and courseware, LMSs are "the most significant enterprise application for teaching and learning" (EDUCAUSE Learning Initiative, 2011, p. 1). LMS usage in the United States is nearly ubiquitous across higher education institutions. Brown, Dehoney, and Millichap (2015) note that 99% of colleges and universities are running an LMS. With the 2013 national survey of computing and information technology, Green (2013) reports that all but 4% of institutions have a single, campus-wide LMS and that 62% of higher education classes utilize an LMS to some degree (up from 58% in 2011 and dramatically up from 17% in 2000). Along with this broad usage, the LMS field is a dynamic one, with two thirds of campuses planning to review their LMS strategy (Green, 2013), 15% of institutions intending to replace the LMS in the next three years (Brown et al., 2015), and fierce competition in the marketplace with both mergers and acquisitions and companies appearing as well as disappearing (Piña, 2010).

As Folden (2012) notes, (a) the LMSs of today have evolved out of an educational technology history that includes programmed learning and teaching machines, computer assisted instruction, correspondence course learning, instructional television, and even video conferencing; (b) like other information communication technologies (e.g., financial, library and student information systems), LMSs mimic many paper-based processes and have grown to support activities that were not possible or easy to do in print form; and (c) LMSs are used to support residential, distance and blended education settings.

Piña (2013) points out that (a) LMSs are also referred to as course management systems, personal learning environments, virtual learning environments, and other monikers; (b) LMSs provide many features and capabilities (e.g., content creation, organization and display tools; synchronous and asynchronous communication and collaboration tools; assignment, assessment, and grading tools; digital storage facilities; student eportfolio tools; etc.); and, (c) LMSs are preferably integrated with an institution's campus administrative systems (e.g., student information system or enterprise resource planning system).

LMS Decision Reports by Higher-Ed Institutions

With the importance of LMS on higher-ed campuses, institutions spend considerable time, effort, and resources in evaluating, selecting, and implementing systems. From an institutional planning perspective, the selection of an LMS is a high stakes decision with considerable risk (Coates, James, & Baldwin, 2005). There are several key drivers of LMS adoption by universities:

- Means of increasing teaching efficiency
- The potential of enriched student learning
- Changing student expectations for technology
- Pressure of competing with other institutions

- A possible response to the demand for greater higher education access
- A potential way of managing the consistency and quality of education.

As the EDUCAUSE Learning Initiative (2011) explains, committees and tasks forces are formed, stakeholders and their priorities identified, technical evaluations completed, institutional information sites and communication plans created, and user input gathered from faculty and students through demonstrations, hands-on sessions, and field-test trials (i.e., pilots) in actual courses; and many institutions make their decision process publically available via the web. Means, Johnson, and Graff (2013) describe how hands-on sessions were conducted at their institution with faculty and staff, including both scripted activities and individual time to explore, followed by a survey of open-ended questions to gather perceptions and a rating for user-friendliness of functions such as discussions, assignments, and gradebook.

The *trialability* and *observability* of an innovation (Rogers, 1983) are key characteristic of innovations because experimenting on a limited basis and making results visible provides the opportunity to lessen the uncertainty around other innovation characteristics such as *relative advantage* (how it is perceived as better to the current or alternate approaches), *compatibility* (how it is perceived to match values, past experiences, and current and future needs), and *complexity* (how difficult it is to use and understand). Mahlow (2010) underscores this same point reflecting on one institution's first comparing systems based on features and finding them basically equivalent, but after evaluating them in real-world scenarios finding one system with considerable limitations that would have required wasting "significant resources for workarounds and third part solutions" (p. 76).

In reviewing a number of publically available reports of LMS evaluations by higher-ed institutions (see *Appendix A*), one observes in most every case the gathering of faculty and student user evaluations after either brief hands-on experiences or during trials/pilots in actual courses of one or more LMSs under consideration. The primary method of gathering faculty and student input is through surveys.

Though the reports do not reference research literature as a source for questions or frameworks for interpreting results, common key factors across the reports are present, often including the user rating of ease-of-use (including related terms such as ease of learning, usability, user-friendliness, look and feel) and user rating of system abilities in meeting needs (including related terms such as functionality, features, usefulness or effectiveness of system tools/features for completing tasks, satisfaction with or likeability of specific tools/features), as well as an indicator of the strength of their recommendation (including interest in switching to or likelihood of using the new system in the future if selected). In addition, demographic questions are asked to help demonstrate the breadth of input, and in pilots users are asked the amount or extent they used the LMS under question.

Problem Statement

With research as a core mission of universities, it might be surprising to a campus audience in the context of a decision/selection of LMSs to observe a disconnect from any research literature regarding user evaluations of systems. It appears that questions are largely crafted locally and results are reported descriptively. LMS pilots are run generally as independent efforts with the exception of sharing reports publically and noting what system is used or recently chosen by peer institutions. In short, an institution looking to conduct user evaluations of LMSs as a part of the decision process is presented a peculiar quandary. Reviewing publically available LMS evaluation reports across institutions, one finds no reference to the academic literature, frameworks or models, but instead finds a list of questions that varies greatly from one institution to another (though common concepts occur frequently across the various reports).

In the LMS academic literature, one does run across studies not unlike the LMS evaluations done by institutions in that they do not reference models, but rather construct ad hoc questions and feature checklists (e.g., Sanders & Morrison-Shetlar, 2001; Chan, Tsui, Chan, & Hong, 2008; Ioannou & Hannafin, 2008). Since technologies in general (and learning technologies and LMSs specifically) are constantly evolving and adding features and capabilities on a frequent basis, evaluation based on feature checklists are inherently limiting and quickly out of date.

Other academic studies focus more on user perceptions of online courses, teaching, and content, where the technology is not the primary focus (e.g., Nistor, 2013; Naveh, Tubin, & Pliskin, 2012). Though this is an interesting and important line of research, including course and content evaluations would in effect be an evaluation of the faculty and curriculum, which is well outside the scope of an institution's technology decision/selection process.

Conversely, there is a rich tradition of technology acceptance and success research, with several competing information system (IS) models having been developed over the past couple decades. In examining more specifically the higher education technology system research, prevalent in the academic literature is considerable investigation that utilizes and adapts one framework or another from the information system (IS) literature.

An underlying assumption of all of these kinds of LMS studies is that LMSs and related e-learning systems are special kinds of information computing systems (Mueller & Strohmeier, 2011) used to conduct "learning activities, making the e-learning system a communication and IS phenomenon", whether the focus is on system acceptance, success, or user impact (Wang, Wang, & Shee, 2007, p. 1795). LMSs do share substantial characteristics with other computing and information systems in that they are all efforts "fueled by a common goal of harnessing new technologies to better meet the needs of their users" (Holsapple & Lee-Post, 2006, p. 68).

Though different IS models have been adopted or adapted for LMS research, the common pattern is to introduce one of the models and then adapt it to the LMS context without explanation for why the particular model has been chosen. The comparison of models and a comparative reason for selecting a particular model is oddly absent. With multiple models available, the lack of comparative investigation of models is a serious gap in the LMS academic literature.

Equally important, while the research usually claims value of its results for the practitioner implementing LMSs, the research studies have not been conducted in the context of an actual LMS adoption process.

Purpose of the Study

This study begins with the basic assumption that user evaluations of a system are a critical and useful component of a selection/decision process in higher education. Through exposure to and experience with a system in the context of a particular course, users are in a unique situation to evaluate the system, with a separate but distinctly important perspective from those who create, implement, support, or fund systems.

The purpose of this study is to examine whether one or more of the most prevalently used IS models in the study of LMSs provides explanatory and useful nomenclature for framing and interpreting the results of user evaluations generated in the context of a higher-education institution's LMS adoption process.

Based upon a review of LMS literature and the origins of the IS acceptance and success models used in that research, the following are the research questions to be examined in the study:

1. What is the utility of the Technology Acceptance Model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?
2. What is the utility of the IS Success Model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?
3. What is the utility of the Technology to Performance Chain model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?
4. What is the relative utility of the three models in their applicability to analyze and interpret the user evaluations generated in the context of a higher education institution's decision for or against a new LMS?

Significance of the Study

This study begins to address the problem of the disconnect between the academic literature and the use of LMS user evaluations in the higher-ed adoption context. The lack of any reference to the academic literature undercuts the credibility of LMS higher-ed institutional reports of their selection/decision process, particularly since university faculty are a key audience for the reports. Where now no academic research is explicitly brought to bear, this study helps show its value and applicability by comparing the utility of the prevalent IS acceptance and success models in the literature.

The results of this study help point to a potentially superior model to use in the context of higher-ed LMS adoption, or may at least lead to refinement of one or more of the tested models for this particular context. If none of the models are considered to be superior to the others, the results may help point to the direction for development of a new model for the LMS decision/selection context.

This study also helps provide practical advice for practitioners and implementers in how to utilize the models to analyze and interpret the results of their LMS users' evaluations. Currently, institutions can readily compare little more than the final LMS choice resulting from their respective decision processes. A much richer sharing of knowledge and users' perspectives is a likely result from a more common approach across institutions. A shared model would provide a common nomenclature for understanding results and a common method of analysis and interpretation of user evaluations, thus providing more common ground to compare results across institutions. The long-term use of a research-driven model in this context may well raise the level of shared discourse across institutions as well as in the academic literature regarding the central nature of user evaluations in the selection of learning technologies, and ultimately lead to better decision-making.

This study also makes a significant contribution to the existing LMS academic literature. Though different IS models have been adapted for LMS research, the common pattern is to introduce a singular model, generally without the recognition and comparison of alternative models and a comparative reason for selecting a particular model. With multiple models available, the lack of any comparative investigation of models is a serious gap in the LMS literature. The direct comparison of the three most prevalent models in the same study begins to help fill that gap.

This research should be of interest to researchers, practitioners, and university administrators alike, since it adds to the fairly limited number of LMS studies utilizing technology success models, offers a comparative understanding of the models, provides an example of using the technology acceptance and success models explicitly in the context of user evaluations in a higher-ed institution's LMS selection/decision process, and provides an example to institutions of how the academic literature can directly contribute to the LMS adoption process.

CHAPTER 2: REVIEW OF THE LITERATURE

The literature review will explicate the three most frequently used IS models in LMS academic research, their origins, evolution, and their adaptation for LMS studies: the Technology Acceptance Model (Davis, 1986, 1989, 1993; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 1996, 2000), the DeLone and McLean IS Success Model (DeLone & McLean, 1992, 2003), and the Task-Performance Chain Model (Goodhue, 1995, 1997; Goodhue, Littlefield, & Straub, 1997; Goodhue & Thompson, 1995).

Prevalent Models

The most prevalent model adapted is the Technology Acceptance Model (TAM), which was originally presented by Davis (1986, 1989) and further developed by him and other researchers. TAM and its derivatives have been adapted for the study of LMS by many researchers (Abdalla, 2007; Al-Bushaidi & Al-Shihi, 2010; Alharbi & Drew, 2014; Arbaugh, 2000; Augudo-Peregrina, Hernádez-Garzia, & Pascual-Miguel, 2014; Chen, Lin, Yeh, & Lou, 2013; Cheung & Vogel, 2013; Chung, Pasquini, & Koh, 2013; Edmunds, Thorpe, & Conole, 2012; Fatheman & Sutton, 2013; Galy, Downey, & Johnson, 2011; Halawi & McCarthy, 2007; Landry, Griffeth, & Hartman, 2006; Jan & Contreras, 2011; Lee, 2006; Liu, Liao, & Peng, 2005; Martínez-Torres et al., 2008; Ngai, Poon, & Chan, 2007; Pan, Sivo, & Brophy, 2003; Persico, Manca, & Pozzi, 2014; Pituch & Lee, 2006; Sánchez & Heuros (2010); Sivo & Pan, 2005; Sivo, Pan, & Brophy, 2004; Schoonenboom, 2012, 2014; Teo, 2009, 2010; Van Raaij & Scheppers, 2008; Venter, van Rensburg, & Davis, 2012; Yi & Hwang, 2003; Yuen, Fox, & Deng, 2009).

Another model used and adapted several times in the study of LMS is the DeLone and McLean (D&M) IS Success Model (1992, 2003). LMS researchers have adapted D&M

and its derivatives as well (Lin, 2007; Klobas & McGill, 2010; Mtebe & Raisamo, 2014; Mueller & Strohmeier, 2011; Tella, 2011; Wang, Doll, Deng, Park, & Yang, 2013; Wang, Wang, & Shee, 2007).

Mueller and Strohmeier (2011) in a review of the literature recognize TAM and D&M as the most prominent theoretical foundation approaches used in the study of virtual learning environments. A third recurring model they missed is the Technology Performance Chain (TPC) first offered by Goodhue and Thompson (1995), which has been adapted for the study of LMSs by McGill and Hobbes (2008), McGill and Klobas (2009), McGill, Klobas, and Renzi (2011), and Baleghi-Zadeh, Ayub, Mahmud, and Daud (2014a).

Other models in the academic literature have different names, but still have roots in models mentioned above. The Hexagonal e-learning assessment model (HELAM) used in research by Ozkan and Koseler (2009) and Ozkan, Koseler, and Baykal (2009) builds on the work of Holsapple and Lee-Post (2006), which is an extension of the D&M model used in an action research study of the development of a single online course. A study by Schaik (2009) uses the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which is a further extension of TAM.

In addition to adding constructs to full or partial versions of each model, researchers have also studied amalgamated versions of the models as well. An early example is Goodhue and Thompson (1995) creating TPC by incorporating Utilization and related constructs into the earlier Task-Technology Fit (TTF) model and explicitly claiming consistency with the model proposed by DeLone and McLean (1992). Alsabawy, Cater-Steel, and Soar (2013) combined aspects of D&M with TAM as have Almarashdeh, Sahari, Zin, and Alsmadi (2010), Wang and Wang (2009), and Al-Busaidi and Al-Shihi (2010).

Combined aspects of TAM and TTF have been studied by Dishaw and Strong (1999), Dishaw, Strong, and Bandy (2003), and Baleghi-Zadeh, Ayub, Mahmud, and Daud (2014a). Aspects of all three models (D&M, TTF/TPC, and TAM) have even been combined by researchers as well, including Daud, Mohamed, Alghanim, and Alhamali (2011) and Lin and Wang (2012). Such amalgamations are perhaps indicative that the three prevalent models are neither duplicative nor completely distinct from one another.

Technology Acceptance Model (TAM)

Introduced by Davis (1986, 1989), the Technology Acceptance Model (TAM) was developed to explain the "effect of system characteristics on user acceptance of computer-based information systems" with the goal of providing (a) a better understanding of the processes of user acceptance and (b) a theoretical base for "a practical 'user acceptance testing' methodology that would enable system designers and implementors to evaluate proposed new systems prior to their implementation" (Davis, 1986, p. 7). TAM has been used in the evaluation of a broad range of information systems, including communication systems, general-purpose systems, office systems, and specialized business systems (Lee, Kozar, & Larson, 2003). It has grown to be one of the most widely used theories for technology acceptance/success and is the "most widely used theory in e-learning acceptance studies" (Šumak, B., Heričko, M., & Pušnik, M., 2011, p. 2068).

Original TAM

The targeted context for applying TAM was originally seen as a brief, one-hour hands-on experience of a system, and in cases where a sufficiently robust prototype is not available, a video of a potential system. The goal is to obtain user reactions to a system before substantial time-intensive development has begun. “The purpose of the hands-on demonstration is to provide subjects a realistic, behaviorally-based exposure to the system from which they can form stable attitudes and perceptions” (Davis, 1986, p. 128).

The focus of TAM involves two constructs (Davis, 1986):

> Perceived Usefulness: The degree to which an individual believes that using a particular system would enhance his or her job performance.
>
> Perceived Ease of Use: The degree to which an individual believes that using a particular system would be free of physical and mental effort. (p. 82)

In reviewing a wide range of theoretical perspectives and research studies, Davis (1989) found “theoretical support for perceived usefulness and ease of use as key determinants of behavior” which are “indicated as fundamental and distinct constructs […] influential in decisions to use information technology” (p. 323).

Adapted from the Theory of Reasoned Action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975, as cited by Davis et al., 1989), TAM (see *Figure 2-1*) is tailored for user acceptance of information systems and reflects several hypotheses:

- A range of external variables (including system characteristics and task characteristics) impact an individual’s perceived usefulness (U) and perceived ease of use (E) of a system.
- E also has a direct impact on U to “the extent that increased [ease of use] contributes to improved performance” (Davis et al., 1989, p. 987).
- Both U and E impact an individual’s attitude (A) towards using a system, which leads to the level of behavioral intention (BI) to use a system.

- In addition to one's general attitude towards a system, an individual's BI is also impacted directly by U because "people form intentions towards using computer systems based largely on a cognitive appraisal of how it will improve their performance" (Davis et al., 1989, p. 986).
- Computer Usage is determined by BI.

The initial TAM model findings were replicated in two studies by Adams, Nelson, & Todd (1992).

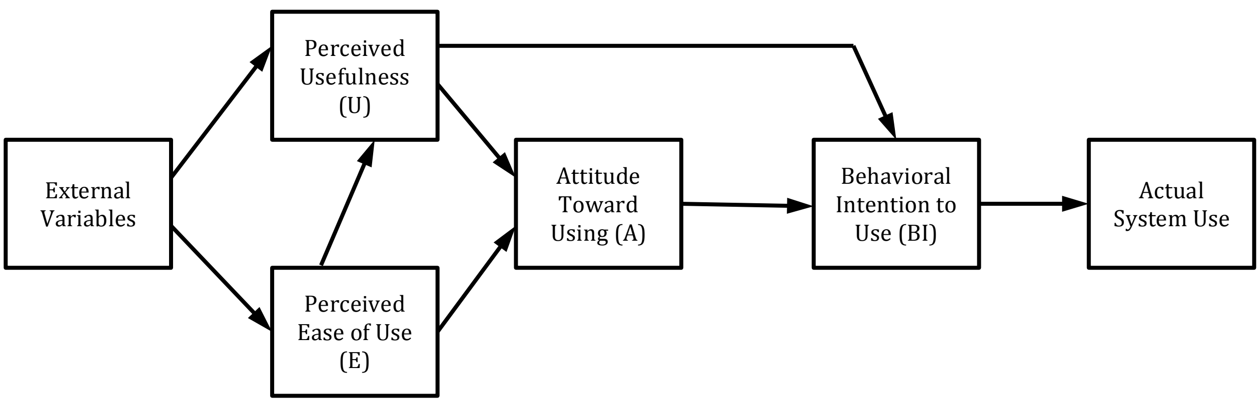


Figure 2-1. Technology Acceptance Model (TAM). From "User acceptance of computer technology: A comparison of two theoretical models," by F. D. Davis, R. P. Bagozzi, and P.R. Warshaw, 1989, *Management Science, 35*(8), p. 985. Reproduced with permission. Copyright © 1989, INFORMS.

In short, TAM attempts to explain the behavior of usage of a specific target system within a specific context (Davis et al., 1989); and, in addition to identifying a parsimonious causal structure including only three constructs (Perceived Usefulness, Perceived Ease of Use, and Behavioral Intention), their study provides three main insights (p. 997):

- The computer use of individuals can be "predicted reasonably well from their intentions."

- “Perceived usefulness is a major determinant of people’s intentions to use” the target system.
- “Perceived ease of use is a secondary determinant of people’s intentions to use” the target system.

Similarly, in his earlier study, Davis (1986) found that perceived usefulness was considerably more important in determining predicted use than ease of use. The effects of external variables (such as characteristics of the target system, the development process used to create the system, and training for users of the system) on behavioral intention are theorized in TAM to be mediated by perceived usefulness and perceived ease of use; and perceived ease of use impacts perceived usefulness because, “other things being equal, the easier the system is to use the more useful it can be” (Venkatesh & Davis, 2000, p. 187).

Updated TAM – TAM2

TAM was extended by Venkatesh & Davis (2000) as TAM2 (see *Figure 2-2*) to include a number of external variables involving social influences (Subjective Norm – the opinion from those who influence the user; Voluntariness – whether system usage is mandated or not; and Image – use enhancing the user’s status) and cognitive instrumental processes (Job Relevance – how well the system matches the user’s job goals; Output Quality – how well the system performs; and Result Demonstrability – how discernable is the system’s usefulness), as well as recognizing that over time (as the user gains Experience with the system), there may be a change “in the strength with which social influence processes affect perceived usefulness and intention to use” (p. 193).

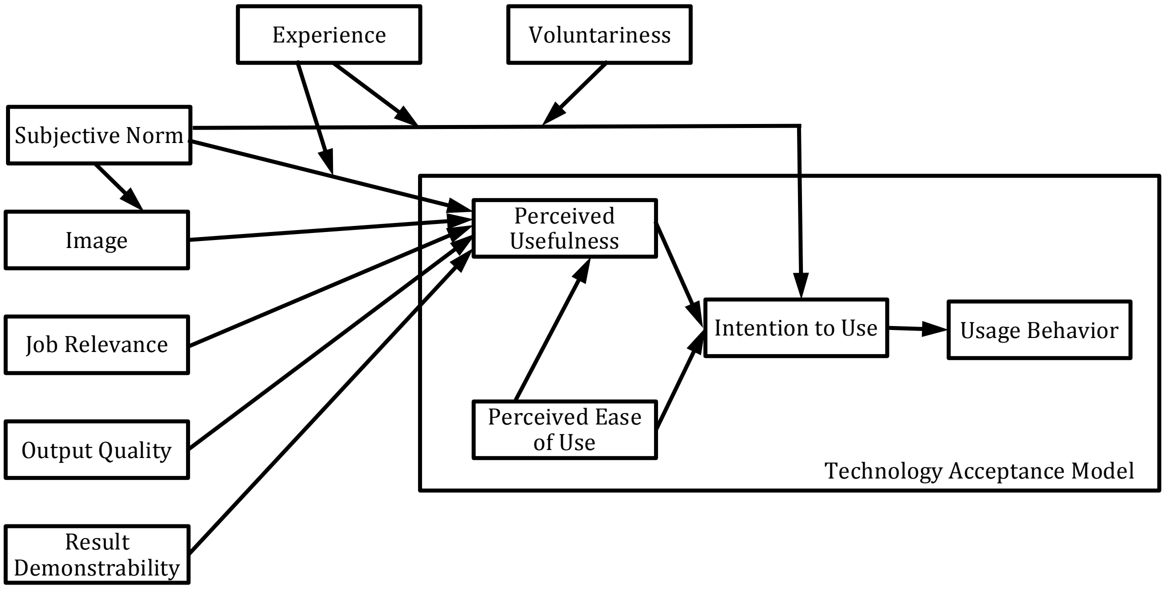


Figure 2-2. TAM2 – Extension of the Technology Acceptance Model. From "A theoretical extension of the technology acceptance model: Four longitudinal field studies," by V. Venkatesh and F. D. Davis, *Management Science, 46*(2), p. 188. Reproduced with permission. Copyright © 2000, INFORMS.

The TAM construct Attitude Towards Using is dropped in the TAM2 model. Furthermore, a generic construct for External Variables has been replaced by a host of constructs and moderating variables. See *Table 2-1* for a summary of TAM/TAM2 construct definitions.

Both TAM and TAM2 focus on how behavioral intentions predict usage because of the high level of interest in predicting future use "based on a brief (e.g., one-hour) hands-on introduction to a system" (Davis et al., 1989, p. 989). This would be particularly valuable for both gathering feedback after a brief introduction to a new system as well as to iterative prototypes as new systems are being developed.

Table 2-1. TAM/TAM2 Construct Definitions

TAM Constructs	
External Variables*	System design features and also user characteristics, individual differences, situational constraints, training, documentation, user support consultants, etc. (Davis et al., 1989)
Perceived Usefulness	"The degree to which an individual believes that using a particular system would enhance his or her [...] performance" (Davis, 1986, p. 82)
Perceived Ease of Use	"The degree to which an individual believes that using a particular system would be free of physical and mental effort" (Davis, 1986, p. 82)
Attitude Towards Using*	A person's general evaluation or overall feeling of favorableness or unfavorableness toward a behavior (Fishbein & Ajzen, 1975)
Behavioral Intention to Use	A measure of the likelihood or subjective probability that a person will engage in a given behavior (Fishbein & Ajzen, 1975)
Perceived or Actual Usage	Self reported frequency of usage or objective usage logs (Davis et al., 1989)
TAM2 Additional Constructs (Venkatesh & Davis, 2000)	
Voluntariness	The "extent to which potential adopters perceived the adoption decision to be non-mandatory" (p. 188).
Experience	"[I]ncreasing user experience over time with the target system" (p. 187)
Subjective Norm	A "'person's perception that most people who are important to him think he should or should not perform the behavior in question' (Fishbein and Ajzen 1975, p. 302)" (p. 187)
Image	"Moore and Benbasat (1991, p. 195) define image as 'the degree to which use of an innovation is perceived to enhance one's ... status in one's social system'" (p. 189)
Job/Task Relevance	"[A]n individual's perception regarding the degree to which the target system is applicable to his or her job" or task (p. 191)
Output Quality	"[H]ow well the system performs" the tasks provided (p. 191)
Result Demonstrability	"[D]efined by Moore and Benbasat (1991, p. 203) as the 'tangibility of the results of using the innovation'" (p. 192)

* The added TAM2 variables replace External Variables. Attitude is dropped in TAM2.

TAM/TAM2 in the Study of LMS

In addition to being used to study the general use of computers in the classroom (Teo, 2009) and adapted to study acceptance of computer technology by student teachers (Ma, Andersson, & Streith, 2005), university students' acceptance of e-learning in general (Park, 2009), and students' adoption behavior of Google Apps (Cheung & Vogel, 2013), TAM has been used frequently in the study of LMSs. As documented in *Appendix B*, the large majority of studies limits constructs to original TAM concepts (except for Subjective Norm which is often added) and usually focuses on additional variables for the particular study.

Yi and Hwang (2003), focusing on predicting the use of an LMS, used core original TAM constructs (minus Attitude Towards Using) and added three intrinsic motivation constructs: Enjoyment, Learning Goal Orientation, and Application Specific Self-Efficacy. All three added constructs had significant impacts on core TAM constructs. With Enjoyment added to the model, Ease of Use no longer had a significant effect on Usefulness, which is a different result than in much of the TAM literature.

Landry, Griffeth, and Hartman (2006), in studying web-enhanced instruction through the use of an LMS in actual courses, found results similar to those in the IS literature, namely that Usefulness, compared to Ease of Use, is a stronger determinant of Usage; the researchers thus concluded that TAM is appropriate for the academic setting and a useful measure of student reactions to an LMS; however, Usefulness differed by types of LMS features, with features related to course content being used more often and perceived as more useful than features related to course support or communication. Abdalla (2007) also confirms the primacy of Perceived Usefulness and Perceived Ease of Use while extending the model by replacing Behavioral Intention and Perceived Usage with Effectiveness of Technology.

Pituch and Lee (2006) added two groups of external variables to core TAM constructs in a study of factors affecting LMS use for supplemental learning and affecting LMS use for distance education. One group of external variables focused on the System (functionality, interactivity, and responsiveness) and the other group focused on individual attributes (self-efficacy and amount of internet experience). They examined the effects of external variables both through a model where their effects are fully mediated through Perceived Usefulness and Perceived Ease of Use and also through a partially mediated model that included the additional direct effects of system functionality and system interactivity on both kinds of use. The partially mediated model outperformed the fully mediated model. Also the individual attributes were not important determinants of use, whereas the system factors and the two core TAM use beliefs were.

Ngai, Poon, and Chan (2007) used all five original constructs of TAM (though Behavioral Intention was removed based on principal component statistical analysis) and added Technical Support. Most causal relationships between constructs were supported and Technical Support had a significant effect on both Perceived Usefulness and Perceived Ease of Use.

Martinez-Torres et al. (2008), focusing on practical and laboratory teaching, used the constructs of the original TAM, but removed Attitude Towards Using, and added several new factors related to student motivation (Enjoyment, User Tools, Diffusion, Methodology, and User Adaption) and new factors related to learning (Interactivity and Control, Feedback, and Communicativeness); all new factors added significant paths to the structural model.

Van Raaij and Schepers (2008) adopted Subjective Norm from TAM2, adding it to the regular TAM model while studying the acceptance of a Virtual Learning Environment designed for an executive MBA. The study also added Personal Innovativeness in the Domain of IT and Computer Anxiety as external variables. Of the three paths linked to Use – Subjective Norm, Perceived Ease of Use, and Perceived Usefulness – only the latter had a significant effect.

Wang and Wang (2009), borrowing from the DeLone & McLean (2003) Information Success (IS) model (discussed in the next section of the literature review), incorporated as external variables in the generic TAM model the constructs of System Quality and Service Quality (affecting Perceived Usefulness and Perceived Ease of Use, respectively) and System Quality (affecting both). They also added Subjective Norm (with potential effects on Perceived Usefulness and Intention to Use) and Self-Efficacy (with potential effects on Perceived Ease of Use and Intention to Use) as psychological dimensions to the model. Their results showed that Information Quality and Service Quality affected their respective targets, while System Quality only affected Perceived Ease of Use. With the psychological dimensions, Self-Efficacy affected only Perceived Ease of Use while Subjective Norm affected both Perceived Usefulness and Intention to Use. Overall, core TAM constructs were supported and followed similar patterns to other TAM research. Al-Bushaidi and Al-Shihi (2010), in proposing an untested framework for instructor acceptance of LMS, also utilized D&M technology factors (System Quality, Information Quality, and Service Quality) as well as other instructor factors and organization factors, all as external variables to core TAM constructs.

Sánchez and Heuros (2010) used TAM to study motivational factors that influence LMS acceptance, extending the model with Technical Support while removing Behavioral Intention and focusing on self-reported Usage. Self-Efficacy was initially included in the model, but its item was eliminated during principal component analysis. TAM constructs were confirmed and Technical Support had a direct effect on both Perceived Ease of Use and Perceived Usefulness. Unlike most other TAM research, Perceived Ease of Use had a much stronger direct effect than Perceived Usefulness on Usage.

Jan and Contreras (2011) added Subjective Norm (as does TAM2) and Compatibility (borrowed from Rogers, 2003) to the basic TAM model; neither Perceived Ease of Use (a foundational variable in TAM) nor Perceived Compatibility influenced the model, leaving just Perceived Usefulness and Subjective Norm as influencing Attitude and Behavioral Intention.

The main purpose of research by Venter, van Rensburg, and Davis (2012) was to identify the antecedents of e-learning among business students at the University of South Africa using an adapted version for e-learning of the TAM2 model. Of all of the studies listed in *Appendix B,* this one attempted to use the most number of TAM2 constructs. However, after factor analysis, items for Results Demonstrability, Attitude, Output Quality, and Subjective Norm were combined into a construct labeled Performance Enhancement. Their findings confirmed core aspects of TAM/TAM2 (namely Perceived Usefulness and Perceived Ease of Use) as well as the extensions of Relevance and Facilitating Conditions. The researchers questioned the usefulness of TAM2 where usage patterns were established over longer time periods.

To better study LMSs in the higher education context, Chung, Pasquini, and Koh (2013) proposed extending the TAM model's external variables with five categories of functionality important for LMS design and development (transmitting course content, evaluating students, evaluating course and instructors, creating class discussions, and creating computer-based instructors); the researchers did not test the model in their study.

Alharbi and Drew (2014) modified TAM to look at academics' behavioral intention to use LMS, retaining (and confirming) TAM's core constructs while adding three external variables: Job Relevance (similar to TAM2), prior Experience with LMS (again, similar to TAM2), and Lack of LMS availability at the institution; the researchers considered these variables particularly relevant considering the relative infancy of LMS in Saudi Arabia.

Schoonenboom (2014) studied why higher education instructors in blended learning settings intend to use some LMS tools more than others by asking users about 18 instructional tasks in terms of performance, importance, and three TAM concepts: Perceived Usefulness, Perceived Ease of Use, and Behavioral Intention. Schoonenboom (2012, 2014) emphasizes that an important step is missing from most studies of learning technologies: First an instructor decides to do a particular instructional task based on its importance before deciding whether or not to use the corresponding tool in the LMS. Based on TAM, the decision to use the LMS tools is based on its Perceived Usefulness and Perceived Ease of Use. Overall, high LMS intention was explained by a high level of usefulness and ease of use, while low LMS intention was explained by a low level of at least one of the following: Task Importance, Task Performance, LMS Usefulness, or LMS Ease of Use. The practical outcome is that in a particular setting "[s]upport should be targeted toward the reason instructors refrain from using an LMS tool" (Schoonenboom, 2014, p. 253); so, support would be quite different in the case of instructors feeling a task was not important (and therefore not a technical issue) compared to the case of instructors feeling the tool to support the task wasn't useful (a question of functionality) or wasn't easy to use (a question of design).

Baleghi-Zadeh, Ayub, Mahmud, and Daud (2014c) utilized five constructs from TAM2 (Perceived Usefulness, Perceived Ease of Use, Behavioral Intention, Social Norm, and Use) to conduct a confirmatory factor analysis of a measurement model for LMS utilization by higher ed students. LMS use—rather than operationalized by hours of use, level of use, or system log—was reflected through ten questions about use, each focused on a different task, e.g., 'I use X to submit my assignments.' After ten items were removed through confirmatory factor analysis, the data did fit the measurement model.

TAM researchers in the study of LMSs have also extended the model with Task-Technology-Fit (Goodhue & Thompson, 1995) constructs (discussed in the third section of the literature review). Ma, Chao, and Cheng (2013), in studying blended e-learning, included Self-Efficacy, User Satisfaction, and three constructs from Task-technology Fit (TTF along with two antecedents — Task Characteristics and Technology Characteristics), with TTF pointing to the TAM construct Perceived Usefulness; while Computer Self-Efficacy had no significant influence on Perceived Usefulness, TTF (with its two significant antecedents) had a significant impact on Perceived Usefulness that was much stronger than the impact of Perceived Ease of Use. Adding the Task-Technology Fit construct as an additional external variable, Baleghi-Zadeh, Ayub, Mahmud, and Daud (2014b) utilized three TAM constructs (Perceived Usefulness, Perceived Ease of Use, and Behavioral Intention) to develop a measurement model for intention to use an LMS by pre-service teachers and also added Technical Support as an external variable; a confirmatory factor analysis led to removing 11 items at which point the five constructs did fit the measurement model.

Collectively, these varied utilizations of TAM in settings using an LMS underline the value of the core constructions of Perceived Usefulness and Perceived Ease of Use, while continuing the practice of selecting external variables based either on local factors or on borrowings from other models considered relevant for the study. A large range of additional, external variables have been included in LMS studies using TAM, but without a clear pattern.

In addition to TAM being the most frequently used model in academic LMS research, the TAM constructs related to usefulness and ease of use are also the most common topics addressed in publically available institutional reports on user LMS evaluations. For brief evaluation of systems, TAM's focus on intention to use matches well; the Usage construct was originally included as delayed actual use. In the study of LMS, both Behavioral Intention and Usage are both included by researchers, even with extended multi-week or multi-month usage in the regular conducting of a course. For semester-long pilots, the intention to use in the future is perhaps more related to the recommendation for adoption in other courses or at the institutional level.

DeLone & McLean Information System Success Model (D&M)

Original D&M

DeLone and McLean's (D&M) information success (IS) model (1992, 2003) rose from a review of conceptual and empirical studies of IS research. The dependent variable measures from 180 articles dating from January 1981 to January 1988 from seven mainstream journals of IS research were placed into categories that were based on Shannon and Weaver's (1949) communications theory (Technical Level, Semantic Level, and Effectiveness or Influence), further refined by Mason's (1978) expansion of the Effectiveness or Influence level, and finalized into six distinct aspects of information systems: System Quality, Information Quality, Use, User Satisfaction, Individual Impact, and Organization Impact (DeLone & McLean,1992).

The selection of empirical studies and which measures fit in which categories had an interrater agreement of over 90%. DeLone and McLean's (1992) conceptualization of IS success reflects a multidimensional construct of interrelated and interdependent categories while noting that, of the research literature reviewed, only roughly a quarter measured multiple categories and rarely more than two.

Updated D&M

After ten years of the model's use by many IS researchers (frequently as a common framework for positioning dependent variables), DeLone and McLean (2003) reviewed more than 100 articles from 1993 to mid-2000 to evaluate the model's usefulness and to update it in light of developments of IS practice. In their review, the authors report that 36 of 38 success factor associations tested in 16 different studies were found statistically significant, giving "strong support for the proposed associations among the IS success dimensions" (p. 15).

Based upon the ten years of follow-up research (including several articles that challenged, criticized or extended the D&M model), DeLone and McLean (2003) updated the dimensions (see *Figure 2-3)* to:

- Include Service Quality (as an additional system characteristic to System Quality and Information Quality) since IS organizations had emerged since the mid-1980s as a service provider in addition to being an information provider.
- Combine for increased parsimony Individual Impact and Organization Impact into Net Benefits (*net* because of combined positive and negative results) since there is clearly a "continuum of ever-increasing entities, from individuals to national economic accounts, which could be affected by IS activity" (p. 19); importantly, "it is impossible to define these 'net benefits' without first defining the context or frame

of reference" (p. 22) as well as the level of analysis (e.g., individual, organization, industry, nation).

- Include arrows to show "demonstrated proposed associations among success dimensions in a process sense, but does not show positive or negative signs for these associations in a causal sense" (p. 23); the causal relationships should be hypothesized as a part of any study's context.

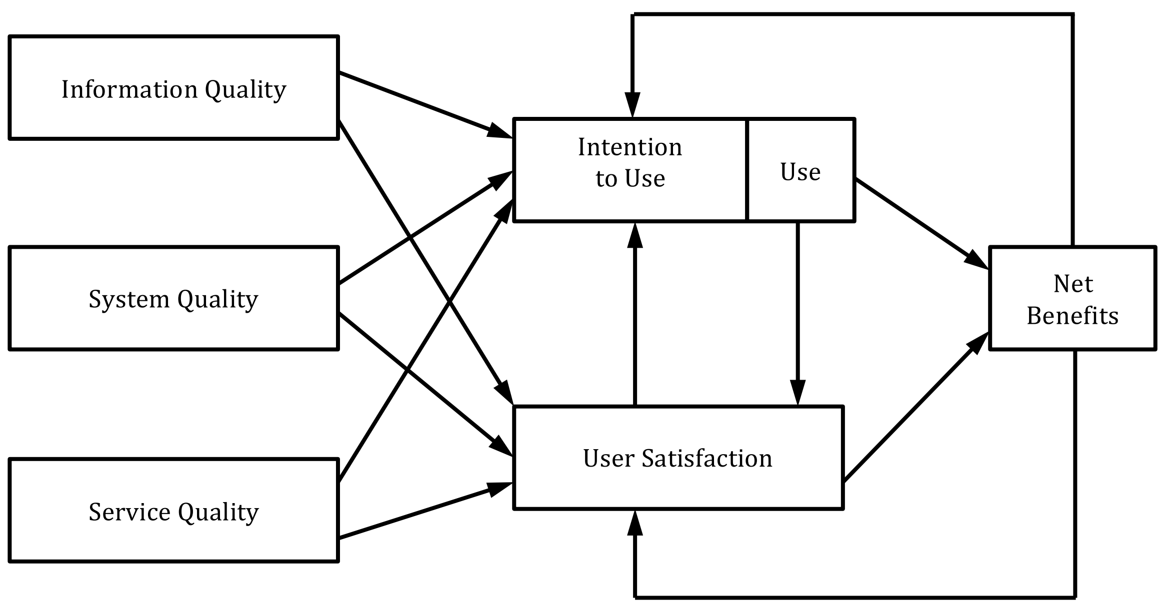


Figure 2-3. Updated D&M IS Success Model. From "The DeLone and McLean model of information systems success: A ten-year update," by W. H. DeLone and E. R. McLean, *Journal of Management Information System, 19*(4), p. 24. Reproduced with permission. Copyright © 2003 by Taylor & Francis Group.

Table 2-2 lists the dimensions and brief definitions for the updated DeLone & McLean model.

Table 2-2. Updated D&M Construct Definitions. Source; Petter, DeLone & McLean, 2008.

Updated D&M Constructs	Brief Definitions
System Quality	"[D]esirable characteristics of an information system. For example: ease of use, system flexibility, system reliability, and ease of learning, as well as system features of intuitiveness, sophistication, flexibility, and response times" (pp. 238-239)
Information Quality	"[D]esirable characteristics of the system outputs [...]. For example: relevance, understandability, accuracy, conciseness, completeness, understandability, currency, timeliness, and usability." (p. 239)
Service Quality	"[Q]uality of the support that system users receive from the IS department and IT support personnel. For example: responsiveness, accuracy, reliability, technical competence, and empathy of the personnel staff." (p. 239)
Use/Intention to Use	"[D]egree and manner in which staff and customers utilize the capabilities of an information system. For example: amount of use, frequency of use, nature of use, appropriateness of use, extent of use, and purpose of use." (p. 239)
User Satisfaction	"[U]sers' level of satisfaction with [outputs] and support services." (p. 239)
Net Benefits	"[E]xtent to which IS are contributing to the success of individuals, groups, organizations, industries, and nations. For example: improved decision-making, improved productivity, increased sales, cost reductions, improved profits, market efficiency, consumer welfare, creation of jobs, and economic development."(p. 239)

The revised model (DeLone & McLean, 2003) fully indicates the interrelationships between the revised dimensions:

- Quality has three major dimensions (Information Quality, System Quality, and Service Quality), which singularly or jointly affect Use and User Satisfaction.
- Intention to Use is offered as an alternative to Use because of the "difficulties in interpreting the multidimensional aspects of use – mandatory versus voluntary, informed versus uninformed, effective versus ineffective, and so on" (p, 23).
- Use and User Satisfaction are interrelated. Use must precede User Satisfaction, while greater User Satisfaction will lead to increased Intention to Use, and thus increased Use.
- Use and User Satisfaction result in Net Benefits, which need to be perceived as positive if the service is to continue. If Net Benefits are negative, the feedback loop to Use and User Satisfaction are still active – the lack of positive benefits likely leads

to decreased use and user satisfaction and ultimately the failure of the system or service.

Petter and McLean (2009) conducted a meta-analytic assessment involving 52 empirical studies utilizing the DeLone and McLean IS success model in the study of individual impacts. The meta-analysis found support for the majority of the implied hypotheses of the interrelationships among the dimensions within the model. The only unsupported hypotheses were associated with the Service Quality construct.

D&M in the Study of LMS

Though the D&M model has been applied in the context of many domains, it has received relatively little use in e-learning contexts (Klobas & McGill, 2010). As shown in *Appendix C*, roughly an equal number of studies of e-learning utilizing D&M use all six constructs and others use roughly half of them; the majority of studies adapt D&M by including additional variables (often the focus of the study) re-labeling constructs, and/or combining constructs.

Holsapple and Lee-Post (2006) adapted the D&M model to guide action research cycles focusing initially on a single e-learning module and then on the delivery of a single online course through an LMS. The adapted D&M model is used by these researchers to make explicit a process approach, where the success of the design stage is evaluated along System Quality, Information Quality and Service Quality; delivery stage success is evaluated along Use and User Satisfaction; and the outcome stage is evaluated along Net Benefits. A course satisfaction survey was constructed with items written by the researchers for each of the D&M dimensions; a standard course evaluation survey was given at the end of the course and those items were also mapped to the D&M dimensions. Students were also asked user characteristics questions related to their GPA, major, gender, opinion of e-learning, and met/unmet expectations. Neither factor analysis nor reliability and validity assessment were conducted. Statistical tests were limited to individual tests for the various user characteristics between online and tradition students and comparing the change in average survey ratings along the D&M dimensions between the last two implementation cycles.

Lin (2007) adapted the updated D&M model to study the determinants for successful use of online learning systems, but removed without explanation the concept of Net Benefits and the feedback effects to Use/Intention to Use and Usefulness.

Wang, Wang, and Shee (2007) adopted D&M to create a model for e-learning systems success (ELSS) in a corporate context. The researchers focused on instrument creation. 46 items representing the six D&M dimensions (System Quality, Information Quality, Service Quality, System Use, User Satisfaction, and Net Benefits) were taken from 23 articles in their review of the IS literature. The 46 items were reduced and revised down to 34 items with the assistance of four professors, three professionals and five managers. Two global measures were added (Perceived Overall Performance and Perceived Overall Success) as criteria along with demographic questions (e.g., management level, gender, age, years of work experience, education level). The survey was subjected to scale purification and reliability and validity assessment. An exploratory factor analysis resulted in a validation of the factor structure of the D&M dimension, though the study did not test the causal relationships among the model's dimensions.

Ozkan and Koseler (2009) greatly expand on D&M to evaluate e-learning more generally and well beyond the system being used, including issues such as student option of face-to-face versus distance education, perceived instructor effectiveness, perceived quality of course content, lectures, notes, and so on.

In a study of LMSs at a university, Klobas and McGill (2010) adopted the D&M model because they considered an LMS to be a type of IS. While utilizing all six constructs of D&M, the focus of their study was to add student and teacher involvement in the LMS (perceptions of importance and relevance of the LMS to the individual student or teacher in a particular course). They hypothesized that Student Involvement and student perception of Teacher Involvement would both positively affect student LMS Use, student Satisfaction with LMS, and Student Benefits. With regard to the D&M model, their findings "confirm the relationship between LMS quality and satisfaction, and satisfaction and benefits of LMS use" (p. 130). In terms of involvement, Student Involvement did not affect LMS Use (contrary to the original hypothesis), but student perception of Instructor Involvement did affect LMS Use, suggesting that instructor involvement plays an important role in determining how students use the system based upon instructor guidance (Klobas & McGill, 2010). The study further indicates a wider set of influences in system success should be considered beyond satisfaction and extent of use.

Almarashdeh, Sahari, Zin, and Alsmadi (2010), in the study of LMS success in Malaysian Universities' distance education, included concepts of TAM (with its emphasis on Perceived Usefulness, Perceived Ease of Use, and Intention to Use), inserting them as aspects of system design (along with System Quality, Information Quality, and Service Quality) into a D&M based model, while keeping the D&M emphasis on User Satisfaction and System Use, with Net Benefit as a system outcome; the combination resulted in what they called an Educational Technology Model (ETM). The researchers found empirical support for the model with almost all hypothesized relationships statistically significant.

Tella (2011) adapted D&M, adding Learning and Teaching Quality and Students' Self-Regulated Learning dimensions, and modifying Information Quality to the construct of Course Content Quality, but did not indicate how the two added dimensions fit in the model.

Lin and Chen (2012), in their work investigating satisfaction and continuance intention of e-learning systems, combine two constructs from D&M (System Quality, Information Quality) and two constructs from TAM (Perceived Usefulness and Perceived Ease of Use) into a model looking at the effects on Continuance Intention. In the study, Usefulness and Satisfaction both determined Continuance Intention; Usefulness and Ease of Use both affected Satisfaction.

Lin and Wang (2012), studying the antecedents for continued usage of blended learning instruction, proposed a research framework that combined system success factors from D&M (Information Quality, Knowledge Quality, and System Quality), the construct Task-Technology Fit (Goodhue & Thompson, 1995), and four constructs from Bhattacherjee's (2001) post acceptance model (Perceived Usefulness from TAM, System Satisfaction, Confirmation of System Acceptance (largely asking about intention), and Continue to Use Intention (with items asking about intention along with a general recommendation question about the e-learning system)). Continue to Use Intention is very similar to TAM's Behavioral Intention. Of the three D&M system success factors, only

Information Quality had a statistically significant impact on Confirmation of System Acceptance. All other parts of this amalgamated model were validated.

Wang, Doll, Deng, Park, and Yang (2013) loosely adapted D&M to focus on faculty doing online course development, dropping Information Quality and Service Quality, redefining System Quality as system configurability, and Use as implementing instructional design objectives.

With D&M, Mtebe and Raisamo (2014), in the context of LMS success in Sub-Saharan countries, renamed constructs for the educational learning context, changing Information Quality to Course Quality and User Satisfaction to Learning Satisfaction; Net Benefits was also changed to Perceived Benefits; in this case, the relationship between both System Quality and Service Quality with Learners' Satisfaction was found not significant.

The constructs of the D&M model echo several of the same issues reflected in the user evaluation key factors gleaned from publically available reports of LMS evaluations, especially around quality issues and perceived benefits. But while cited broadly in the IS success literature, it has seen more limited use on its own in LMS research. Many studies reflect a pattern across all the models of adding constructs in pursuit of an ever-growing list of critical factors that when added to the basic model may improve explanatory power; however, across studies there is no consistency in the added constructs.

Task-Technology Fit (TTF) – Technology Performance Chain (TPC) Model

Original TTF

Created to help with understanding user evaluations (UE) of information systems, task-technology fit (TTF) (Goodhue, 1995) proposes a "specific UE construct, defined within a theoretical perspective that can usefully link underlying systems to their relevant impacts" (p. 1827).

From a TTF perspective (Goodhue, 1995):

- Technology is a combination of the hardware, software, and data of computer systems and their accompanying support services.
- "Technologies are viewed as tools used by individuals in carrying out their tasks" (p. 1828).
- TTF is the extent of the match between technology functionality and both individual abilities and task requirements.
- A better match between tool functionalities (Technology), the requirements to complete Tasks, and the abilities of the Individual will lead to more effective or more efficient task accomplishment. In short, TTF impacts an individual's performance.
- Unless utilization of a system is voluntary for users, the model can remain simplified and not include the construct of utilization.
- If users use a technology as means to accomplish tasks, we might assume users capable of providing an informative evaluation of TTF from the context of their own experience, based on the degree that a technology's functionality meets their needs and abilities. In short, UE of TTF stand as a surrogate for actual TTF.

In the initial study of TTF (applied to the task domain of using quantitative information in managerial tasks, with data from 259 individuals in 9 companies) the four general propositions about what causes users to give higher or lower evaluations are (Goodhue, 1995):

- *"Proposition 1. Characteristics of information systems/services will affect UE of TTF"*

  Key to the efficacy of utilizing user evaluations as diagnostics, this proposition claims that UE is not random, but reflects "the objective characteristics of the systems and services available" (p. 1832).

- *"Proposition 2. Task characteristics will affect UE of TTF"*

  This proposition claims that as users' tasks are more various, difficult, interdependent, and complex, they "will place more demands on their information systems and [may] find them less able to meet their needs" (p. 1833).
  This implies that different kinds of users, with different kinds of tasks may likely have different evaluations of the same technology.

- *"Proposition 3. Individual skills and abilities will affect UE of TTF"* (p. 1834)

  This proposition claims that the difficulty for a particular task for a particular individual may vary depending on the individual's competency, training, or familiarity with the information system or technology in general.

- *"Proposition 4. The interaction between task and technology (and individual) will affect UE of TTF"*

  This proposition deals with the interaction of the technology and the task and the interaction of the technology and the individual. "Such interaction effects are the essence of what is meant by a 'fit' relationship" (p. 1834).

The questions asked of users in Goodhue (1995) were tied specifically to the task domain and asked users to rate the technology functionality the individuals actually used rather than rating systems characteristics in the abstract. The user was asked to measure each technology along multiple aspects, requiring very lengthy surveys; since any user can potentially use many technologies, there are as many units for analysis as individuals times technologies. Measurement validity analysis used Cronbach's alpha as an approach to winnowing measured dimensions. Discriminant validity was tested with LISREL in a confirmatory factor analysis.

The study found support for two key assertions needed for the utilization of UE of TTF as a measure of technology success (Goodhue, 1995):

- The value of a technology appears to depend on a user's tasks. Users view technologies as tools "which assist or hinder them" in their tasks (p. 1840).
- "Users appear to be capable of evaluating the task-technology fit of their technologies. User evaluations accurately reflect differences in the underlying systems and services provided to them" (p. 1840).

The Goodhue (1995) study concludes that for the practitioner, this "adds persuasive evidence that carefully developed user evaluations can provide fairly detailed diagnostics of information systems and services" (p. 1840).

Updated TTF – Technology Performance Chain (TPC)

Goodhue and Thompson (1995), recognizing an important missing dimension in their model, expanded TTF to the Technology Productivity Chain (TPC) (see *Figure 2-4)*, combining the original TTF model with theories of attitudes and behavior that focus on utilization; the researchers assert the new model is now consistent with the D&M IS Success model "in that both utilization and user attitudes about the technology lead to individual performance impacts" while retaining the TTF construct which is either missing or assumed in other models (p. 213).

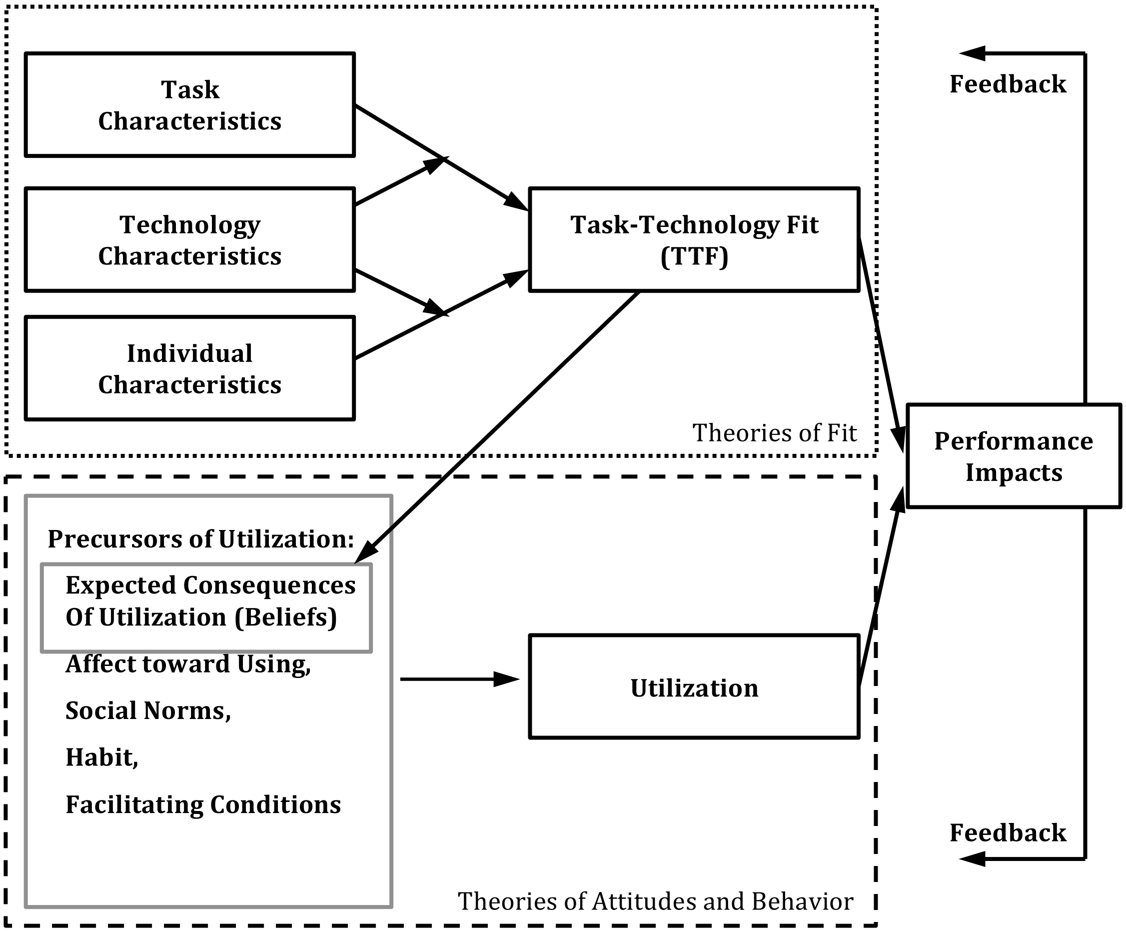


Figure 2-4. The Technology-to-Performance Chain. From D. L. Goodhue and R. L. Thompson, "Task-Technology Fit and Individual Performance," *MIS Quarterly 19*(2), p. 217. Copyright © 1995, Regents of the University of Minnesota. Used with permission conveyed through Copyright Clearance Center, Inc.

Goodhue and Thompson (1995) caution, however, about the limitations of the utilization focused models because utilization is not always voluntary. The researchers state (p. 216):

> To the extent that utilization is not voluntary, performance impacts will depend increasingly upon task-technology fit rather than utilization [… furthermore] more utilization will not necessarily lead to higher performance. Utilization of a poor system (i.e., one with low TTF) will not improve performance, and poor systems may be utilized extensively due to social factors, habit, ignorance, availability, etc., even when utilization is voluntary.

Feedback arrows (similar to the Updated D&M IS Success model) has been added in the TPC model as well, since with additional experience with the technology and the resulting performance impacts, users may conclude the system has better or worse impact than anticipated and/or may find better ways to use the system (affecting overall TTF), both of which affect future utilization (Goodhue & Thompson, 1995). See *Table 2-3* for TTF/TPC construct definitions.

Goodhue and Thompson (1995) were only able to test a subset of the model (including the core components of Task Characteristics, Technology Characteristics, Task-Technology Fit, Utilization, and Performance Impacts) in two different settings, one that had mandatory use and the other voluntary use; the study supported the proposition that "performance impacts are a function of both task-technology fit and utilization, not utilization alone" (p. 228).

Staples and Seddon (2004) tested additional aspects of the TPC model in voluntary and mandatory settings, including several precursors of utilization (Expected Consequences of Use, Affect Towards Use, Social Norms, and Facilitating Conditions) while leaving out precursors of Task-Technology Fit (i.e., the interactions between Task Characteristics, Technology Characteristics, and Individual Characteristics) because they had been well-tested in other studies. The researchers found that the relationships in the TPC model do vary under voluntary and mandatory situations: "The data confirm that when users do not have a choice about system use, their beliefs and feelings about such use may be largely irrelevant in predicting utilization" (pp. 28-29).

Table 2-3. TTF/TPC Construct Definitions.

TTF Constructs	Brief Definitions
Task Characteristics	"Task Characteristics of interest include those that might move a user to rely more heavily on certain aspects of the information technology" (Goodhue & Thompson, 1995, p. 216)
Technology Characteristics	"[T]echnology refers to computer systems (hardware, software, and data) and user support services (training, help lines, etc.) provided to assist users in their tasks" (Goodhue & Thompson, 1995, p. 216)
Individual Characteristics	Individual Characteristics "(training, computer experience, motivation) could affect how easily and well he or she will utilize the technology" (Goodhue & Thompson, 1995, p. 216)
Task Technology Fit	"TTF is the degree to which a technology assists an individual in performing his or her portfolio of tasks" ((Goodhue & Thompson, 1995, p. 216)
Performance Impacts	PI "relates to the accomplishment of a portfolio of tasks by an individual. Higher performance implies some mix of improved efficiency, improved effectiveness, and/or higher quality" (Goodhue & Thompson, 1995, p. 218)
TPC Additional Constructs	
Utilization	For "a single individual engaged in a portfolio of tasks, utilization becomes the percentage of her portfolio of tasks for which an individual chooses to use the technology" (Goodhue, 1997, p. 451). Also operationalized as overall dependence on systems (Goodhue, 1995).
Precursors of Utilization:	
Expected Consequences	"Beliefs about the consequences of use" (Goodhue & Thompson, 1995, p. 218)
Affect Towards Using	"Feelings about the consequences of using a system" (Staples & Seddon, 2004, p. 21)
Social Norms	A "person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein and Ajzen 1975, p. 302).
Habit	"A habit is an action that has been done many times and has become automatic. That is, it is done without conscious thought" (Ronis, Yates, & Kirscht, 1989).
Facilitating Conditions	Situational factors or constraints (Goodhue, Littlefield, & Straub, 1997)

Goodhue (1997) recognizes the conceptual link between Task-Technology Fit and Davis' (1989) concept of Perceived Usefulness, as both recognize that when successful, "technology provides the necessary functionality to perform the task at hand" (p. 451). On the other hand, Goodhue, Klein, & March (2000) differentiate TAM, which seeks to predict use, and other models, which seek to predict individual performance. Goodhue (1997) also argues that the TPC model is "consistent with that proposed by DeLone and McLean (1992) in that both utilization and user attitudes about the technology lead to individual performance impacts" (p. 449). The concept of Relative Advantage (Rogers, 1983) is also seen as closely associated with the notion of a particular technology fitting the task needs of individuals (Moore & Benbasat, 1992, as cited in Goodhue, 1997).

TTF/TPC in the Study of LMS

TTF/TCP has been recognized as broadly applicable to the study of a range of technologies and their impact on student performance (Cruz, 2009). In addition to use in the research of LMS, constructs of TTF/TPC have also been used in the study of other learning technologies such as student response systems (Jones II, 2010) and digital video tool use (Raven, Le, & Park, 2010), adapted to study specific technology characteristics of instructional materials (Nicholson, Nicholson, & Valacich, 2008), and even used to study general internet usage by students (Norzaidi & Salwani, 2009) and overall web technology features and their fit with instructional tasks (Strader, Reed, Suh, & Njorege, 2015). As documented in *Appendix D*, the majority of LMS studies do not use the constructs of Task Characteristics, Technology Characteristics, and Individual Characteristics. The constructs TTF, Performance Impacts, and Utilization are most commonly used, followed by Social Norms and Facilitating Conditions. McGill and various colleagues have been the most frequent users of TTF/TPC in the study of LMS.

McGill and Hobbs (2008) used the TPC model to study LMS task-technology fit and utilization in the performance impacts for both instructors and students, using parallel questions that, for example, changed the task from learning (for students) to teaching (for instructors); the researchers found both User Satisfaction and Task-Technology Fit were higher for students compared to the instructors. The researchers note that "student and instructor tasks differ and the interaction with the system required by instructors to complete their tasks is more complex than that required of students" (p. 197). These results support the early work of Goodhue (1995), where he states:

> All other things being equal, as users are engaged in more various, difficult, interdependent and "hands-on" tasks, they will place more demands on their information systems and find them less able to meet their needs, leading to lower user evaluations on many dimensions (p. 1833).

McGill and Klobas (2009) used TPC as a framework to look at how task-technology fit influences the performance impacts of LMS for students and found that

> the results provide strong support for the importance of task–technology fit, which influenced perceived impact on learning both directly and indirectly via level of utilization [… and c]ontrary to expectations, facilitating conditions and common social norms did not play a role in the performance impact of LMSs. However, instructor norms had a significant effect on perceived impact on learning via LMS utilization (p. 496).

Effect of instructor guidance is similar to what the researchers found in their use of D&M in studying LMS (Klobas & McGill, 2010). Basing their approach on the work of Staples and Seddon (2004), McGill and Klobas (2009) did not include Task Characteristics, Technology Characteristics, and Individual Characteristics, but included several Precursors of Utilization (Expected Consequences of Use, Attitude towards Use, Social Norms, and Facilitating Conditions). In general, the usefulness of the TPC model for the study of LMS was supported; common social norms were not found influential, but instructor norms (i.e., guidance) did have a positive influence; Facilitating Conditions did not play a differentiating role, perhaps because in this study "the LMS was well established and stable, and students had relatively high levels of experience with it" (p. 504). Perceived Impact on Learning was not found to influence student grades; a possible weakness of this study, however, was the measure for student grade, since it was a single student reported percentage grade of the most recent test, exam, or assignment. Again, overall the study showed the potential usefulness of TPC in the study of LMS, though it had individual users as the unit of analysis and asking their general views on the LMS overall, rather than having users rate each of the portfolio of tools in an LMS on multiple aspects as the original TTF/TPC research did (e.g., Goodhue, 1995; Goodhue, Littlefield, & Straub, 1997; Goodhue & Thompson, 1995; Staples & Seddon, 2004).

In a related study, McGill, Klobas, and Renzi (2011) utilized TPC to study LMS task-technology fit and utilization in the performance impacts for instructors. Testing a reduced model (including only the constructs of Task-Technology Fit, Social Norms, Facilitating Conditions, Utilization, and Performance Impacts), the study took a closer look at LMS Utilization by instructors, the effects of Task-Technology Fit and Utilization on LMS Performance Impacts, and the effects of two precursors to Use: Social Norms (expectancy that instructors will use the LMS) and Facilitating Conditions (organizational support for system use). The study produced unexpected results in that the only strong relationship was between Task-Technology Fit and LMS Performance Impacts.

Yu & Yu (2010), attempting to model factors that affect individuals' utilization of online learning systems, combined four constructs based on TTF/TPC (Technology Characteristics, Individual Characteristics, Learner-Technology Fit, and Learning Utilization) with four constructs from Ajzen's (2002) theory of planned behavior (TPB) -- (Attitude, Social Influences, Perceived Behavioral Control, and Behavioral Intention). Eight of nine causal paths of the model were found to be statistically significant. The researchers claimed that combining TPB and TTF constructs provides a better model than either of the two models does separately, though no statistical analysis was provided to support the claim.

Additional studies have adapted other theoretical models by adding the TTF construct, in addition to ones mentioned in prior sections on TAM/TAM2 (Baleghi-Zadeh et al., 2014b; Ma, Chao, & Cheng, 2013) and D&M (Lin & Wang, 2012). Larsen, Sørebø, and Sørebø (2009), looked at the role of TTF as users' motivation to continue information system use in e-learning by adding the constructs of TTF and Utilization to Bhattacherjee's (2001) post-acceptance model (which included Perceived Usefulness from TAM). Lin (2012), in looking at web learning performance with a virtual learning system, combined two constructs from TPC (TTF & Performance Impacts) with two constructs from Bhattacherjee's (2001) post-acceptance model (Satisfaction and Continuance Intention). Baleghi-Zadeh et al. (2014a), in exploring views of LMS by Malaysian higher education students, posed questions about the construct TTF along with Internet Experience and Subjective Norms; in a comparison of means, TTF was the lowest scoring and, furthermore, no testing of interrelationships among the constructs was conducted.

As Goodhue (1998) states, "TTF measures are intended to assess all systems and services of the IS department" (p. 127), and may be an appropriate model to study the suite of tools (and services) that comprise an LMS. In LMS studies (and even studies in the IS literature), however, only partial models have been tested. In LMS studies in particular, the three Characteristics constructs (Task, Technology, and Individual) have often been left out. McGill and colleagues have largely been the only researchers to use TTF/TPC in multiple studies; otherwise, Task-Technology Fit has been a construct added on to other models to help provide additional task orientation. Though spottily used in LMS research, TTF/TPC's core notion that LMSs, if they are to succeed, should match up with teaching and learning tasks and lead to performance impacts, is a concept that aligns at face value with the intent of most LMS selection/decision contexts. However, in the LMS research, users rate system characteristics in the abstract, rather than rating each technology along multiple aspects; and the unit of analysis is the individual rather than individuals times technologies, as was the case in the original research on TTF (Goodhue 1995) and TPC (e.g., Goodhue & Thompson, 1995; Goodhue, Littlefield, & Straub, 1997).

Summary

The most frequently used Information Success (IS) models in LMS academic research are derived from the Technology Acceptance Model (TAM) (Davis, 1993; Davis, Bagozzi, & Warshaw, 1989; Venkatesh & Davis, 2000), the DeLone and McLean IS Success Model (D&M) (DeLone & McLean, 1992, 2003) and the Task-Technology Fit Model (TTF) (Goodhue, 1995, 1997; Goodhue & Thompson, 1995).

TAM, an adaptation of the Theory of Reasoned Action (Ajzen & Fishbein, 1980), originated with the purpose of gathering user evaluations after brief exposure to a system. The core constructs are Perceived Usefulness and Perceived Ease of Use and their impact on Behavioral Intent to Use and, ultimately, Actual Use. Perceived Usefulness is considerably more important than Perceived Ease of Use in determining Predicted Use, though Ease of Use does impact Predicted Use indirectly through Perceived Usefulness.

The model is considered parsimonious, though perhaps too simplistic. An original generic construct in TAM for External Variables was replaced with several external variables involving social influences and cognitive instrumental processes, which are affected by the experience a user gains over time and whether system use is required or voluntary. Still further model iterations have brought on additional constructs (e.g., Venkatesh, Morris, Davis, & Davis, 2003), though resulting in confusion over which version or iteration is best to use (Benbasat & Barki, 2007). Agudo-Peregrina, Hernández-García, and Pascual-Miguel (2014) found more complex TAM models do "not offer a much better explanation than previous and more parsimonious models, such as TAM, TAM2" (p. 310). Furthermore, TAM has also been frequently criticized for its lack of task focus (e.g., Dishaw & Strong, 1999; Goodhue, 2007; Nance & Straub, 1996; Schoonenboom, 2014) as well as questioned for its appropriateness in situations with mandatory use (Bradley, 2012; Brown, Massey, Montoya-Weiss, & Burkman, 2002; Goodhue, Klein, & Marsh, 2000; Koh, Prybutok, Ryan, & Wu, 2010).

Use of TAM in LMS studies has largely been limited to using initial TAM constructs and the added construct Social Norms. LMS studies (as well as further studies in the IS literature) often add additional constructs to reflect the particular setting or the particular context of use, though nothing consistent across the many studies. There are also limited examples of bringing in constructs explicitly from D&M and TTF, though usually without a strong theoretical basis except to point out that the added construct(s) come from other established models. The notions of Usefulness and Ease-of-Use are frequently found in LMS selection/decision settings, gauging by publically available reports, but without any reference to the TAM model itself.

The D&M model was created out of a review of the range of dependent variables used in conceptual and empirical studies in IS research and were categorized based on a model adapted from Shannon and Weaver's (1949) communication theory. D&M emphasizes the idea that IS success reflects a multidimensional model of interrelated and interdependent constructs. As reflected in the updated D&M model, quality has three major dimensions (Information, System, and Service), which affect Use and User Satisfaction, which ultimately lead to Benefits (to the individual and beyond). In both IS and LMS academic literature, more often than not only partial models are studied. As with the use of TAM, in most D&M studies additional constructs are added base on the particular context or research interest. The focus on quality and benefits echoes institutional reports on LMS selection.

The original TTF Model was created to help understand user evaluations of systems (and even a portfolio of systems and services) with the assumption that users are capable of providing an informative evaluation of the extent of the match between system functionality and both task requirements and their individual abilities. The expansion of the model to the Task Performance Chain (TPC) adds theories of attitudes and behavior that focus on utilization, which resolved the criticism from other researchers (e.g., Dishaw & Strong, 1999) that the original TTF model lacked utilization and attitudes towards information technology. In TPC, both the TTF construct and Utilization lead ultimately to Performance Impacts. As with the other models, because of complexity research almost always utilizes a partial model. Though perhaps its research may still be in its "divergence phase" (Cane & McCarthy, 2009, p. 121) and less developed than the other two models, in recent years TTF/TPC has received additional attention (Furneaux, 2012). The approach has also been used in studying other teaching and learning technologies in addition to the LMS, and research has been conducted taking the one TTF construct and adding it to other adaptations of the TAM and D&M models. To provide shorter surveys, the unit of analysis moved from individuals times technologies to individuals, with users rating the LMS system more in the abstract rather than rating each LMS tool or feature along multiple aspects.

Overall, in the review of technology success models in this study, a few key trends emerge:

- No one model has emerged as a definitive model for the study of IS success in general or LMS success specifically, though TAM may be the most prevalent.
- In the literature, it is a common occurrence to see only partial models tested with customizations adding constructs based on the technology in question, the specific context and goal of the study, and the conceptual basis of the study; however, there is no particular trend across the added constructs.
- Though generally dealing with issues affecting technology adoption, none of the LMS studies are in the specific context of conducting pilots with user evaluations as a part of an institution's evaluation and decision process.

All three models have found a place in the study of LMS and have the potential of informing the use of user evaluations in a higher-ed LMS decision context. There appears to be lacking any direct connection between the academic literature and the selection/decision processes conducted at institutions, since institutional reports do not reference any models, and LMS academic research has not been conducted in a decision context. At the same time, topics such as ease of use, usefulness, quality, utilization, and impact are common themes in both the academic research and the public institutional reports. Furthermore, the three models in their updated forms have not had a close comparison before and all three have not had shared data with which to analyze them more closely.

CHAPTER 3: METHODOLOGY

The purpose of this study was to examine whether one or more of the most prevalently used IS acceptance and success models in the study of LMS provides relative utility and useful nomenclature for framing and interpreting the results of user evaluations generated in the context of a higher education institution's LMS adoption process.

Based upon a review of LMS literature and the origins of the IS acceptance and success models used in that research, the following research questions were examined in the study:

1. What is the utility of the Technology Acceptance Model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?
2. What is the utility of the IS Success Model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?
3. What is the utility of the Technology to Performance Chain model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?
4. What is the relative utility of the three models in their applicability to analyze and interpret the user evaluations generated in the context of a higher education institution's decision for or against a new LMS?

Design of the Study

This study conducted comparison testing of TAM2, updated D&M, and TPC models using existing data from a cross-sectional survey study conducted in a higher education

LMS selection/decision process. Content analysis was used to map survey items to model constructs as well as to analyze open-ended question responses. Model testing and comparison utilized partial least squares based structural equation modeling (PLS-SEM) methodology. *See Table 3-1* to see a summary of the research questions, data sources, and analysis methods.

Data Sources

The study used secondary data from an IRB approved study, utilizing student survey data collected during the piloting of an alternative LMS at a large, U.S. Midwestern, multi-campus public institution of higher education (see *Appendix E* for the survey questions). LMS pilots conducted in actual courses over the period of an entire academic semester provide rich data specifically used as an important component of the institution's LMS decision process. 895 students across 25 courses participated in an LMS pilot, with a student survey response rate of 22 percent (197/895). Participant demographic characteristics are listed in *Table 3-2* and course characteristics for participants are listed in *Table 3-3.*

The student survey included closed-ended and open-ended questions related to the users' experience of the alternative LMS, providing the opportunity to use the constructs from the IS models for both qualitative and quantitate analysis. For this study, student data was preferred over faculty data because the LMS pilot student sample size (197) was many times higher than faculty sample size (14 of 25), providing a much larger number of user responses for qualitative analysis and providing greater statistical power for the quantitative analysis.

Table 3-1. Summary of Research Questions, Data Sources, And Analysis Methods

Research Questions	Data Sources	Analysis Methods
What is the utility of the Technology Acceptance Model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?	Existing student survey data of an LMS pilot evaluation*	a. Open-ended survey question responses coded using TAM constructs. b. Content analysis is used to map survey question items to TAM2 constructs. c. PLS-SEM analysis of the measurement model. d. PLS-SEM analysis of the structural model. e. Result of constructs' causal relationships compared to prior research.
What is the utility of the IS Success Model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?	Existing student survey data of an LMS pilot evaluation*	a. Open-ended survey question responses coded using updated D&M constructs. b. Content analysis is used to map survey question items to updated D&M constructs. c. PLS-SEM analysis of the measurement model. d. PLS-SEM analysis of the structural model. e. Result of constructs' causal relationships compared to prior research.
What is the utility of the Technology to Performance Chain Model's constructs in explaining and interpreting the results of user evaluations of an LMS in a higher-ed adoption context?	Existing student survey data of an LMS pilot evaluation*	a. Open-ended survey question responses coded using TPC constructs. b. Content analysis is used to map survey question items to TPC constructs. c. PLS-SEM analysis of the measurement model. d. PLS-SEM analysis of the structural model. e. Result of constructs' causal relationships compared to prior research.
What is the relative utility of the three models in their applicability to analyze and interpret the user evaluations generated in the context of a higher education institution's decision for or against a new LMS?	Summary results of TAM2, updated D&M, and TPC model analysis.	Compare and contrast: a. The qualitative results, including the number of open-ended question responses codable with constructs and the number of constructs used when coding responses. b. The quantitative results, including constructs' causal relationships, predictive relevance, and comparisons to prior research.

* Secondary data from an IRB approved student survey gathered during the piloting of an alternative LMS at a large U.S. Midwestern higher education institution.

Table 3-2. Pilot Study Survey Participants' Demographic Characteristics

Demographic Characteristics	Frequency	Percentage
Gender (N=195)		
Female	123	63%
Male	71	36%
N/A	1	
Age (N=195)	Range 18-62	
Greatest identifier	18-25 yrs old	69%
Campus (N=196)		
From a large campus	143	73%
From a small campus	53	27%
Academic level (N=197)		
1st year undergraduate	29	15%
2nd year undergraduate	53	27%
3rd year undergraduate	30	15%
4 or more years undergrad	66	34%
Masters	12	6%
Doctoral	7	4%

Table 3-3. Pilot Study Participants' Course Characteristics

Course Characteristics	Frequency	Percentage
Course Discipline (N=176)		
Business	10	6%
Chemistry	42	24%
Computer Science	19	11%
Engineering	2	1%
English	10	6%
Organizational Leadership	35	20%
Philosophy	5	3%
Psychology	4	2%
Social Work	11	6%
Sociology	7	4%
Sports Management	8	5%
Other	23	13%
Course format (N=195)		
Face-to-face	113	58%
Hybrid	45	23%
Fully online	33	17%
Other	4	2%

Models to Test

Based upon the literature review, three models were used for the comparative analysis: the Technology Acceptance Model 2 (TAM2; see *Figure 3-1*), the updated D&M IS Success Model (see *Figure 3-2*), and the Task-Performance Chain model (TPC; see *Figure 3-3*).

Utilizing the survey data, this research attempted to answer if one (or more) of the examined models exhibits relatively greater utility compared to the others in its applicability to analyze and interpret the user evaluations generated in the context of a higher education institution making a decision for or against a new LMS.

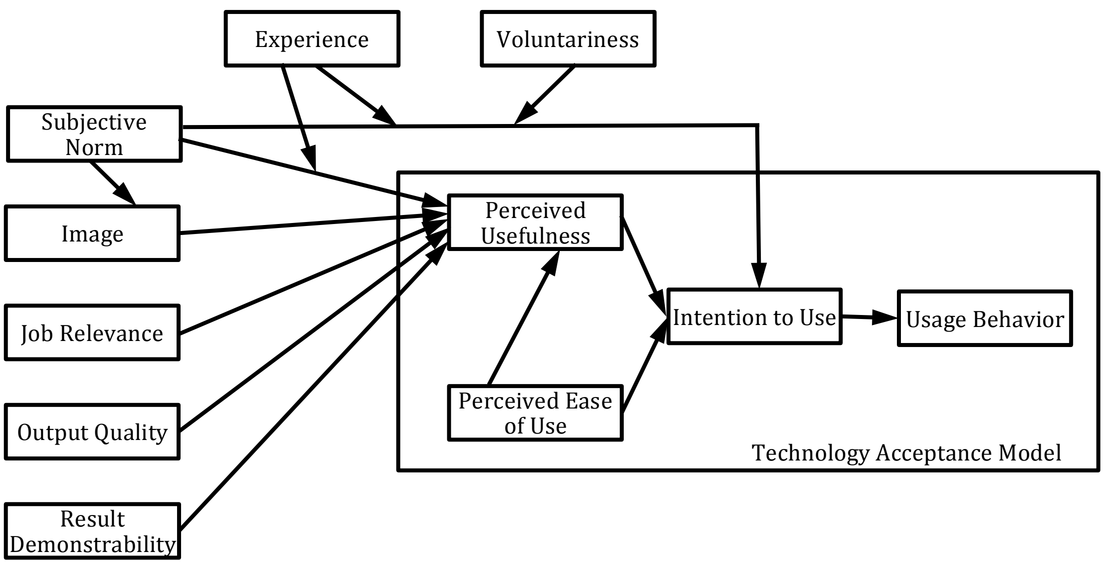


Figure 3-1. TAM2 – Extension of the Technology Acceptance Model. From “A theoretical extension of the technology acceptance model: Four longitudinal field studies,” by V. Venkatesh and F. D. Davis, *Management Science, 46*(2), p. 188. Reproduced with permission. Copyright © 2000, INFORMS.

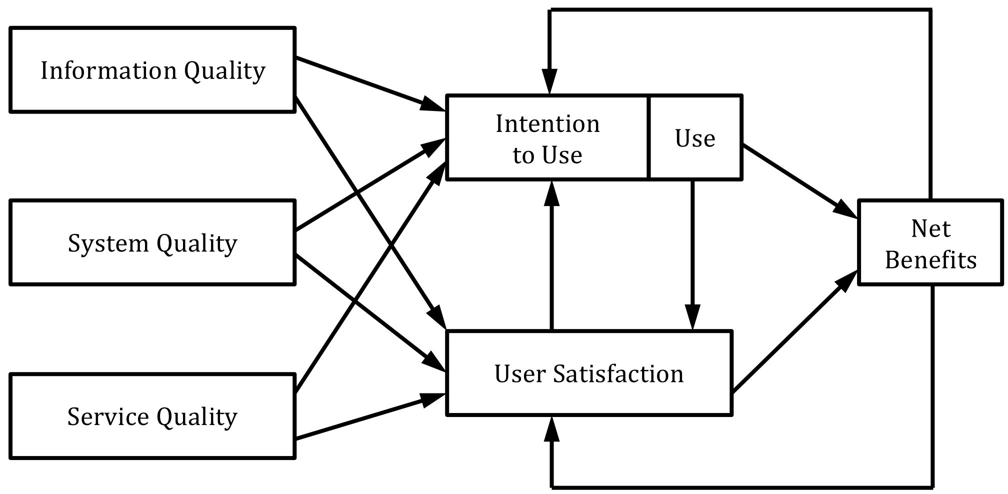


Figure 3-2. Updated D&M IS Success Model. From "The DeLone and McLean model of information systems success: A ten-year update," by W. H. DeLone and E. R. McLean, *Journal of Management Information System, 19*(4), p. 24. Reproduced with permission. Copyright © 2003 by Taylor & Francis Group.

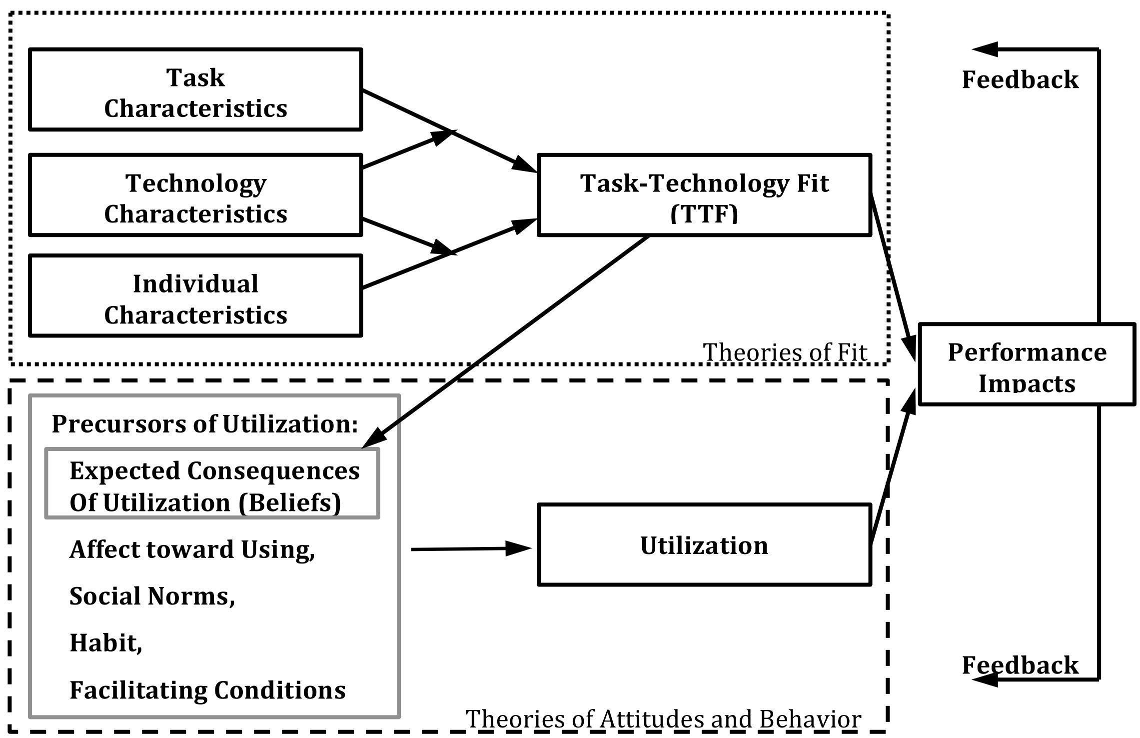


Figure 3-3. The Technology-to-Performance Chain. From D. L. Goodhue and R. L. Thompson, "Task-Technology Fit and Individual Performance," *MIS Quarterly 19*(2), p. 217. Copyright © 1995, Regents of the University of Minnesota. Used with permission conveyed through Copyright Clearance Center, Inc.

Mapping Survey Data Using Content Analysis

Using secondary data and with a good understanding of a model's latent variables, researchers can rely on the wording of questionnaire items (Rigdon, 1998). This study conducted a content analysis of questionnaire items compared to model construct definitions (Krippendorff, 2004). As shown by Fathema and Sutton (2013), a directive content analysis approach can begin with a predefined theory, where the constructs provide *a priori* coding categories with which to conduct the analysis (Hsieh & Shannon, 2005).

A content analysis of users' answers to open-ended questions was conducted against each model's constructs and definitions. The number of classifiable answers is one indication of a model's usefulness as well as the number of a model's constructs used in the analysis. Two coders, with prior research experience in content coding, analyzed the open question answers after familiarizing themselves with the questions and responses. After initial coding, a crude agreement index was calculated for the agreement among the coders, who then discussed the differences in their views. After the discussion, the coders came to further agreement and revise their coding accordingly.

In an analogous manner, the closed-ended survey questions were mapped to each model's constructs, using construct definitions and sample question items from prior research (both the original model researchers and the LMS researchers who have adapted the models). A mapping guide consisting of each model's constructs and their definitions and sample questions from the literature were given to three coders. Coders coded one model at a time. After initial coding to each model, a crude agreement index was calculated for the agreement among the coders, who then discussed the differences in their views.

After the discussion, the coders came to further agreement and revised their coding accordingly. There could be questions that cannot be mapped against any of the constructs of a particular model, which would be one indicator of the utility of each model in the LMS decision context. It is quite likely that only partial models would result for testing; however, nearly all of the IS research and LMS research using the models utilize partial models.

Data Analysis using PLS-SEM

After survey questions have been mapped to each models' constructs, statistical analysis of each model and its constructs was conducted using the existing LMS user survey data, and the results of each analysis are described, as well as compared and contrasted. Explanation of endogenous variables and their interrelationships, significant paths, and effect sizes for each model would be another indicator of each model's possible utility in the LMS decision context.

The conceptualization of IS success reflects a multidimensional construct of interrelated and interdependent categories (DeLone & McLean, 1992). As Goodhue, Littlefield and Straub (1997) point out, an "effective test of [a] model requires being able to test simultaneous impacts of several constructs on another construct" (p. 459). SEM statistical methods model causal networks of effect simultaneously; "measures and structures are tested together and all of the indicators in the measures are fully accounted for" (Lowry & Gaskin, 2014, p. 129). Other researchers (e.g., Kang, 2015) have used SEM analysis of secondary data mapped to constructs to test a model.

PLS-SEM is an alternative to covariance-based SEM (CB-SEM) and has become more recently "a key research method" (Hair, Hult, Ringle, & Sarstedt, 2014, p. xii). PLS-SEM focuses:

> on the **prediction** of a specific set of hypothesized relationships that maximizes the explained variance in the dependent variables, similar to OLS regression models. Therefore, the focus of PLS-SEM is more on prediction than on explanation. (p. 78)

There are prior examples of PLS-SEM being used in the study of IS success models. For example, Chin (1998), in an explanatory book chapter on PLS-SEM, used a TAM study as a concrete example; Van Raaij and Schepers (2008) used PLS-SEM in their LMS study of the TAM model; McGill and Klobas (2009) used PLS-SEM in their LMS study of the TPC model. All of these PLS-SEM based studies use a reflective measurement model, where all items are modeled as reflective indicators that are considered as effects, rather than causes, of latent variable constructs.

For this study, PLS-SEM is preferred over CB-SEM because of the greater ability to deal with relatively small sample sizes. Furthermore, PLS-SEM is also considered a good alternative to CB-SEM for handling several other aspects of this study: its exploratory nature (in this case, mapping secondary data survey questions to multiple models' constructs to create measurement models); the likelihood of nonnormal distribution of answers to quality and satisfaction questions about LMS; the likelihood of single items mapping to a model's latent constructs; the complexity of the models under consideration; and, the ability of PLS-SEM to handle such situations as well as provide a higher level of statistical power (Hair et al., 2014). Therefore, for each model, data from the mapped close-ended survey questions was analyzed using a partial least squares structural equation modeling (PLS-SEM) approach. See *Appendix F* for a glossary of PLS-SEM related terms.

As documented by Hair et al. (2014), a SEM-PLS analysis is a two-step process, where the measurement model is tested and reliability and validity of constructs are established in the first step and the structural model is tested in the second step. Following recommendations by Hair et al. (2014), the following parameter settings were used with PLS-SEM (v. 3.2.3; Ringle, Wende, & Becker, 2015): a path weighting scheme as the weighting method; a stop criterion of $1 \cdot 10^{-7}$; 300 or more as maximum number of iterations to ensure convergence; mean replacement algorithm to handle missing data; and +1 for the initial value of all outer weights.

To use SEM-PLS, one should meet estimates of minimum sample size. The study used G*Power 3.1.9 (http://www.gpower.hhu.de/en.html) (Faul, Erdfelder, Buchner, & Lang, 2009) with settings recommended by Hair et al. (2014) and Ringle, Silva, & Bido (2014) of 'F-tests: Linear multiple regression for fixed models, R^2 from zero,' type of analysis 'A priori: Compute required sample size – given α, power and effect size,' power of 0.80, effect size $f^2 = 0.15$, $\alpha = 0.05$, and the highest number of predictors within each model. As noted by Ringle, Silva, and Bido (2014), having double or triple the resulting minimum sample sizes will lead to more consistent models.

Evaluating the Measurement Model

The measurement model analysis examines the relationship between the constructs and the corresponding indicator variables; in PLS-SEM the measurement model is also referred to as the outer model (Hair et al., 2014).

Composite Reliability: Following recommendations by Hair et al. (2014) for evaluating the reflective measurement model, composite reliability (which measures the level of internal consistency reliability of a constructs indicators, based on outer loadings) should attain values above 0.60 and preferably above 0.70. Composite reliability below 0.60 indicates a lack of internal consistency reliability. Outer loading for indicators should generally be higher than 0.708; with outer loadings between 0.40 and 0.70, indicators should be examined and considered for removal (though sometimes are retained because of their contributions to content validity); and indicators below 0.40 should definitely be eliminated; at a minimum, outer loadings for indicators should be statistically significant.

<u>Testing for Statistical Significance</u>: Statistical significance is tested in SEM-PLS through the bootstrapping procedure. As noted by Hair et al. (2014), "PLS-SEM does not assume the data are normally distributed, which implies that parametric significance tests used in regression analysis cannot be applied to test whether coefficients such as […] outer loadings and path coefficients are significant" (p. 130). Instead, bootstrapping is used, which uses a large number of data subsamples (typically 5,000) to estimate the model; indicator outer loading estimates are used to derive standard errors for the estimates, with which *t* values are calculated to assess the statistical significance of the indicator's outer loading. Following the recommended settings by Hair et al. (2014), PLS-SEM bootstrapping was run on the models with 5,000 Subsamples, No Sign Changes, and Bias-Corrected and Accelerated Bootstrap, which provide the most conservative and stable results; also Test Type was set to Two Tailed at a Significance Level of 0.05.

<u>Convergent Validity</u>: To test convergent validity, which indicates the extent a measure has a positive correlation with alternative measures of the same construct, one should examine the average variance extracted (AVE) (Hair et al., 2014). AVE is the average of the indicator reliabilities for a construct and AVE values should not be below 0.50.

Discriminant Validity: Following recommendations by Hair et al. (2014) to test discriminant validity (which tests whether a construct is distinct from other constructs), two criterion should be examined: a) outer loadings of an indicator for a construct should be higher than all its cross loadings with other constructs, and b) the square root of the AVE of each construct should be higher than its highest correlation with any other construct (also known as the Fornell-Larcker criterion).

Evaluating the Structural Model

Following recommendations by Hair et al. (2014), to evaluate the structural model with SEM-PLS, there is not a single goodness of fit measure, but rather several heuristic criteria determined by the model's predictive capabilities:

- Assess for collinearity issues by examining the Variance Inflation Factor (VIF) for each predictor variable for levels above 5.00, and if higher possibly eliminating constructs, merging predictors into a single construct, or creating higher order constructs;
- Assess the significance of path coefficients through the PLS Bootstrapping procedure, with the number of bootstrap samples at least as large as the number of observations, but preferably 5,000; in addition, assess the relevance of the structural model relationships by examining the relative importance of path coefficients and the direct and total effects of constructs;
- Assess the level of the coefficient of determination (R^2 value) of the latent endogenous variables, with higher levels indicating higher levels of predictive

accuracy; values of 0.25, 0.50, and 0.75 are considered, respectively, weak, moderate, and substantial.

- Assess the model's predictive relevance through the blindfolding procedure, which is a "resampling technique that systematically deletes and predicts every data point of the indicators in the reflective measurement model of endogenous constructs." (p. 198-199). As noted by Hair et al. (2014), the Stone-Geisser's Q^2 value, which should be greater than zero, adds to the analysis of the size of the R^2 values by testing for predictive relevance.
- Assess the effect sizes: a) f^2, which indicate the substantive impact of latent endogenous constructs, reflecting the "change in the R^2 value when a specified exogenous construct is omitted from the model" (p. 177), and b) q^2, which in a similar fashion indicates the relative impact of the predictive relevance of constructs. For effect sizes, values of 0.02, 0.15, and 0.35 are considered, respectively, small, medium, and large.
- Test for unobserved heterogeneity. As noted by Hair et al. (2014), heterogeneity of observations is a "threat to the validity of PLS-SEM results" (p. 199) and "[u]nfortunately, the presence of heterogeneity in a sample can never be fully known a priori" (p. 184). An approach to identifying unobserved heterogeneity in SEM-PLS is finite mixture partial least squares (FIMIX-PLS) which is recommended for routine use to evaluate whether results are potentially distorted. FIMIX is run multiple times, with each run specifying a specific and increasing number of hypothetical segments; the results provide a number of indices; smaller values indicate better solutions (Rigdon, Ringle, Sarstedt, & Gudergan, 2011). If the analysis

using only one segment has the lowest values, that would indicate that unobserved heterogeneity is likely not an issue.

- While models with greater numbers of constructs may lead to higher values, parsimony should also be valued as well. Following recommendations by Hair et al. (2014), the study will use the adjusted R^2 value (R^2_{adj}) when comparing models with different exogenous constructs in order to avoid bias toward complex models.

CHAPTER 4: RESULTS

This chapter addresses the results of the study in two main parts: (a) qualitative analysis of the coding of unitized responses to open-ended survey questions using the constructs of the three models, and (b) quantitative results of the PLS-SEM analysis of the three models using as latent variable indicators the closed-ended survey items that have been mapped to the models' constructs.

Qualitative Analysis

A content analysis (Krippendorff, 2004) of users' answers to open-ended questions was conducted against each model's constructs and definitions. Open-ended responses from a different, small LMS pilot were used to practice unitizing the responses as well as coding responses against each of the three model's constructs. After initial coding, a crude agreement index was calculated for the agreement among the coders, who then discussed the differences in their views. After the discussion, the coders reached further agreement and revised their final coding accordingly.

The number of responses to open-ended questions in the actual pilot study was 148 for Q14 (What did you like MOST about [the pilot LMS]? Why?), 156 for Q15 (What did you like LEAST about [the pilot LMS? Why?], and 55 for Q18 (Is there anything else you would like to tell us about your experience using [the pilot LMS] this semester?), for a total of 359 responses. The two coders initial agreement on unitizing was 298 of 359 responses (83%). After discussing responses with differing numbers of initial units, the coders reached consensus, creating a total of 615 units.

Coding of Unitized Responses to Open-Ended Survey Questions

At the end of each practice coding session, initial guidelines were summarized out of the consensus discussion. The guidelines were neither meant as exhaustive nor always strictly touching on the same issues across all three models, but represented more how the coders resolved particular issues that arose while walking through the sample response units each time. The initial guidelines are summarized in *Table 4-1*. See *Appendix G* for examples of unitized sample responses and their coding.

Table 4-1. Summary of Guidelines from Practice Coding Sessions of Open-Ended Response Units

TAM
Easy/Difficult to learn - Perceived Ease of Use Navigation/Organization/Layout - Perceived Ease of Use Mention of specific features - tends to be Perceived Usefulness Comparison on specific feature/capability - Perceived Usefulness Convenience - Perceived Usefulness Grades, content, or information “up to date” - Output Quality General attitude statement - Attitude Statement of clear preference between systems - Attitude Challenge of using two LMSs - [none]
D&M
Layout, Navigation, Ease of Use, Usefulness - System Quality Comparison on specific feature/capability - System Quality Outputs, Confirmation, Notification, Accuracy, Completeness - Information Quality Statement of clear preference between systems - Satisfaction Challenge of using two LMSs - [none]
TPC
Look, layout, etc. - [none] Navigation, organization, etc. - Task-Technology Fit Ease of use, ease of learning - Task-Technology Fit Feature - Task-Technology Fit Statement of clear preference between systems - Affect Towards Using Challenge of using two LMSs - Facilitating Conditions

TAM Coding of Open-Ended Response Units

Following the guidelines that resulted from the practice coding walkthroughs and using the TAM construct definitions and sample research questions, two coders coded the 615 open-ended response units. The two coders initial agreement on coding was 492 of

615 responses (80%). The two coders discussed each unit for which they had provided different codes, until reaching consensus.

In total, 486 (79%) of response units were matched with constructs, while 129 (21%) of response units could not be matched to any construct. 463 (75.3%) of the response units were coded to constructs from the original TAM model. Only 23 (3.7%) of the response units were coded to additional constructs added in the TAM2 model. Five TAM2 constructs remained unused through the entire coding process.

Overall, the Perceived Ease of Use (PEU) construct garnered the highest number of coded response units, 244 (39.7%), which was more than double than the next two – 102 (16.6%) for Perceived Usefulness (PU) and 106 (17.2%) for Attitude Towards Using (A). The seven statements that referred to prior use of the pilot system were classified to Experience.

The following units were not coded to any TAM construct: 45 statements referring to technical issues (such as bugs and glitches, system speed/responsiveness); 43 units referring to the difficulty for students to use multiple LMSs, with the pilot system used for only one of several courses; the few statements that referred to the prior use and familiarity of the institution's current LMS (and based on that led to preference of the current system); the few statements about the instructor's experience level with the pilot system; the few statements about entirely different systems.

A summary of the TAM coding of open-ended response units is in *Table 4-2*.

Table 4-2. Summary of TAM Coding of Open-Ended Response Units

Constructs: TAM	*Q14 (liked most)*	*Q15 (liked least)*	*Q18 (anything else)*	*Overall*	*Count*
Perceived Ease of Use	34.4%	47.2%	28.3%	39.7%	244
Perceived Usefulness	31.3%	9.8%	9.7%	16.6%	102
Attitude Towards Using	22.1%	11.4%	24.8%	17.2%	106
Perceived or Actual Usage	1.5%	0.7%	1.8%	1.1%	7
Behavioral Intention to Use	0.0%	0.0%	3.5%	0.7%	4
Constructs: Added in TAM2					
Output Quality	0.0%	4.6%	1.8%	2.6%	16
Experience	1.5%	0.7%	1.8%	1.1%	7
Voluntariness	-	-	-	-	0
Subjective Norm	-	-	-	-	0
Image	-	-	-	-	0
Job/Task Relevance	-	-	-	-	0
Result Demonstrability	-	-	-	-	0
Not Coded	9.2%	25.7%	28.3%	21.0%	129

D&M Coding of Open-Ended Response Units

Following the guidelines that resulted from the practice coding walkthroughs and using the D&M construct definitions and sample research questions, two coders coded the 615 open-ended response units. The two coders initial agreement on coding was 495 of 615 responses (80%). The two coders discussed each unit for which they had provided different codes, until reaching consensus. In total, 538 (87.5%) of response units were matched with constructs, while 77 (12.5%) of response units could not be matched to any construct. All six D&M constructs were used in the coding process.

Overall, the System Quality (SysQ) construct garnered the highest number of coded response units, 357 (58.0%), which was more than triple the 107 (17.4%) for Satisfaction (S) and nearly eight times more than 46 (7.5%) for Information Quality (InfoQ). The remaining constructs had minimal codings.

The following units were not coded to any D&M construct: 43 units referring to the difficulty for students to use multiple LMSs and the pilot system used for only one of several courses; statements that referred to prior use of the pilot system; statements that referred to the prior use and familiarity of the institution's current LMS; the few statements about the instructor's experience level with the pilot; the few statements about entirely different systems.

A summary of the D&M coding of open-ended response units is in *Table 4-3*.

Table 4-3. Summary of D&M Coding of Open-Ended Response Units

Constructs	*Q14 (liked most)*	*Q15 (liked least)*	*Q18 (anything else)*	*Overall*	*Count*
System Quality	56.9%	65.1%	40.7%	58.0%	357
Satisfaction	21.5%	12.1%	24.8%	17.4%	107
Information Quality	13.3%	6.2%	0.9%	7.5%	46
Use/Intention to Use	3.6%	1.0%	7.1%	2.9%	18
Net Benefits	0.0%	1.0%	2.7%	1.0%	6
Service Quality	0.5%	1.0%	0.0%	0.7%	4
Not Coded	4.1%	13.7%	23.9%	12.5%	77

TPC Coding of Open-Ended Response Units

Following the guidelines that resulted from the practice coding walkthroughs and using the TPC construct definitions and sample research questions, two coders coded the 615 open-ended response units. The two coders initial agreement on coding was 525 of 615 responses (85%).

The two coders discussed each unit for which they had provided different codes, until reaching consensus. In total, 590 (95.9%) of response units were matched with constructs, while 25 (4.1%) of response units could not be matched to any construct. 415

(67.5%) of the response units were coded to constructs from the original TTF model while 175 (28.5%) of the response units were coded to constructs added in the TPC model.

Overall, the Task-Technology Fit (TTF) construct garnered the highest number of coded response units, 404 (65.7%), which was nearly more than four times the 104 (16.9%) for Affect towards Using (A) and nearly eight times more than 54 (8.8%) for Facilitating Conditions (FC). Four other constructs had minimal codings. Four TTF/TPC constructs remained unused through the entire coding process.

The following units were not coded to any TPC construct: Statements specifically about layout, colors, looks, etc.; neutral statements about the similarity between the pilot system and the current system; the few statements about entirely different systems.

A summary of the TPC coding of open-ended response units is in *Table 4-4*.

Table 4-4. Summary of TPC Coding of Open-Ended Response Units

Constructs: in original TTF	*Q14 (liked most)*	*Q15 (liked least)*	*Q18 (anything else)*	*Overall*	*Count*
Task-Technology Fit	67.2%	71.7%	46.9%	65.7%	404
Performance Impacts	0.0%	1.0%	2.7%	1.0%	6
Individual Characteristics	1.0%	1.0%	0.0%	0.8%	5
Task Characteristics	-	-	-	-	0
Technology Characteristics	-	-	-	-	0
Constructs: Added in TPC					
Affect towards Using	21.5%	11.1%	24.8%	16.9%	104
Facilitating Conditions	3.6%	11.1%	11.5%	8.8%	54
Utilization	3.1%	0.3%	1.8%	1.5%	9
Habit	0.0%	0.7%	5.3%	1.3%	8
Expected Consequences	-	-	-	-	0
Social Norms	-	-	-	-	0
Not Coded	3.6%	3.3%	7.1%	4.1%	25

Comparison of Open-Ended Response Coding by the Models' Constructs

Examining coding across all three models reveals several trends. Generally, items coded Perceived Ease of Use, Perceived Usefulness, and Output Quality in TAM were all three coded to System Quality in D&M and Task-Technology Fit in TPC, except for a) items more specifically about the information quality (including being up-to-date) which in D&M were coded Information Quality, and b) items speaking to the effect the system had on the course, grade, or individual, which were coded Net Benefits in D&M and Performance Impacts in TPC. Items related to general attitude towards the pilot system (including all-encompassing statements such as "nothing" and explicit statements of LMS system preference) were similarly coded Attitude Towards Using in TAM, Satisfaction in D&M, and Affect Towards Using in TPC. Similarly, the few statements explicitly about how the pilot system was used or the amount of use were coded as Perceived or Actual Usage in TAM, Use/Intention to Use in D&M, and Utilization in TPC.

Regarding units that were not coded to any construct of at least one of the models, technical issues (e.g., bugs and glitches, system speed/responsiveness) were not coded to any construct of TAM, but were coded to System Quality in D&M and Task-Technology Fit in TPC. Statements that referred to prior use of the pilot system were classified to Experience in TAM, not coded in D&M, and coded to Individual Characteristics in TPC. Statements that referred to the prior use and familiarity of the institution's current LMS were not coded to either TAM or D&M, but were coded to Habit in TPC. The few statements about the instructor's experience level with the pilot system were not coded to either TAM or D&M, but were coded to Facilitating Conditions in TPC.

One quite revealing kind of comments was the many students who pointed out the challenge of having to use during the semester more one than LMS; students frequently mentioned that having only one of their multiple courses using the pilot LMS in the same semester was more than an inconvenience and, thus, a strong point of contention. Such statements were not coded in either TAM or D&M, but were coded to Facilitating Conditions in TPC.

A summary comparison of the coding of unitized student survey responses to open-ended questions is in *Table 4-5*.

In comparing the results across the three models, TAM2, with the largest number of uncoded responses (as well as the largest number of unused constructs), lacked constructs that addressed two key issues: a) technical problems and b) the challenge for students in using multiple LMSs in the same semester, which do not arise in demos or limited system access. This aligns with how the TAM model originated specifically to meet the needs of understanding user evaluations of systems based on a brief hands-on session or on a demo or video of a potential system. The D&M model, which had all of its constructs utilized in the coding process, has the construct System Quality to address technical issues, but still lacked a construct to address the challenge for students using more than one LMS in a semester. TPC had the highest utility in the coding of responses and addressed both of the two key issues not fully addressed in the other two models; the primary weakness is the high percentage of responses coded with the Task-Technology Fit construct (65.7%).

Table 4-5. Summary Comparison of Open-Ended Response Coding by Models' Constructs

General Topic	*Examples*	*TAM*	*D&M*	*TPC*
Ease of use	ease of use	Perceived Ease of Use (PEU)	System Quality (SysQ)	Task-Technology Fit (TTF)
	ease of access	PEU	SysQ	TTF
	ease of finding	PEU	SysQ	TTF
	ease of getting to	PEU	SysQ	TTF
	user-friendliness	PEU	SysQ	TTF
	clarity	PEU	SysQ	TTF
	ease of navigation	PEU	SysQ	TTF
	ease of specific features	PEU	SysQ	TTF
	setup	PEU	SysQ	TTF
	organization	PEU	SysQ	TTF
	layout, colors, etc.	PEU	SysQ	-
Usefulness	general statement (e.g., helpful, useful, efficient)	Perceived Usefulness (PU)	SysQ	TTF
	of specific features	PU	SysQ	TTF
	comparison on features	PU	SysQ	TTF
	convenience	PU	SysQ	TTF
Effect	on course, grade, or individual	PU	Net Benefits	Performance Impacts
Output	reliability	OQ	SysQ	TTF
	quality	OQ	Information Quality (InfoQ)	TTF
	up-to-date	OQ	InfoQ	TTF
Attitude	general statements	Attitude Towards Using (A)	User Satisfaction (S)	Affect Towards Using (A)
	all encompassing statements (e.g., nothing)	A	S	A
	explicit system preference	A	S	A
Technical	bugs, glitches	-	SysQ	TTF
	speed/responsiveness	-	SysQ	TTF
	other technical issues	-	SysQ	TTF
Use in Context	how used or amount of use	Perceived or Actual Usage	Use/Intention to Use	Utilization
Prior Use	of pilot system	Experience	-	Individual Characteristics
	of current system, so prefer	-	-	Habit
Instructor	system experience level	-	-	Facilitating Conditions (FC)
multi-LMS use	don't like using 2 systems	-	-	FC

Quantitative Analysis

To provide a full comparison of the three models, quantitative analysis of the models have been conducted in addition to the qualitative analysis above. Before a comparative quantitative analysis of the three models, the survey questions first needed to be mapped as indicators to model constructs and secondly the model indicators and data needed to be prepared for analysis.

After survey questions were mapped to each models' constructs, statistical analysis of each model and its constructs were conducted using the LMS pilot student user survey data. For each model, data from the mapped close-ended survey questions were analyzed using a partial least squares structural equation modeling (PLS-SEM) approach with a reflective measurement model, where all items are modeled as reflective indicators that are considered as effects, rather than causes of latent constructs.

Following the process documented by Hair, Hult, Ringle, and Sarstedt (2014), a two step SEM-PLS analysis was conducted, where the measurement model was tested and reliability and validity of constructs were established in the first step and the structural model is tested in the second step.

Construct Mapping

To map closed-ended survey items to model constructs, three coders conducted a mapping exercise using a mapping guide consisting of each model's constructs and their definitions as well as sample questions from the literature. After the initial mapping of survey items to constructs, a crude agreement index was calculated and the three coders discusses the differences in their mappings until reaching consensus.

All survey questions were assigned to the three model constructs, except for question 8, which asks about the user's comfort level in using different types of technology; Q8 was not assigned to a construct in either TAM or D&M models, but was assigned to the construct Individual Characteristics in the TPC model. The survey items Q11.1 through Q11.18, which are a list of LMS tools (preceded by the general question "Please rate the usefulness of the following tools and features of [the pilot LMS] in contributing to your learning in this course"), were mapped collectively to a single construct. The survey items Q16.1 through Q16.9, which have some similar construction, but are comprised as complete sentences, were mapped to constructs separately, though largely were still assigned to the same construct within a model.

Across all three models, Q10 (which asks "On average, how many *hours per week* have you been spending in [the pilot LMS] for this course?" was assigned to similar constructs: Perceived or Actual Usage in TAM, Use/Intention to Use in D&M, and Utilization in TPC. Also across all three models, Q17 (which asks for a user's preference for the current LMS, the pilot LMS, or no preference at all) was assigned to similar constructs: Attitude in TAM, Satisfaction in D&M, and Affect Towards Using in TPC; the wording of the survey item does differ from the sample questions from research on each of the three models, but for all three coders still was considered to map to the constructs' definitions.

Initial pairwise agreement among the three individuals mapping items to constructs was generally high for both TAM and D&M models and consensus on disagreements was straightforward. All three individuals struggled in mapping to TPC constructs, largely because there were few example questions from the research and definitions alone were interpreted in different ways. A summary of the construct mapping is in *Table 4-6*.

Table 4-6. Construct Mapping Summary

Survey Question	**TAM/ TAM2**	**D&M**	**TPC**
Q8: In terms of my level of comfort in using different types of technology, I am *[Scale: very uncomfortable, somewhat uncomfortable, somewhat comfortable, very comfortable]*	[none]	[none]	Individual Character-istics
Q10: On average, how many *hours per week* have you been spending in *X* for this course?*[Scale: none, fewer than 5 hours, 5-10 hours, 11-15 hours, 16-20 hours, more than 20 hours]*	Perceived or Actual Usage	Use	Utilization
Q11: Please rate the <u>usefulness</u> of the following tools and features of *X* in contributing to your learning in this course. *[Scale: did not use this feature, not at all useful, slightly useful, moderately useful, highly useful]* Announcements, Course Messages, Quizzes/Tests Assignments, Discussions, Roster Blog and Wikis, Groups, Rubrics Calendar, Journal, Send Email Chat, My Content, Surveys Content, My Grades, Tasks	Perceived Usefulness (PU)	System Quality (SysQ)	Task-Technology Fit (TTF)
Q12: Please rate the overall <u>ease of use</u> of *X. [Scale: difficult to use, slightly easy to use, moderately easy to use, very easy to use]*	Perceived Ease of Use	SysQ	TTF
Q13: Please rate the overall <u>usefulness</u> of *X's* online documentation for students. *[Scale: same as Q11]*	PU	Service Quality	TTF
Q16: <u>Perceived impact on learning</u> *[Scale: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree, not applicable]*			
Q16.1. *X* helps me to learn the course materials/content.	PU	Net Benefits (NB)	Performance Impacts (PI)
Q16.2. *X* helps me to study for exams/tests.	PU	NB	PI
Q16.3. *X* helps me to complete course assignments.	PU	NB	PI
Q16.4. *X* helps me to take quizzes/exams.	PU	NB	PI
Q16.5. *X* helps me to make efficient use of my time in the course.	PU	NB	PI
Q16.6. *X* helps me to be in control of my own learning in the course.	PU	NB	PI
Q16.7. *X* helps me to communicate with my professor.	PU	NB	PI
Q16.8. *X* expands access to learning materials/ resources available to me (e.g., print, audio, video, etc.).	PU	SysQ	PI
Q16.9. *X* was beneficial to my overall learning in the course.	PU	NB	PI
Q17: Overall, compared to [our institution's] current LMS (title), please select the choice that best describes your preference for [current LMS] versus *X*: I prefer *X* over [current LMS]. I prefer [current LMS] over *X*. I have no preference.	Attitude	Satisfaction	Affect Towards Using
Pairwise coder agreement	1&2: 80% 2&3: 87% 1&3: 87%	1&2: 80% 2&3: 87% 1&3: 80%	1&2: 33% 2&3: 33% 1&3: 87%

With TAM, the construct Perceived Usefulness was used for the overwhelming majority of the (11 of 15) closed-ended survey items; three additional constructs (Perceived or Actual Usage, Perceived Ease of Use, and Attitude) each were assigned a single item. Similar to the coding of open-ended survey response question responses, the mapping of closed-ended survey items to constructs utilized the constructs from the original TAM model, with no use of additional constructs added in the TAM2 revised model; TAM2 constructs are also relatively unused in the LMS research using the TAM model.

With D&M, the construct Net Benefits was used for roughly half (8 of 15) of the items, System Quality was used for three items, and three additional constructs (Use, Service Quality, and Satisfaction) each were assigned a single item. Similar to the coding of open-ended survey response question responses, all of the D&M constructs were utilized.

With TPC, the construct Performance Impacts was used for roughly half (9 of 15) of the items, Task-Technology Fit was used for three items, and three additional constructs (Individual Characteristics, Utilization, and Affect Towards Using) each were assigned a single item. Similar to the coding of open-ended survey response question responses, the mapping of closed-ended questions utilized constructs from both the original TTF model and the revised TPC model. All three models provided useful constructs for the mapping of survey questions, though TPC was the only model to map all of the questions. A summary of construct usage in the mapping exercise is in *Table 4-7*.

Table 4-7. Summary of Construct Usage in Mapping

Constructs: TAM	Items
Perceived Ease of Use	1
Perceived Usefulness	11
Attitude Towards Using	1
Perceived or Actual Usage	1
Behavioral Intention to Use	0
Constructs: Added in TAM2	
Output Quality	0
Experience	0
Voluntariness	0
Subjective Norm	0
Image	0
Job/Task Relevance	0
Result Demonstrability	0
Not Coded	1
Total	**15**

Constructs D&M	Items
System Quality	3
Satisfaction	1
Information Quality	0
Use/Intention to Use	1
Net Benefits	8
Service Quality	1
Not Coded	1
Total	**15**

Constructs: in original TTF	Items
Task-Technology Fit	3
Performance Impacts	9
Individual Characteristics	1
Task Characteristics	0
Technology Characteristics	0
Constructs: Added in TPC	
Affect towards Using	1
Facilitating Conditions	0
Utilization	1
Habit	0
Expected Consequences	0
Social Norms	0
Not Coded	0
Total	**15**

Preparing the Model Indicators and Data

Parceling Usefulness Ratings

Because of the wide range of use of individual tools indicated by student participating in the LMS pilot survey, more than one third of possible usefulness ratings were not given by users. From a practical perspective, a person's general perception of the usefulness of the pilot LMS will be based on the parts of the pilots the individual actually utilized. The average usefulness rating of pilot LMS tools utilized can represent the individual's overall perception of the usefulness of the system.

Parceling is somewhat controversial measurement practice used particularly with latent-variable analysis techniques, where a parcel is an "aggregate level indicator comprised of the sum (or average) of two or more items, responses, or behaviors" (Little, Cunningham, & Shahar, 2002, p. 152). The researcher decided to parcel a usefulness subscale for the following reasons:

- The researcher takes the *pragmatic-liberal position* for parceling, which believes that "researchers should concentrate on building replicable models based on solid and meaningful indicators of core constructs that will replicate across samples and studies" (Little et al., 2002, p. 154). The 18 items of Q11 will vary from one LMS to another, and so a general representative of system usefulness makes more sense.
- Because of the structure of question Q11, where the user is asked for the usefulness of a list of tools and features, the construct is "implicitly subsuming additional content of the same type" (Little et al., 2002, p. 153).
- Similarly, the construct indicated by Q11 is presented in the survey as being unidimensional, which from the most conservative approach is the only condition under which parceling should be considered (Little et al., 2002).
- 15% of responding students gave the same rating to all of the tools they indicated they used.

Recoding the Preference Question

Q17 asked for the user's preference of systems by posing the question "Overall, compared to [our institution's] current LMS [system], please select the choice that best describes your preference for [current LMS] vs [pilot LMS]" with answer choices (1) "I prefer [the pilot LMS] over [current LMS]", (2) I prefer [current LMS] over [pilot LMS], and (3) "I have no preference." To reflect better a continuum of preference, the item was recoded as (1) I prefer [current LMS] over [pilot LMS], (2) "I have no preference," and (3) "I prefer [the pilot LMS] over [current LMS]."

Missing Data

With survey research, missing data is often a problem, occurring when a respondent leaves one or more questions blank, either on purpose or by accident; if missing data "exceeds 15%, the observation is typically removed from the data file" (Hair et al., 2014, p.

51). In this research, 18 respondents left empty more than 15% of the survey questions (ranging from 23% to 93%) and were removed from the data.

Outliers

Respondents answering with extreme responses are considered outliers and if only a few exist it may be best to remove them from the data (Hair et al., 2014). For the study of the use of a pilot system, use of tools and features and perceived impacts are key to a user's evaluation.

Three respondents selected "did not use this feature" for 17 or all 18 tools and features listed in Q11 and were removed from the data. In other words, all respondents in the final data set indicated they used more than 1 tool or feature.

For Q16.1-Q16.9, which asks about the perceived impact on learning, three respondents selected "not applicable" to eight or all nine items and were removed from the data. In other words, all respondents in the final data set indicated that more than 1 learning impact was applicable.

The final number of observations used in the study was 173.

Resulting Partial Models to Test

Based on the mapping process, the utilizing of the level of use indications in Q11.1-Q11.8, and the parceling of the usefulness ratings in Q11.1-Q11.8, the following three figures represent the models for further testing:

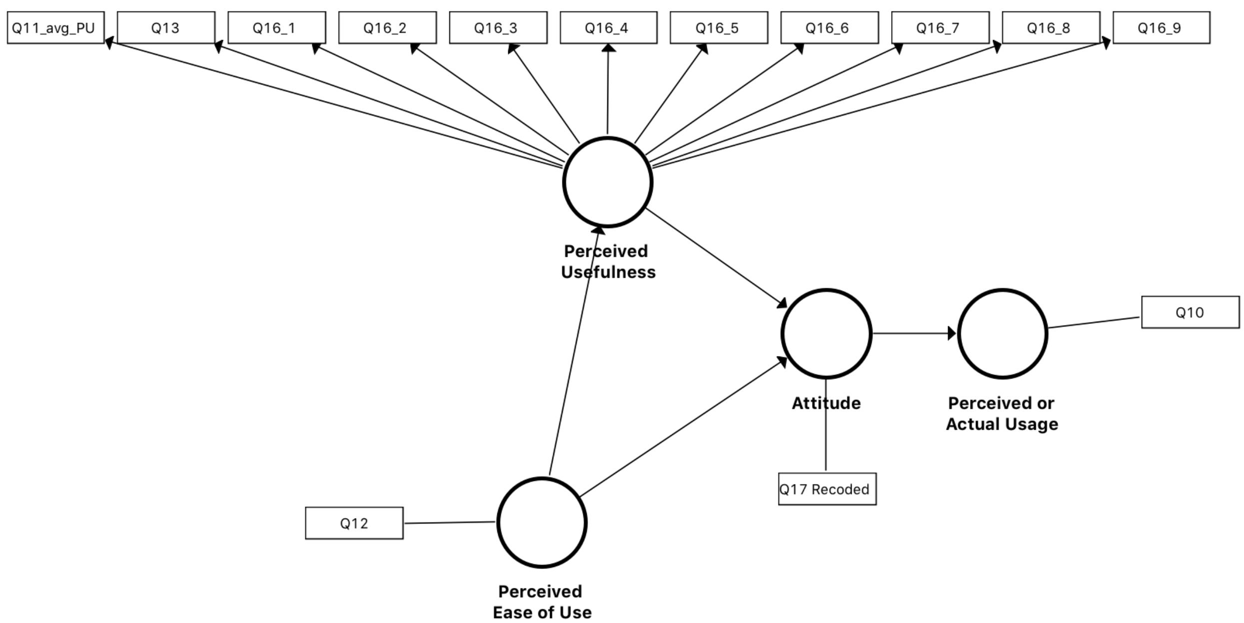


Figure 4-1. Survey Items Mapped to an Adapted Technology Acceptance Model

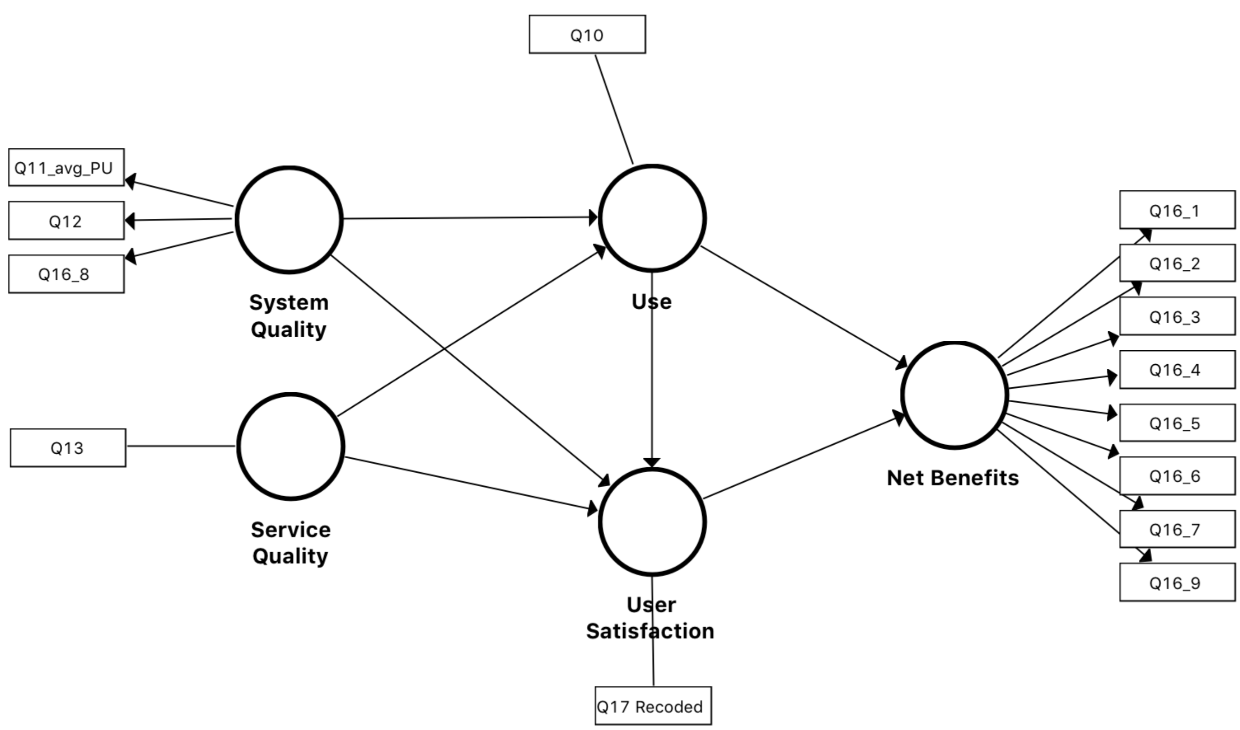


Figure 4-2. Survey Items Mapped to an Adapted D&M IS Success Model

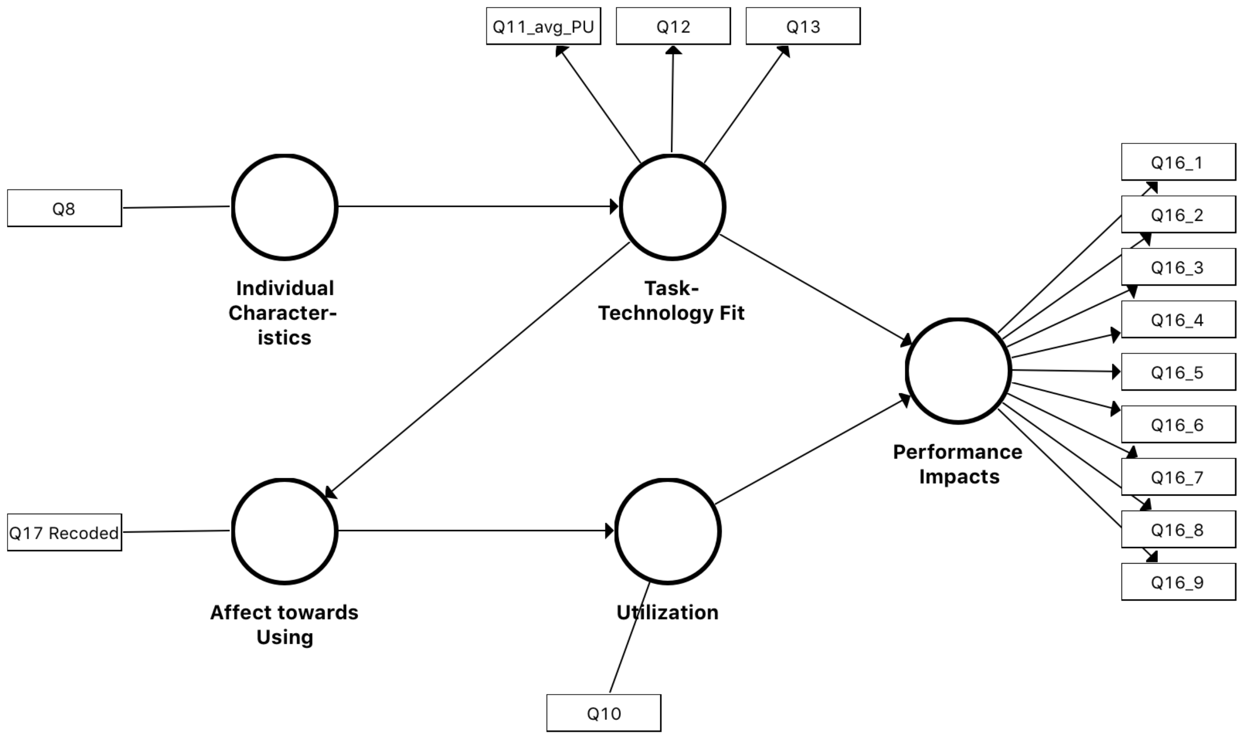


Figure 4-3. Survey Items Mapped to an Adapted Technology Performance Chain Model

Quantitative Results

As documented by Hair et al. (2014), SEM-PLS analysis is a two-step process, where the measurement model is tested and reliability and validity of constructs are established in the first step and the structural model is tested in the second step. Using G*Power 3.1.9 (www.gpower.hhu.de/en.html) (Faul, Erdfelder, Buchner, & Lang, 2009) with settings recommended by Hair et al. (2014) and Ringle, Silva and Bido (2014) and for the highest number of predictors for a single construct (2 for TAM Attitude construct, 2 for TPC Performance Impact construct, and 3 for D&M User Satisfaction Construct), the minimum sample size is 68 for two constructs and 74 for three constructs. The 173 observations in the data file are more than double of each of the two minimum sample sizes.

Measurement Model Testing

The measurement model analysis examines the relationship between the constructs and the corresponding indicator variables and is the first step in analysis with PLS-SEM.

An initial evaluation of the TAM, D&M, and TPC measurement models using the SEM-PLS analysis and bootstrapping procedure found all items for the constructs with multiple indicators statistically significant. The resulting composite reliability and convergent reliability values are both at acceptable levels. In the test to evaluate the discriminant reliability, examining the cross loadings of indicators within each model (see *Appendix H*), showed that indicators for each construct are larger than the indicators' cross loadings with other constructs in their respective models. The results of the more conservative Fornell-Larcker Criterion discriminant reliability analysis provided for each model additional confirmation for discriminant reliability. With the reflexive measurement models meeting appropriate tests, *Appendix I* summarizes the results of the tests of the respective TAM, D&M, and TPC measurement models.

The measurement models for TAM, D&M, and TPC had some similarities. All the models share two constructs with the same single indicators (Q10 and Q17 Recoded) and also share considerable overlap in constructs that contain all or almost all of the Q16.1-16.9 survey items on learning impacts.

Structural Model Testing

The study follows Hair et al.'s (2014) recommendations to evaluate the structural models, beginning with assessing for collinearity issues by examining the Variance Inflation Factor (VIF) for each predictor variable. Key results are then tested by:

- Assessing the significance of path coefficients through the PLS Bootstrapping procedure and also assessing the relevance of the structural model relationships by examining the relative importance of path coefficients and the direct and total effects of constructs.
- Assessing the level of explained variance of latent endogenous constructs by examining the coefficient of determination (R^2 value). As noted by Hair et al. (2014), the Stone Geisser's Q^2 value adds to the analysis of the R^2 values by testing for predictive relevance using the PLS Blindfolding procedure. Also, the use of the adjusted R^2 value (R^2_{adj}) is recommended when comparing models with different exogenous constructs in order to avoid bias toward complex models.

Assessing effect sizes helps further interpret results with a) f^2, which indicates the substantive impact of an exogenous construct by assessing its contribution to an endogenous latent variable's R^2 value; and b) q^2, which indicates the relative impact of predictive relevance by assessing its contribution to an endogenous latent variable's Q^2 value. Hair et al. (2014) also recommend a final test with the PLS Finite Mixture (FIMIX) procedure for unobserved heterogeneity, which could otherwise affect results.

In the PLS-SEM analysis, each of three structural models converged, resulting with confirmation of appropriate *VIF* values (< 5.00), assessing for collinearity for the exogenous construct with multiple predictors constructs (see *Appendix J*). Also, an analysis of the structural models with FIMIX procedures did not indicate unobserved heterogeneity since the 1-Segment analysis for each model resulted in the smallest criteria values (see *Appendix K*).

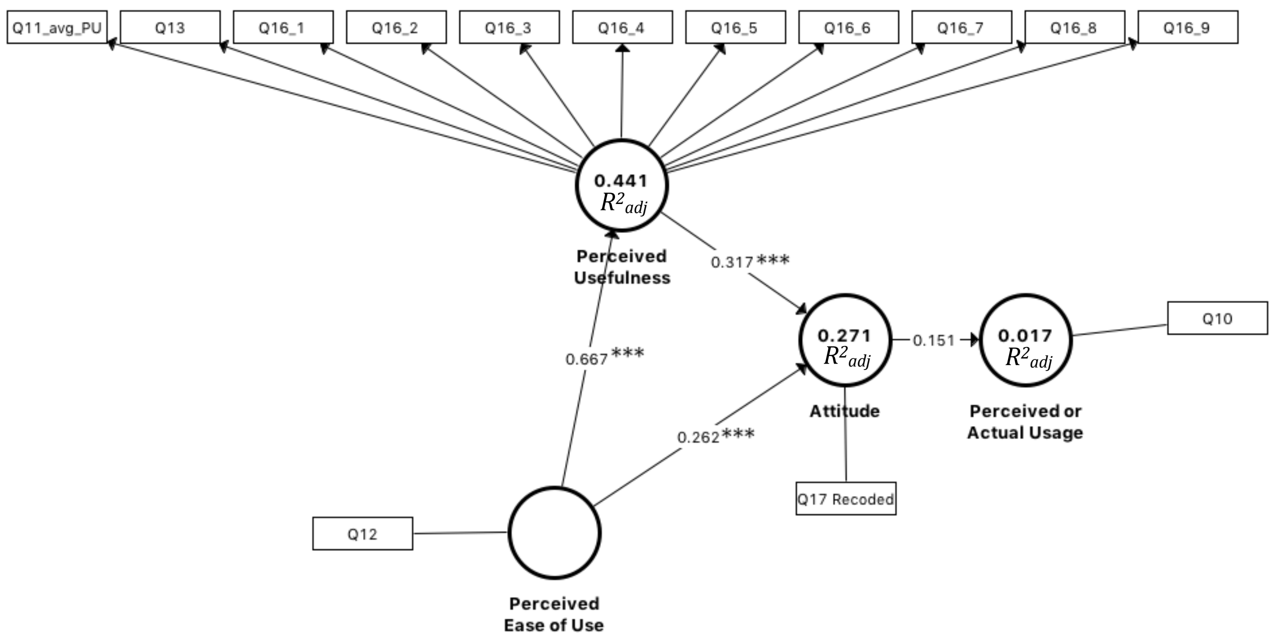
For key results, all three structural models did have statistically significant path coefficients as well as constructs with statistically significant explained variance and predictive relevance. Also, all models had constructs with large or medium effect sizes.

Adapted TAM Key Results

Path Coefficients: Using the PLS Bootstrapping procedure, three of the four path coefficients were found significant. The path coefficient for *Attitude -> Perceived or Actual Usage* was found not significant at the 0.05 level. The path coefficient for *Perceived Ease of Use -> Perceived Usefulness* (0.667), *Perceived Usefulness -> Attitude* (0.317), and *Perceived Ease of Use -> Attitude* (0.262) were significant. Also, for additional effects, Perceived Ease of Use had a statistically significant indirect effect of 0.211 ($p < .001$) and indicated that the effect of Perceived Ease of Use on Attitude was partially mediated through Perceived Usefulness.

Explained Variance (R^2_{adj}): The TAM model tested explained a nearly moderate amount of the variance of Perceived Usefulness ($R^2_{\text{adj}} = 0.441$) and by comparison a weak amount of the variance of Attitude ($R^2_{\text{adj}} = 0.271$). The extremely small amount of explained variance of Perceived Usage ($R^2_{\text{adj}} = 0.017$) was not statistically significant. The Stone-Geisser's Q^2 values found the endogenous variables Perceived Usefulness ($Q^2 = 0.289$) and Attitude ($Q^2 = 0.265$) both with predictive relevance whereas Perceived or Actual Usage did not ($Q^2 = -0.006$).

The TAM Model results for path coefficients, their level of statistical significance, and the resulting coefficients of determination (R^2_{adj}) are reflected in *Figure 4-4*.



*$p<0.05$; **$p<0.01$; ***$p<0.001$

Figure 4-4. Adapted TAM Model Results

Adapted D&M Key Results

Path Coefficients: Three of the seven path coefficients in the D&M structural model were found significant. One path coefficient to Use (*System Quality -> Use*) was significant at the 0.05 level while the other was not (*Service Quality -> Use*). One of three path coefficients to User Satisfaction was significant (*System Quality -> User Satisfaction*) while the other two were not (*Service Quality -> User Satisfaction* and *Use -> User Satisfaction*). One of two path coefficients to Net Benefits was significant (*User Satisfaction -> Net Benefits*) while the other was not (*Use -> Net Benefits*). Also for additional effects, System Quality had a statistically significant indirect effect of 0.193, indicating that the effect of System Quality on Net Benefits was partially mediated.

Explained Variance (R^2_{adj}): The D&M model explained a weak amount of the variance of User Satisfaction (R^2_{adj} = 0.250) and close to the cutoff for a weak amount of the variance of Net Benefits (R^2_{adj} = 0.225). The extremely small amount of explained variance of Use (R^2_{adj} = 0.030) was not statistically significant. The Stone-Geisser's Q^2 values found the endogenous variables User Satisfaction (Q^2 = 0.215) and Net Benefits (Q^2 = 0.163) both with having predictive relevance because of values greater than zero; the predictive value for Use (Q^2 = 0.010) is greater than but very near to zero.

The D&M Model results for path coefficients, their level of statistical significance, and the resulting coefficients of determination (R^2_{adj}) are reflected in *Figure 4-5.*

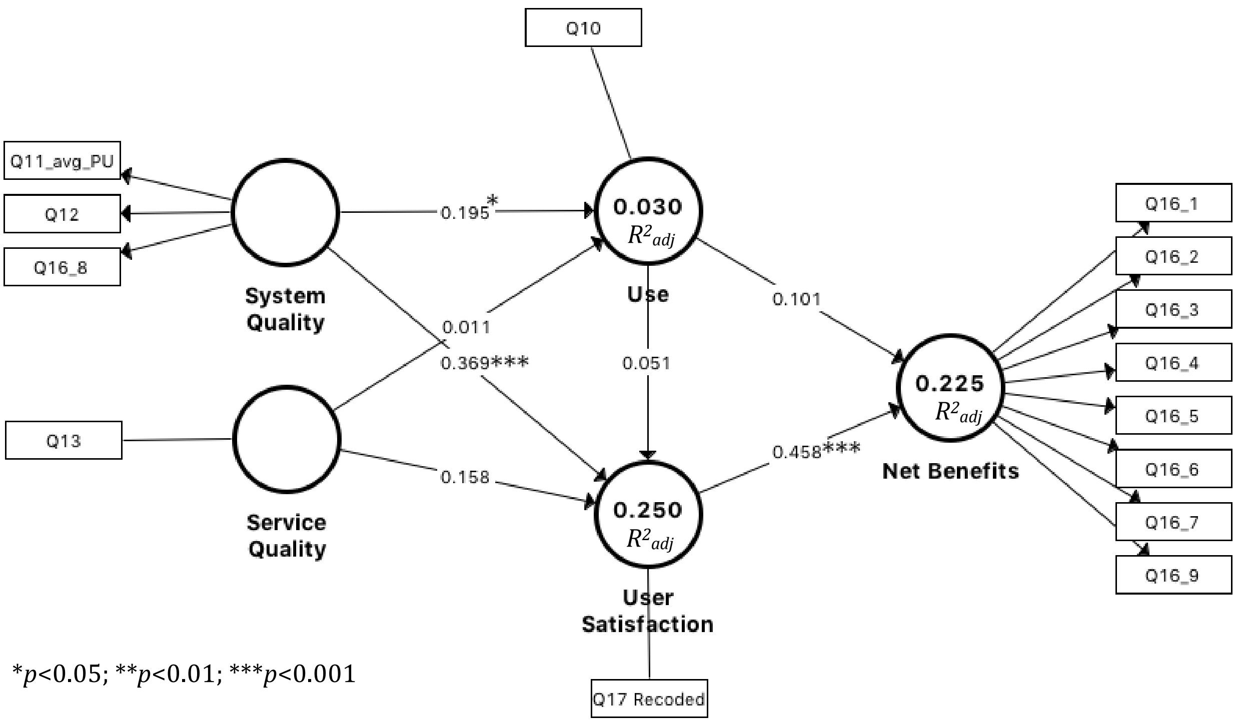


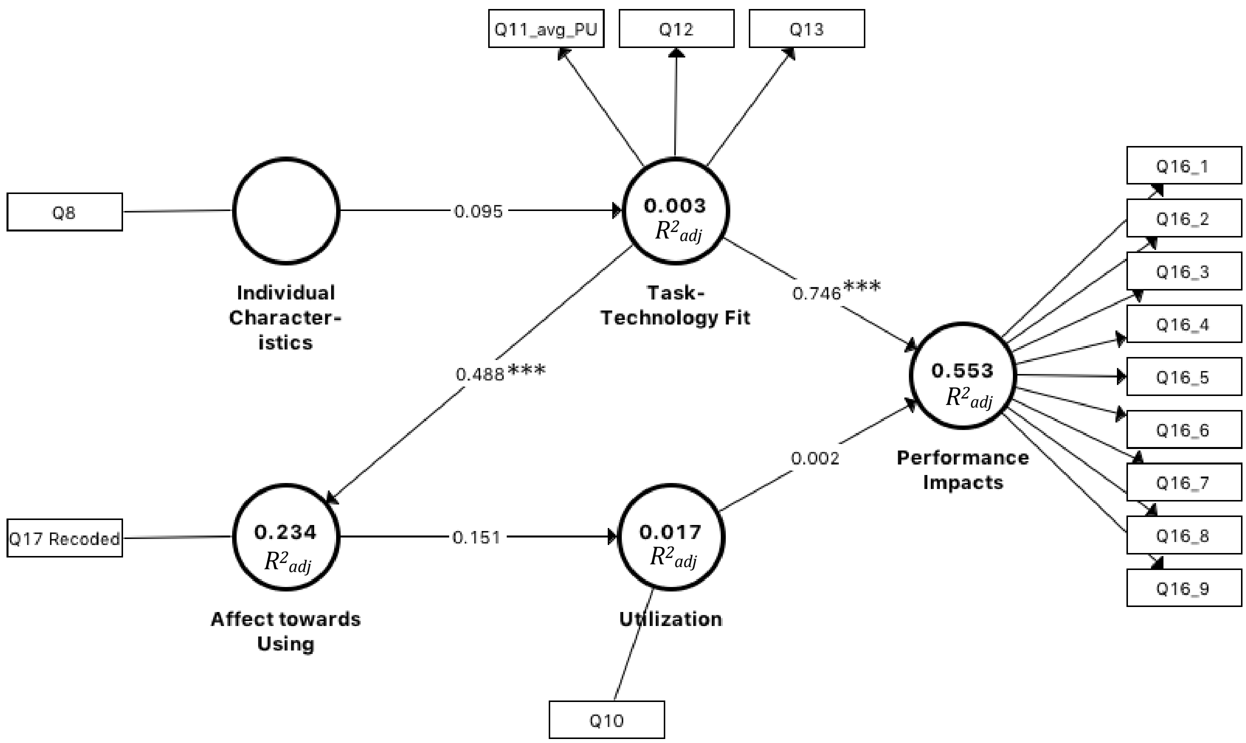
Figure 4-5. Adapted D&M Model Results

Adapted TPC Key Results

Path Coefficients: Two of the five path coefficients in the TPC structural model were found significant. The path coefficient for *Individual Characteristics -> Task Technology Fit* was not significant. The path coefficient for *Task-Technology Fit -> Affect Towards Using* was found significant at the 0.001 level. The path coefficient for *Affect towards Using ->* Utilization was not significant. One path coefficient to Performance Impacts (*Task-Technology Fit -> Performance Impacts*) was significant at the 0.001 level while the other path coefficient was not significant (*Utilization -> Performance Impacts*). There were no significant indirect effects.

Explained Variance (R^2): The TPC model explained a moderate amount of the variance of Performance Impacts (R^2_{adj} = 0.553) and close to the cutoff for a weak amount of the variance of Affect towards Using (R^2_{adj} = 0.234). The extremely small amounts of explained variance of Utilization (R^2_{adj} = 0.017) and Task-Technology Fit (R^2_{adj} = 0.003) were not statistically significant. The Stone-Geisser's Q^2 values found the endogenous variables Affect towards Using (Q^2 = 0.225) and Performance Impacts (Q^2 = 0.396) have predictive relevance because of values greater than zero; the predictive value of Task-Technology Fit (Q^2 = 0.002) is greater than but very near to zero, and the predictive value of Utilization (Q^2 = -0.006) is less than zero and therefore has no predictive relevance.

The TPC Model results for path coefficients, their level of statistical significance, and the resulting coefficients of determination (R^2_{adj}) are reflected in *Figure 4-6.*



*p<0.05; **p<0.01; ***p<0.001

Figure 4-6. Adapted TPC Model Results

Comparison of Structural Model Testing Results

There are several similarities across the results of the structural model testing of the three models. With PLS-SEM, there is not a single value (e.g., goodness-of-fit) with which to compare the models to each other, but one can look across the various structural tests used to evaluate the models. The three models, after passing the collinearity assessments:

- Had statistically significant path coefficients, though the TAM model had the highest ratio of significant path coefficients (3 of 4) with both D&M and TPC with similarly lower ratios (3 of 7 and 2 of 5, respectively).

- Were evaluated for additional significant indirect effects; two of three models had constructs with additional indirect effects, TAM's Perceived Ease of Use on Attitude and D&M's System Quality on Net Benefits.
- Had constructs with statistically significant amounts of explained variance, with some directly comparable:
    - The models' constructs with the single Q10 indicator ("how many hours per week have you been spending in [the pilot system] for this course") had extremely low and non-significant R^2_{adj} values, whether preceded in the model by TAM's Attitude, by TPC's Affect towards Using, or D&M's System Quality and Service Quality.
    - The models' constructs with the single Q17 Recoded indicator ("your preference for [current LMS] versus [pilot LMS]") all had relatively similar values of explained variance (27%, TAM Attitude; 25% D&M User Satisfaction; and 23% TPC Affect towards Using) even though there were different predictors for the respective constructs.
    - The model's constructs that included all or most of the Q16 items regarding impact on learning had significant levels of explained variance, though they varied substantially. TAM's construct Perceived Usefulness, which included the additional indicators of Q11 (average perceived usefulness) and Q13 (usefulness of online documentation) and which had the single predictor construct Perceived Ease of Use, had 44% explained variance. The two other models' constructs, D&M's Net Benefits and TPC's Performance Impacts, had nearly identical indicators (the single difference being Q16_8 regarding

expanded “access to learning materials”), but had very different levels of explained variance, 23% and 55% for D&M and TPC respectively.

  - The models had two similar constructs with predictive relevance (the same that had statistically significant levels of explained variance): (1) TAM’s Attitude, D&M’s User Satisfaction and TPC’s Affect towards Using, and (2) TAM’s Perceived Usefulness, D&M’s Net Benefits, and TPC’s, Performance Impacts.

- Had differing levels of effect sizes (see *Appendix L*):
  - Both TAM and TPC had one path each with large effect sizes (> 0.35) – TAM’s *Perceived Ease of Use -> Perceived Usefulness* and TPC’s *Task-Technology Fit -> Performance Impacts*. TPC’s *Task-Technology Fit -> Affect towards Using* is relatively close to a large effect size as well (> 0.3).
  - D&M, with no large effect sizes, had one path with a consistent medium effect sizes (> 0.15) – D&M’s *User Satisfaction -> Net Benefits*.
  - TAM had the largest number of additional small effects.
  - D&M had the largest number of effects near zero or below.
- Passed the test for unobserved heterogeneity.

A summary comparison of the structural model tests is reflected in *Table 4-8*.

Table 4-8. Summary Comparison of Structural Model Tests

	TAM	*D&M*	*TPC*
Collinearity Assessment	OK	OK	OK
Significant Path Coefficients	3 of 4	3 of 7	2 of 5
Indirect Effects	Perceived Ease of Use on Attitude	System Quality on Net Benefits	none
R^2_{adj} of Q10 indicator for hours of use	non-significant	non-significant	non-significant
R^2_{adj} of system preference question	27% (Attitude)	25% (User Satisfaction)	23% (Affect Towards Using)
R^2_{adj} of construct that includes learning impact questions	44% (Perceived Usefulness)	23% (Net Benefits)	55% (Performance Impacts)
Constructs with predictive relevance	2	2	2
f^2 effect sizes on explained variance, with or near large, small, and medium effects *q^2 effect sizes on predictive relevance, with or near large, small, and medium effects*	1 large effect 3 small effects 1 large effect 2 small effects 1 zero effect	1 medium effect 4 near 0 effects 1 medium effect 1 small effect 4 near 0 effects	2 large effects 1 small effect 2 near 0 effects 2 large effects 3 zero effects
Unobserved Heterogeneity	No	No	No

CHAPTER 5: DISCUSSION AND CONCLUSIONS

The importance of LMSs at higher-ed institutions is widely recognized (Means, Johnson, & Graff, 2013) with over 95% of institutions having a single, campus-wide LMS and two-thirds of campuses planning to review their LMS strategy (Green, 2013). With the importance of LMSs on higher-ed campuses, institutions spend considerable time, effort, and resources in evaluating, selecting, and implementing systems, with an important aspect being the involvement of students (and faculty) and including their feedback on potential systems as an important component of the decision/selection process. From an institutional planning perspective, the selection of an LMS is a high stakes decision with considerable risk (Coates, James, & Baldwin, 2005). In the higher-education context, it may be surprising to the campus audience to find in the LMS evaluation report no mention of any research literature, frameworks, or models regarding user evaluations of systems. The purpose of this study was to examine whether one or more of the most prevalently used Information Systems (IS) acceptance and success models in the study of LMSs provides relative greater utility and useful nomenclature for framing and interpreting the results of user evaluations. Based upon a review of the LMS literature and the origins of the IS acceptance and success models used in such research, the researcher studied three models: The Technology Acceptance Model (Davis, 1986, 1989; Venkatesh & Davis, 2000), the DeLone and McLean IS Success Model (1992, 2003), and Goodhue and Thompson's (1995) Technology Performance Chain model. The study used secondary data, utilizing student survey data collected during the piloting of an alternative LMS at a large, U.S. Midwestern, multi-campus public institution of higher education. The survey included open-ended and closed-ended questions, which provided the opportunity to use the selected models for both qualitative and quantitative analysis.

Summary of Findings and Discussion

RQ1: What is the utility of the Technology Acceptance Model's constructs in explaining and interpreting the results of student user evaluations of LMS in a higher-ed adoption context?

The original TAM's focus on its two key predictors – Perceived Ease of Use and Perceived Usefulness – is reflected in the terminology of the existing data source used in this study as well as in many of the higher-ed LMS evaluation reports (see *Appendix A*). Though not directly cited by higher-ed LMS evaluation reports, TAM's influence is still present. The five constructs of original TAM were useful in coding open-ended responses and four of five original TAM constructs were utilized in the mapping of close-ended survey questions to model constructs.

The original constructs of TAM also dominate the LMS research studies that use TAM (see *Appendix B*). However, as with all three models, it is difficult to compare this study to other quantitative studies based off the same model in the LMS literature because each study (a) chooses a different mix of constructs (for example, using Behavioral Intention instead of Attitude, or neither of them; not including the Use construct), (b) includes additional constructs specific to the study (again, see *Appendix B*), (c) uses a wide range of different measures for constructs, and (d) utilizes varying methods of analysis. However, examining common points of possible comparison between LMS studies using TAM and also analyzed with a structural equation modeling (SEM) method (see *Appendix M*), one notices this study's explained variance of the construct Perceived Usefulness is within the broad range of other studies and the explained variance of Use is well below the range of other studies. The core structure of TAM in this study is similar to most with three common path coefficients (between Perceived Ease of Use and Perceived Usefulness and between both of those and Attitude). Also, like this study the majority of listed studies include additional indirect effects between Perceived Ease of Use and Attitude. Therefore, a core structure of the TAM model is reflected in this study as well.

This study, unlike many others, did not have a significant path from Attitude (or Behavioral Intention) to Use. However, the Use construct across the whole TAM literature (while generally measured by amount of time used, number of usages, and/or diversity of usage) is frequently not measured, either because the variable is ignored or the use is considered mandatory (Legris, Ingham, & Collerette, 2003).

If the Use construct were removed, then the culminating construct in the model is Attitude (or Behavioral Intention in many studies). The last closed-ended survey question from this study's source data, which asks the user's LMS system preference (with choices current LMS, no preference, and pilot LMS) is a related but also different question to ones normally used in the literature for either Attitude or Behavioral Intention constructs. Such a question is unique to the context where the institution is considering moving away from the current LMS to a different one and where an LMS is already used by most every student and for many if not most or all of their courses.

An important weakness of the TAM model for this study is the lack of constructs for dealing with technical issues experienced in a pilot and with the special condition of an LMS pilot where students, having been included in the pilot by their instructors, are using the pilot system for only one of several classes over the course of the semester. Issues of quality can in part be handled with the construct Output Quality, though the coding of open-ended survey responses in this study was hampered by the example questions from other studies that asked specifically about the 'quality of output.' Being guided solely by the more general definition 'how well the system performs the tasks provided' would encompass most if not all comments about additional technical issues such as bugs, glitches, accuracy, and reliability.

Responses about both technical quality and multiple LMS use are ones that would arise in the experience of using a pilot LMS for a considerable length of time (such as a semester) for the actual work of a real course the student is taking. These two kinds of responses are much less likely to occur in an LMS evaluation where students are given a demo of the pilot system or have a brief period of time to try the pilot system hands-on.

RQ2: What is the utility of the DeLone & McLean IS Success Model's constructs in explaining and interpreting the results of student user evaluations of LMS in a higher-ed adoption context?

The D&M's emphasis on *quality* – with the three constructs System Quality, Information Quality, and Service Quality – and *satisfaction* certainly mirrors core values reflected in LMS evaluations in higher education. In contrast to the TAM model, D&M is a model focused ultimately on benefits, where utilization can be a factor, but not the model's culminating focus. Satisfaction is also not the culminating construct, but something that may help predict the user's perceived or actual benefits to using the system. In addition, the question about LMS preference in this study, because of its uniqueness to the context of a decision/selection process, is not a close match with the sample questions from LMS research in studies using the D&M model's construct of User Satisfaction.

Examining common points of possible comparison between the small number of LMS studies using D&M model (see *Appendix N*), one notices that this study's explained variance of the three endogenous constructs are well below other studies with those constructs. This study has a much greater ratio of non-significant path coefficients (4 of 7) than other studies that have multiple similar paths such as 2 of 7 in Mtebe and Raisamo (2014), 0 of 7 in Almarashdeh, Sahari, Zin, and Alsmadi (2010), 2 of 5 in Klobas & McGill (2010), and 0 of 6 in Lin (2007). The construct of Use in the few studies is also very different than this study's with two focusing on use intention in the future (Lin, 2007; Lin & Chen, 2012), two focusing on agree/disagree levels with different types of system use (Wang, Doll, Deng, Park, & Yang, 2013; Mtebe & Raisamo, 2014), and only one using a measure of total reported hours of use (Klobas & McGill, 2010) which, like this study, had non-significant paths between *Use -> Satisfaction* and *Use -> Net Benefits*.

Though largely useful in the coding of user's responses to open-ended survey questions, the D&M model by comparison faired poorly in the quantitative analysis, with the highest number of non-significant paths, comparatively small explained variance for constructs (particularly for Net Benefits), and multiple low effect sizes. Furthermore, the structure of significant paths, which is linear from System Quality to User Satisfaction to Net Benefits, does little to understand the inter-relationships among multiple constructs.

RQ3: What is the utility of the Technology Performance Chain model's constructs in explaining and interpreting the results of student user evaluations of LMS in a higher-ed adoption context?

Though the underlying concerns resonate, the nomenclature of the key TPC construct Task-Technology Fit (TTF) does not echo the language used in LMS evaluation reports. Furthermore, the few indicators attributed to the TTF construct in this study lack the complexity of the multiple factors included in Goodhue's (1995) original TTF construct (with factors data quality, locatability, compatibility, timeliness, reliability, ease/training) or in the Klobas and McGill's (2010) LMS research using the TTF construct (with factors ease of use, ease of learning, information quality). However, the model's culminating emphasis on Performance Impacts, similar to D&M's Net Benefits, is of particular interest because ultimately higher-ed institutions are concerned whether the LMS makes a difference in teaching and learning.

In the qualitative analysis, it was the TPC Facilitating Conditions construct that helped raise the total number of codable open-ended responses, for it helped classify the many responses from students commenting on the challenge of using the pilot LMS for one course and the institution's current LMS for several other courses in the same semester. On the other hand, a weakness of the TPC model in the qualitative study was that the TTF construct gathered such a high proportion (two thirds) of all responses, where considerable additional analysis would be necessary to explain the myriad of facets.

In the quantitative analysis, the TPC model reflected the highest amount of explained variance (55%) for Performance Impacts, the model's culminating focus, which was counterbalanced by the high percentage of non-significant path coefficients and high number of near zero effect sizes. Furthermore, the structure of significant paths, which is split from Task-Technology Fit in one direction to Affect towards Using and in another direction to Performance Impacts, does not provide much understanding of the inter-relationships among the constructs.

Compared to the few quantitative studies in the LMS literature that use the TPC model (see *Appendix O*), one notices this study's explained variance of Performance Impacts is in the middle of the range of other studies, the explained variance of Affect towards Using is nearly within the range of other studies, and the explained variance of Utilization is well below other studies. Though this study had practically no explained variance of the Task-Technology Fit construct, almost all other LMS studies did not have TTF as an endogenous construct (however, this is contrary to the original research on the TTF model). This study has a much higher ratio of non-significant path coefficients (3 of 5) than other studies in the literature that have multiple similar paths, such as 0 of 4 in McGill & Klobas (2009), 0 of 5 in Yu & Yu (2010), 0 of 2 in Lin (2012). Regarding the construct Utilization, this study does have some similar results as McGill, Klobas, and Renzi (2011), where usage is similarly measured by hours per week, only 8% of Utilization explained variance is accounted for, and the path coefficient from *Utilization -> Performance Impacts* is non-significant.

The construct Utilization has a unique history in the TPC framework, where it was not included as a construct in the original TTF model; from Goodhue's (1995) perspective, utilization (unless voluntary) can be excluded and thus simplify the model. Utilization was added to the TPC model by Goodhue and Thompson (1995) to gain consistency with the D&M IS Success Model, though the researchers cautioned, "to the extent that utilization is not voluntary, performance impacts will depend increasingly upon task-technology fit rather than utilization" (p. 216).

The LMS preference question used in this study varied substantially from the Affect Towards Using questions used in the TPC related LMS research, a similar problem as with the other two models. Much closer to the LMS preference question is the culminating Feedback construct added to a study by one of the original TPC authors and his colleagues (Goodhue, Littlefield, & Straub, 1997). In that study,

> it seemed quite appropriate to measure the feedback construct via "allocation of resources," i.e., would users allocate more, less, or the same resources to this technology in the future? Decisions about future resource allocation is one form of feedback from an individual's experience with the technologies (p. 454).

In that study, there were statistically significant path coefficients from both Task-Technology Fit and Performance Impact to the Feedback construct, which had R^2_{adj} values of 0.34 and 0.27 in the two phases of the study. This is similar to the TPC results in this study, with the significant path coefficient from Task-Technology Fit to Affect towards Using (which had the LMS preference question as an indicator).

RQ4: What is the relative utility of the three models in their applicability to analyze and interpret the user evaluations generated in the context of a higher education institution's decision for or against a new learning management system?

In the qualitative analysis, all three models exhibited considerable but not equivalent levels of utility in helping to frame the coding of open-ended responses (see *Table 5-1*). D&M, though having all of its constructs used, was surpassed on the one hand by TPC, which left the lowest percentage of responses uncoded, and on the other hand by TAM2, which had responses spread more evenly across multiple constructs than the other two models. As noted, TAM2 constructs left unaddressed the highest percentage of uncoded responses; these responses, more likely to arise in a full semester long pilot, were better handled by the D&M quality constructs and the TPC construct addressing facilitating conditions. In turn, the TAM constructs would likely work well in a pilot context that included only demos or short hands-on experiences. In sum, no single model was superior in all respects to the others in the qualitative analysis.

Table 5-1. Summary of Differentiating Qualitative Analysis Results

	TAM2	*D&M*	*TPC*
Constructs used in qualitative study	7 of 14; 5 of 5 from original TAM; 2 of 7 added in TAM2	6 of 6	7 of 11; 3 of 5 original TTF; 4 of 6 added in TPC
Largest % coded to a single construct	39.7% (Perceived Ease of Use)	58.0% (System Quality)	65.7% (Task-Technology Fit)
Responses codable vs not codable	79% vs 21.0%	87.5% vs 12.5%	95.9% vs 4.1%
Primary weaknesses	Unaddressed responses for both technical issues and multiple LMS use	Unaddressed responses for multiple LMS use; high % coding to one construct	Highest % coding to a single construct.

In the mapping of survey items, all three models provided useful constructs, with TAM2 and D&M models utilizing all but one item and TPC utilizing all items. All three models had three constructs with single item indicators (which is not preferred for statistical analysis) and individual constructs with an over-weighted share of items (TAM's Perceived Usefulness, 11 of 14 items used; D&M's Net Benefits, 8 of 14 items used; TPC's Perceived Impacts, 9 of 15 items used). In conducting the mapping process, the two coders struggled most in two ways: a) initial mapping and reaching consensus with TPC constructs because of few example questions in the LMS research literature, and b) mapping the LMS preference question to all three models because the item did not readily align with sample questions and seemed unique to the decision/selection context. Despite such shortcomings, the mapping process showed that the survey questions were mostly quite similar to those asked in actual research, which indicates the potential for explicitly adopting in future pilot studies better validated items and measures from the research literature.

In the quantitative analysis, though each model had two constructs with statistically significant explained variance and predictive relevance, the models differed in the number and the ratio of statistically significant path coefficients and the mix of effect sizes. TAM2 had the highest ratio of significant path coefficients and the lowest number of near zero effect sizes as well as the highest explained variance for the construct with the 'system preference' question, exhibiting a higher level of parsimony. TPC had the construct with the largest amount of explained variance (Performance Impacts), which was also the construct with the largest explained variance for a model's culminating construct. D&M showed less utility in comparison with the other two models, with a high number of non-significant paths, no large effect sizes, most near zero effects, and a final construct (Net Benefits) with nearly identical indicators as TPC's Performance Impacts, but with half the explained variance. All three models offered similar support for the notion that usage itself was not an effective measure of system success and that the LMS is, certainly for students, a mandatory part of their courses. The amount of usage may still be of interest, either as one of the demographic questions frequently asked, or as a way to establish a minimum level of usage for inclusion in an analysis. A summary comparison of quantitative results is in *Table 5-2*. Similar to the qualitative analysis results, no single model was superior in all respects to the other two in the quantitative analysis.

As noted earlier, the LMS Preference question was challenging to map to all three models because of a limited match to TAM's Attitude (or Behavioral Intention), D&M's User Satisfaction, and TPC's Affect towards Using constructs. Though there was not a similar LMS Preference question asked in the LMS studies using any of these models, the Feedback construct in the Goodhue et al. (1997) study provides a potential indication for how to integrate it as a culminating construct in a model with paths from both impacts and questions mapped in this study to both TAM2's Perceived Usefulness and TPC's TTF constructs.

Table 5-2. Summary of Differentiating Quantitative Results

	TAM2	*D&M*	*TPC*
Constructs used in quantitative study	4 of 5 from original TAM; 0 of 7 added in TAM2	5 of 6	5 of 11; 3 of 5 original TTF; 2 of 6 added in TPC
Survey items mapped to constructs	14 of 15	14 of 15	All 15
Survey items mapped to a single construct	11 (Perceived Usefulness)	8 (Net Benefits)	9 (Performance Impacts)
Significant Path Coefficients	3 of 4	3 of 7	2 of 5
Statistical significant constructs with predictive relevance	2 (Perceived Usefulness; Attitude)	2 (User Satisfaction; Net Benefits)	2 (Task-Technology Fit; Performance Impacts)
% of explained variance of 'system preference' question	27% (Attitude)	25% (User Satisfaction)	23% (Affect Towards Using)
% of explained variance of construct that included 'learning impact' questions	44% (Perceived Usefulness)	23% (Net Benefits)	55% (Performance Impacts)
% of explained variance of final construct	2% (Perceived or Actual Use)	23% (Net Benefits)	55% (Performance Impacts)
Trends of effect sizes (f^2 and q^2)	Lowest number of near 0 effects	No large effect sizes and most near 0 effects;	Most large effects; several near 0 effects.
Primary weakness(es)	Final predicted construct (Use) was not significant; construct including 'learning impacts' noticeably lower than TPC.	High number of non-significant paths; no large effect sizes and most near 0 effects; variance explained for Net Benefits less than half of TPC's similar construct Performance Impacts.	High number of non-significant paths; higher number of near 0 effect sizes compared to TAM2.

Overall, systematically coding open-ended responses and mapping survey questions using the constructs of each of the three models provided valuable points of comparisons. In the response coding, where issues of quality were readily addressed with D&M constructs, they were only partially dealt with in TAM2, and clumped together with a variety of other concerns in TPC; and where the comments regarding the use of multiple

LMSs were readily matched to a TPC construct, there was no place for them in the other two models. In the mapping of survey questions to the respective models' constructs, all of the survey items related to both usefulness and broader impact were pooled together in TAM2, whereas in both D&M and TPC there was a separation of a) specific tool usefulness for specific activities and b) broader goals for teaching and learning, which better reflected the concerns in the LMS pilot survey.

In both the qualitative analysis and quantitative analysis separately and combined, no one model was superior to the others. If one had started with any single model and evaluated it for its applicability to understanding user evaluations in the LMS selection/decision context, the results from either a qualitative or quantitative analysis would likely have appeared largely successful and seemed to validate further use of the model. Echoing what was reflected in the literature review, the results of this study are further indication that the three prevalent models are neither duplicative nor completely distinct from one another. In comparing the three models for their utility in a higher-ed LMS selection/decision context, all three models offer perspectives and frameworks that can contribute to the understanding of user responses to a pilot system. TAM/TAM2 provides the core concepts (and relationship between) ease of use and usefulness; TAM also has the greater amount of available research literature to provide possible examples of measures for the two core constructs, and from its origins was designed to address the demo or brief hands-on experience with a potential new system. Both TPC and D&M showcase the importance of impacts on broad benefits, which echoes a key concern, generally across LMS evaluations, that focuses beyond the usefulness of tools for specific tasks and to the potential impact on broader teaching and learning goals. D&M's emphasis on Quality gives further credence to expanding on TAM's definition of Output Quality. And TPC's Facilitating Conditions provides a construct that was valuable in helping explain the many student comments dealing with the required use of multiple LMS systems in the same semester and which could possibly impact a user's ultimate system preference. These two aspects of quality and situational conditions also help fill the gap between what's needed to understand student input in a demo or hands-on setting and understand student input from use of a pilot system in an actual course over a considerable period of time.

Implications of This Study

Though in a review of LMS evaluation reports there was no explicit connection found to the research literature, this exploratory study using existing data from an LMS selection/decision context has shown considerable evidence that such a connection can be made and provides a potential framework as well as useful nomenclature for the understanding of student feedback on a pilot LMS.

Greater utility may be found by combining the strengths of the models evaluated in this study to meet the two kinds of evaluation settings discussed – the LMS demo/short hands-on experience and the LMS full pilot in actual courses over the course of a grading term. In an initial attempt to bring together a set of interrelated constructs to meet the concerns of higher-ed LMS evaluations and the needs for interpreting user responses to an LMS pilot, *Table 5-3* builds on the two core TAM model constructs of ease of use and usefulness, broadens the emphasis on quality, includes an additional core emphasis on the larger impacts on teaching and learning, provides a construct to consider the special conditions users face in a full semester long pilot, and adjusts the notion of attitude to reflect the LMS system preference decision.

Table 5-3. Summary of Combined Constructs and Definitions for Two Evaluation Settings

Constructs	*Definitions*	*Evaluation Settings*	
		LMS Demo/Short Hands-On Experience	*LMS Full Pilot*
LMS Quality	How well the system performs the tasks provided (adapted from Venkatesh & Davis, 2000).		X
LMS Pilot Conditions	Situational factors of the pilot system use in context, including the student experience of multiple LMS systems in the same semester (adapted from Goodhue and Thompson, 1995).		X
Perceived Ease of Use	The degree to which an individual believes that using a particular system would be free of effort (adapted from Davis, 1986).	X	X
Perceived Usefulness	The degree to which an individual believes that using a particular system would enhance his or her learning task performance (adapted from Davis, 1986).	X	X
Perceived/ Anticipated Impact on Learning	Extent to which an LMS is contributing to accomplishment of a portfolio of learning goals by an individual. (adapted from the Performance Impact construct in Goodhue & Thompson, 1995, and the Net Benefits construct in DeLone & McLean, 2003)	Anticipated	Perceived
Feedback: LMS Preference	Decisions about the selection of the future LMS is one form of feedback from an individual's experience with the technologies (adapted from Goodhue, Littlefield, & Straub, 1997). Similarly, a measure of the likelihood or subjective probability that a person will engage in a given behavior (adapted from the Behavioral Intention construct in Davis, 1986).	X	X

Using these constructs to create a possible structural model, *Figure 5-1* attempts to reflect the relationships between the constructs for a proposed LMS-Pilot Model, maintaining the core interrelationship among TAM's Perceived Ease of Use and Perceived Usefulness constructs with the LMS Preference construct, while adding into those interrelationships an additional key construct related to the broader impact on learning reflected in the D&M and TPC models. The inner part of the figure represents a potential model for the evaluation setting of a demo or short hands-on experience with the pilot system. In addition, LMS Quality and LMS Pilot Conditions are added to reflect the two key differences in needs arising from the use of a pilot LMS in real courses over a full grading period.

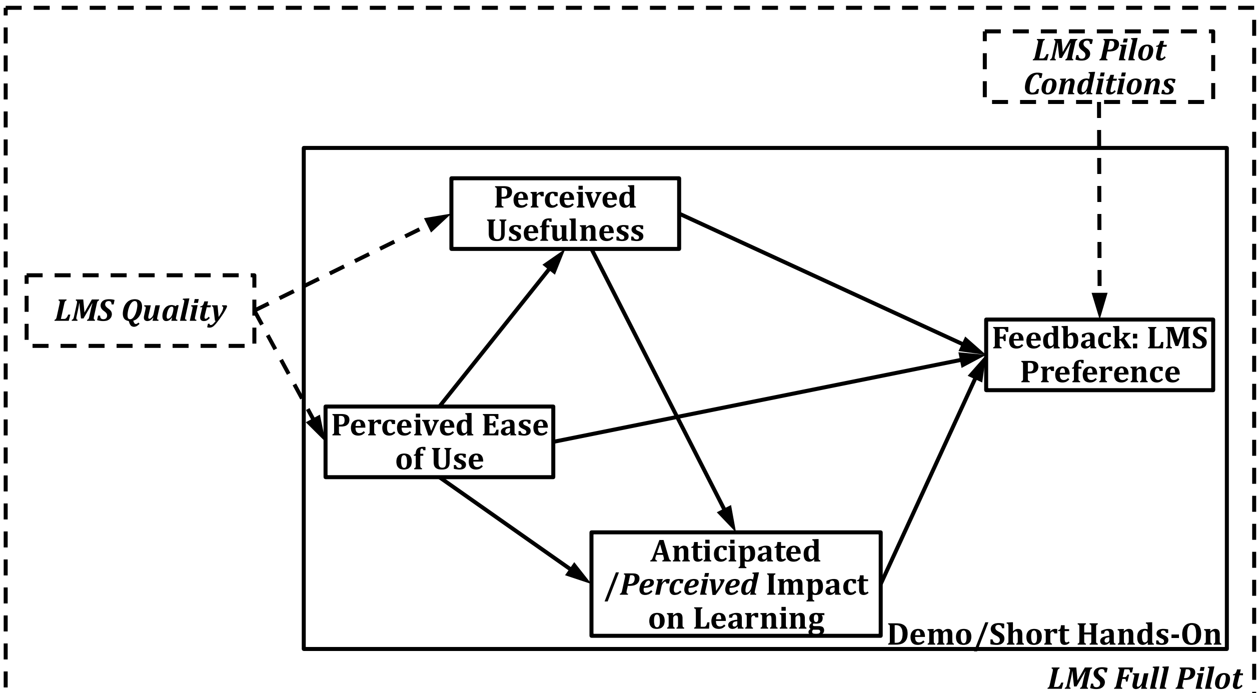


Figure 5-1. Proposed Conceptual Relationships for an LMS-Pilot Model

Such common nomenclature and definitions, with a basis in the academic literature, have the potential to increase the possibility of sharable and comparable results among institutions, even for LMS evaluations with relatively small number of participants. An LMS evaluation team need not and should not feel compelled (or have the skill set) to conduct an SEM analysis of survey results (though there is, of course, a need for additional research on the proposed model), but could still benefit from the framework's interrelationships in presenting and discussing the results of their own survey's findings.

Building on the coding summary of open-ended responses (see *Table 4-5*), a suggested coding guide based on the proposed constructs of the LMS-PM model is in *Table 5-4*. Such a guide would facilitate the interpretation of open-ended responses to questions such as what users liked most and liked least about the pilot LMS as well as any general comments offered. Of course, these would not account for every comment made, but based on this study's results, it is anticipated they would apply to most or nearly all comments.

Table 5-4: LMS-PM Coding Guide for Open-Ended Question Responses

General Topic	*Examples*	*LMS-PM Construct*
Ease of use	ease of use	Perceived Ease of Use
	ease of access	Perceived Ease of Use
	ease of finding	Perceived Ease of Use
	ease of getting to	Perceived Ease of Use
	user-friendliness	Perceived Ease of Use
	clarity	Perceived Ease of Use
	ease of navigation	Perceived Ease of Use
	ease of specific features	Perceived Ease of Use
	setup	Perceived Ease of Use
	organization	Perceived Ease of Use
	layout, colors, etc.	Perceived Ease of Use
Usefulness	general statement (e.g., helpful, useful, efficient)	Perceived Usefulness
	of specific features	Perceived Usefulness
	comparison on features	Perceived Usefulness
	convenience	Perceived Usefulness
Effect	on course, grade, or individual	Anticipated/Perceived Impact on Learning
Output	reliability	LMS Quality
	quality	LMS Quality
	up-to-date	LMS Quality
Attitude	general statements	Feedback: LMS Preference
	all encompassing statements (e.g., nothing)	Feedback: LMS Preference
	explicit system preference	Feedback: LMS Preference
Technical	bugs, glitches	LMS Quality
	speed/responsiveness	LMS Quality
	other technical issues	LMS Quality
Use in Context	how used or amount of use	-
Prior Use	of pilot system	-
	of current system, so prefer	Feedback: LMS Preference
Instructor	system experience level	LMS Pilot Conditions
multi-LMS use	don't like using 2 systems	LMS Pilot Conditions

Though the questions used in this study were successfully mapped to the model's constructs and resulted in statistically significant paths, construct relationships, and explained variance of constructs, there are several recommendations for improving them through direct borrowing of question items from the research literature (when possible), through avoiding single indicators for LMS-PM constructs, and by refining questions to better match with construct definitions:

- Continuing to use several demographic questions is recommended; for a pilot it helps to indicate the breadth of participants; and it provides data if comparing differences between or among groups is of particular interest (e.g., based on gender, location, academic level, type of course, etc.).
- Though the LMS-PM model does not focus on the level of usage because the utilization of an LMS is generally expected for courses (and, if chosen for a course, is mandatory for the students), the inclusion of usage questions is still recommended. Possible items to include for a full pilot survey are:

  (Adapted from McGill & Klobas, 2009)
  On average, how many hours per week did you use X during the semester for this course?
  Your use of X for this course is light … heavy.

  The range of use of different LMS components may be of interest to implementers and a minimum threshold level of use may be desired to include user data.
- This study saw many student comments related to the quality of the LMS; however, there were no related closed-ended survey questions. The inclusion of

LMS Quality survey questions is recommended, especially for full pilots. Possible ones to include for a full pilot survey are:

> (Adapted from Jan & Contreras, 2011)
> I have no problem with the overall quality of X.
>
> (Adapted from Lin, 2007)
> The operation of X is reliable.
>
> (Adapted from Klobas & McGill, 2010)
> X is available when I need it.
> Output is in the needed form.
>
> (new question in draft form)
> I frequently encounter glitches and errors while using X.

If the LMS data will be used for broader research purposes (or might be at some point in the future), the use of multiple items for each construct is recommended. If not, then at least use an 'overall' type question for this, and other, constructs.

- This study saw many student comments about the challenge of using multiple LMSs in the same semester, with some students wondering why they had to use the pilot LMS. Questions related to *LMS Pilot Conditions* to include in a full pilot survey are:

> (new questions in draft form)
> I understand why this course was trying out X.
> It was not a problem to use X for only one course this semester.
> Help was available when I had difficulties using X.

- This study saw a substantial number of student comments related to ease of use; however, the survey included only a single question on ease of use. Because of the prevalence of related comments, multiple items for the *Perceived Ease of Use* construct are recommended. Possible questions to include for a pilot survey are:

(new questions in draft form)
It is easy to navigate around X.
Finding things in X is not a problem.
Using X is very confusing.

(Adapted from Yi & Hwang, 2003)
Learning to use X is easy for me.
Overall, I find X easy to use.

If, instead of a full pilot, only a brief demonstration or short hands-on experience were provided, modified versions of these and other constructs' questions would be needed to reflect the user's perception of how actual use of the LMS in real courses would be experienced, for example, 'It would be easy to navigate' instead of 'It is easy to navigate.'

- In this study, the *Perceived Usefulness* measure was reduced to an individual's average rating of the subset of eighteen tools and features he/she used:

(from this study)
Please rate the <u>usefulness</u> of the following tools and features of *X* in contributing to your work in this course. Scale: did not use this feature, not at all useful, slightly useful, moderately useful, highly useful: [list of specific tools and features]

In addition to creating an overall rating by the individual based on the tools and features used, such a question can also provide implementers information on which tools were used a lot and which tools were used much less so. Additional questions related to general usefulness of the pilot LMS would also be worth considering:

(Adapted from Yi & Hwang, 2003)
Using X improves my performance in this course.
Using X increases my productivity in this course.
Using X enhances my effectiveness in this course.
Overall, I find X useful in this course.

- This study had nine questions regarding impact on learning, though on closer examination some appear to focus on narrow versus broad impact (e.g., 'take a test' compared to 'study for tests'). Furthermore, other broad impacts are not included. In order to improve the separation between general usefulness and learning impact questions, a suggested revision to this studies' questions on *Perceived Impact on Learning* would include:

> (revised from this study)
> <u>Perceived impact on learning</u>
> [Scale: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree, not applicable]
> *X* helps me to learn the course materials/content.
> *X* helps me to study for exams/tests.
> *X* helps me to complete course assignments.
> *X* helps me to make efficient use of my time in the course.
> *X* helps me to be in control of my own learning in the course.
> *X* helps me to communicate with my professor.
> X helps me to communicate with my fellow students.
> X helps me to know how I am doing in the course.
> *X* was beneficial to my overall learning in the course.

- For the LMS-PM construct *Feedback: LMS Preference*, this study's question explicitly about the individual student's preference was recoded to better reflect a continuum of preference:

> (revised from this study)
> Overall, compared to [our institution's] current LMS [title], please select the choice that best describes your preference for [current LMS] versus *X*:
> > I prefer [current LMS] over *X*.
> > I have no preference.
> > I prefer *X* over [current LMS]

Additional items for the *Feedback: LMS Preference* construct could include:

> (new questions in draft form)
> In the future, my instructor should continue to use X in this course.
> I would recommend X for use in other courses at [our institution].

Appendix P provides a summary of suggested survey questions for LMS-PM core constructs for use in either full pilots or a brief demo/short hands-on experience.

In summary, based on the results of this study, an LMS-PM model is proposed to facilitate the interpretation of user evaluations of an LMS under consideration to replace a current system. To assist applying the proposed model in a higher-ed decision context, several items have been provided:

- Construct terms and definitions
- Model of the interrelationships among the constructs
- Coding guide for interpreting responses to open-ended questions, and
- Recommendations for closed-ended survey questions for each construct, with language targeted for two different evaluation settings.

Following the above recommendations, the assertion is that the data generated in the current study would have provided an improved understanding of the students' evaluations of the pilot LMS based on their experience in a semester-long course. It is hoped these items will provide a starting framework for further research and would help others in the process of selecting a new LMS for their higher-ed institution.

Limitations of the Study

As with any research, this study comes with its limitations. Findings from this exploratory study attempting to establish a connection between the research and practice should be read keeping the following in mind:

1. The source survey questions for the study – taken from an LMS evaluation at an institution and without any clear or explicit linkage to research literature – were not created as a validated measure or groups of measures.
2. With the use of secondary data, the needs of this study may not be aligned with the original intent of the data's origin and the data may not be aligned with the models used in both qualitative and quantitative analysis.
3. The mapping of survey questions to constructs, though based on prior questions used in research, created constructs with a wide range of indicators and often created constructs with single indicators. It is generally recommended to have multiple indicators per construct and "if single item measures are used, researchers typically must accept the consequences of lower predictive validity" (Hair et al., 2014, p. 48).
4. The data is from a convenient sampling and involved a single LMS, both of which decrease the generalizability of the results.
5. User data is self-reported and may be less reliable than objective data. For example, self-reported usage "should not be regarded as precise measures of actual usage frequency, although previous research suggests they are appropriate as relative measures" (Davis, Bagozzi, & Warshaw, 1989, p. 991).
6. It should also be recognized that the study examined only the survey results from students, and the evaluation of an LMS in a higher-ed context also importantly depends on faculty user input.

Suggestions for Future Research

In light of the findings, implications, and limitations of this study, there is a need for future research to more deeply establish a connection between the research literature and the LMS evaluations done in a higher-ed selection decision context.

- The study needs to be replicated in other situations, including different institutions and different pilot systems.
- In addition to further study with student input, research should be conducted with faculty users.
- Measures should be constructed and validated for use with the proposed model, with multiple indicators for any construct, and items drawn from existing literature when available.
- The proposed model should be tested in other LMS evaluation settings, including both the demo/brief hands-on approach as well as the use in actual courses.
- The proposed model should be tested for usefulness in the evaluation/selection of other learning technologies.

Conclusions

The use of learning management systems in higher education is here to stay, as well the evolving nature of what vendors or service providers deliver. Under such dynamic conditions, the need for institutions to regularly evaluate potential systems will persist, and if a change in systems is truly considered, the need to gather user input is an important aspect of the selection process. This study was the first attempt to address the disconnect between the academic literature and the use of LMS user evaluations in a higher-ed pilot system decision context. The lack of any reference to the academic literature potentially undercuts the credibility of LMS higher-ed institutional reports on their selection/decision process. Where formerly no academic research was explicitly brought to bear, this study helped show its value and applicability by comparing the relative utility of the prevalent IS acceptance and success models in the literature.

In an exploratory study, this research used the existing data from an LMS evaluation process to compare, through both qualitative and quantitative analysis, the relative utility of the three most frequently used IS models in LMS academic studies – the Technology Acceptance Model (Davis, 1989; Vankatesh & Davis, 2000), the IS Success Model (DeLone & McLain, 1992, 2003), and the Task-Performance Chain Model (Goodhue & Thompson, 1995).

All three models exhibited utility in analyzing the student user-evaluations from an LMS pilot and contributed to the foundation for building a proposed Learning Management System – Pilot Model (LMS-PM) that could provide for practitioners common nomenclature and a framework for understanding and sharing LMS pilot evaluation results. The resulting constructs – including ease of use, usefulness, impact on learning, and the user's resulting system preference – and their inter-relationships represent the key concerns generally addressed in LMS evaluations reports resulting from providing users a brief demonstration or hands-on experience. With LMS evaluations using full pilots – where a pilot system is used in actual courses for a full grading term – additional constructs are added, dealing with system quality issues and with the unique pilot conditions where students must use the pilot system for only one course and an existing system for all other courses in the term. It is hoped that this study and the resulting proposed model will lead both to additional research, cementing an explicit connection between the academic literature and the LMS decision processes used in higher education, and to the practical application of more common terms and framework across institutions conducting a selection process and making a decision that will impact the institution for years.

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APPENDICES

Appendix A: Higher-Ed LMS Evaluation Reports – User Input Approaches

Institution	Site/Report	Pilots	Pilot Survey Framework	Key indicators
University of Iowa (2003)	http://www.uiowa.edu/%7Eprovost/elearning/ http://www.uiowa.edu/%7Eprovost/elearning/cms_selection/index.shtml	No. Randomly assigned faculty and student participants to a system to complete task sets	No referenced framework	Usability
St. Petersburg College (2004)	http://it.spcollege.edu/lms/supportDocs.htm http://it.spcollege.edu/lms/documents/Discovery%20Days%20Evaluation%20Sheet.doc	No. Faculty provided access and given a task-based comparison rubric.	No reference framework	Ease of use
California State University - Chico (2005)	http://www.csuchico.edu/tlp/LMS2/ http://www.csuchico.edu/tlp/LMS2/LMSStrategicReview.pdf	No. On campus demonstrations only of final candidates.	EDUTOOLS Course Management System Features and Criteria	Availability (downtime) Ability to perform, execute Satisfaction: technical support Responsive to customer needs
MonMouth University (2005)	http://its.monmouth.edu/CLEAR/	No. Faculty provided access and given a task-based system comparison rubric.	No referenced framework	Key tools/Features comparison across four alternate systems providing first and second choice and overall importance of the item Single system feedback for a systems across key tools/features: Would you use it and Ease of Use
Idaho State University (2007)	http://www.isu.edu/itrc/resources/lms_final_report_moodle.pdf	Yes, confirmatory pilot of final selection	No referenced framework	Ease of Use Functionality Help and training
Louisiana State University and A&M (2007)	http://moodle.wiki.usfca.edu/file/view/moodle.pdf	No. Hands on sessions of final candidates.	No referenced framework	Individual tools meet faculty needs

Institution	Site/Report	Pilots	Pilot Survey Framework	Key indicators
North Carolina State (2008)	http://wikis.lib.ncsu.edu/index.php/LMS_Strategy	Yes	No referenced framework	Ease of Use Reliability and performance Likeability
DePauw University (2009)	http://teachingcommons.depaul.edu/P_S_C/LMS/review.html	No. Faculty provided access and given a task-based rubric.	No referenced framework	Rate how the system meets the user's needs for specific tasks in terms of functionality and ease of use
University of Florida (2009)	https://lss.at.ufl.edu/services/reports/cms/CMS%20Report-April-2009.pdf	No. On campus demonstrations and hands-on sessions of final candidates.	No referenced framework	Usability (User-Friendly) Functionality
Duke University (2010)	http://elearning.duke.edu/wp-content/uploads/2011/03/Public-eLearning-October-Report.pdf	No	No referenced framework	[no user survey indicated]
Miami University (2010)	https://sites.google.com/site/altlmspro/	No.	No referenced framework	Survey of existing system, ranking features and concerns Hands-on access survey comparing systems on ease of use and how well particular tools meet needs
North Carolina Community College System (2010)	http://oscmoodlereport.wordpress.com http://oscmoodlereport.files.wordpress.com/2009/08/osc_full_report.pdf	Yes	No referenced framework	Student perceived instructor comfort Ease of use Specific tasks
California State University - Channel Islands (2011)	http://www.csuci.edu/ats/lmsreview/finalreport/index.htm	Yes	No referenced framework	Individual tools meet faculty needs Easy to learn (faculty) Easy to learn (students) Would you like to use this LMS? (faculty) Would you like to use this LMS? (students)

Institution	Site/Report	Pilots	Pilot Survey Framework	Key indicators
Florida Southwestern State College – Edison Online (2011)	https://edison.instructure.com/courses/36089/ https://edison.instructure.com/courses/36089/pages/pilot-feedback	Yes	No referenced framework	Likeability, general Likeability of specific features
Framingham State University (2011)	http://elearning.fscmedia.com/wp-content/uploads/2011/01/Assessment-Summary_final.pdf	No. Vendor presentations and hands-on 'sandbox' sessions	No reference framework	Overall recommendation
University of Texas – Austin (2011)	http://www.utexas.edu/its/course-mgmt/governance/LMS%20Project%20Report%20and%20Recommendations-FINAL.pdf	Recommended (pilot report not publically available) Initial User testing participants were given access and ranked specific tasks and also overall impressions	No referenced framework	Ease of Use Speed Likelihood of using it if switch occurs
Butler University (2012)	http://blogs.butler.edu/lms/files/2012/04/Executive-Summary-and-Recommendation.pdf http://blogs.butler.edu/lms/evaluation-process/survey-data/	Yes	No referenced framework	Ease of Use by task Overall Satisfaction

Institution	Site/Report	Pilots	Pilot Survey Framework	Key indicators
Durham Technical Community College (2012)	http://lanyrd.com/2013/nc3adl/scpfhd/ http://courses.durhamtech.edu/wiki/index.php/LMS_Team (general information) http://courses.durhamtech.edu/wiki/index.php/Sakai_Pilot (empty)	Yes [report unavailable online]	[Report unavailable online]	[Report unavailable online]
University of California, Berkeley (2013)	https://drive.google.com/file/d/0B27IWIFK9C1pbVlQUjY1aHViVjA/edit	Yes	No referenced framework	Satisfaction Ease of Use (of various features) Perceived value (e.g., enhanced class experience; helps to learn more effectively)
DeSales University (2013)	http://blogs.desales.edu/deit/files/2013/07/LMS_Evaluation_Report_BbWorld.pdf	Yes	No referenced framework	Transfer of content from current system Overall design and ease of use Satisfaction with specific tools/features
Harvard University (2013)	http://tlt.harvard.edu/news/fall-2013-canvas-pilot-results-published	Yes	No referenced framework	Functionality Look and feel Navigation Ease of Use Overall experience
Indiana University (2013)	https://uits.iu.edu/next/reports	Yes	No referenced framework	Usability (e.g., ease of use) Usefulness Impact (e.g., help learn, study, communicate; efficiency) Satisfaction Preference compared to current LMS
University of Washington (2013)	https://www.washington.edu/itconnect/wp-content/uploads/2013/12/document2.pdf https://www.washington.edu/itconnect/wp-content/uploads/2013/10/Canvas_2013FullReport.pdf	Yes. Report also includes first year of UW-wide adoption	No referenced framework	Satisfaction Impact How LMS is Used Effectiveness of training

Institution	Site/Report	Pilots	Pilot Survey Framework	Key indicators
Valencia College (2013)	http://valenciacollege.edu/oit/learning-technology-services/faculty-resources/documents/CanvasPilotOITReport.pdf	Yes	No referenced framework	[No survey mentioned]
Western Washington University (2013)	https://west.wwu.edu/atus/canvas/Canvas%20Recomendation%201-11-13.pdf	Yes, confirmatory pilot of final selection	No referenced framework	Overall satisfaction Look and feel New valuable features
University of Wisconsin System (2013)	http://www.wisconsin.edu/olit/luwexec/projects/LMS%20Task%20Force%20Report%202012%20FINAL.pdf http://www.wisconsin.edu/olit/luwexec/projects/CanvasFinalReport.pdf	Survey of current system users Pilot of alternate system	No referenced framework No referenced framework	Ease of Use of specific features Usefulness of specific features Effectiveness of specific features for specific tasks Choice between existing and alternate system Usefulness of key specific tasks Ease of use
Baylor University (2013-14)	http://www.baylor.edu/itslib/doc.php/225505.pdf	Yes	No referenced framework	[Survey questions and results not available]
University of Denver (2014)	http://otl.du.edu/blog/report-on-the-canvas-pilot-project/ http://otl.du.edu/wp-content/uploads/2014/05/Canvas-Faculty-and-Student-Survey-Report.pdf	Yes, confirmatory pilot of final selection	No referenced framework	Ease of Use to accomplish task Effectiveness to accomplish task Comparison to current system for key tasks Overall satisfaction
University of Missouri (2014)	http://lmsreview.missouri.edu/wp-content/uploads/2015/02/LMS-recommendation_Official.pdf	No. Demonstrations from vendors and available trial sites	No referenced framework	[Survey questions and results not available]
Northwestern University (2014)	http://www.it.northwestern.edu/bin/docs/The-Canvas-Recommendation-Report_4-10-2014.pdf	Yes, confirmatory pilot of final selection	No referenced framework	Switch decision Features and functionality Time to learn Overall satisfaction

Institution	Site/Report	Pilots	Pilot Survey Framework	Key indicators
Virginia Tech University (2014)	https://tlos.vt.edu/NextGenerationLMS/wp-content/uploads/2014/11/Investigation-and-Selection-Report_Final.pdf	No. Proof of concept conducted	No referenced framework.	[No survey. Relied on evaluations by other institutions]
University of Miami of Ohio (2014)	https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=23&cad=rja&uact=8&ved=0CCgQFjACOBRqFQoTCPnu9OL7t8cCFcg4PgodDugJrQ&url=http%3A%2F%2Fmiamioh.edu%2F_files%2Fdocuments%2Fabout-miami%2Fprovost%2Freports%2FLMS-evaluation-final-committee-report-may-2014.docx	Yes	No reference framework	[Survey report behind login]
University of Michigan (2014-2015)	https://docs.google.com/document/d/10APmtj3xm5c8dniUK_tEqPJ0Y0F0zezRP9sl4bODBLE/	Yes	No referenced framework	Ease of use Helpfulness (of various features) Comparison to current LMS
Penn State (2014-2015)	http://newlms.psu.edu/completed-pilots/	Yes	No referenced framework	Ease of use, navigation, to learn Usefulness of feature set Impact (e.g., help learn, study, communicate; beneficial)
Purdue University (2014-15)	https://www.itap.purdue.edu/learning/docs/canvas/FinalCanvasReptWV.pdf	Yes	No referenced framework	Satisfaction level and importance (per feature)
University of California, Irvine (2015)	http://sites.uci.edu/canvaspilot/2015/07/01/summary-of-student-responses-to-post-quarter-survey-for-spring-2015/	Yes	No referenced framework	Ease of use (to accomplish various tasks) Impact on quality of the class Preference compared to current system

Institution	Site/Report	Pilots	Pilot Survey Framework	Key indicators
University of Iowa (2016)	http://teach.its.uiowa.edu/files/teach.its.uiowa.edu/files/wysiwyg_uploads/Canvas_pilot_report_final_0.pdf	Yes, confirmatory pilots	No referenced framework	Usability (easy to learn, use, navigate, interact, monitor progress, organize materials, grade) Effectiveness (for student learning, for teaching) Satisfaction with specific tools and features Overall Satisfaction Ease of transitioning from current LMS Experience of technical problems Preference of pilot LMS over current LMS

Institutions with public links no longer active:
[originally linked from https://confluence.umassonline.net/pages/viewpage.action?pageId=21627790 and http://www.masmithers.com/2009/09/20/public-lms-evaluations/]

Australian National University
Central Queensland University
Elon University
McMaster University
Queensland University of Technology
SUNY Learning Network
University of California. Los Angeles
University of Canterbury, New Zealand
University of Minnesota
University of North Carolina – Charlotte
University of Northern Texas
University of Notre Dame
Western Michigan University

Appendix B: TAM/TAM2 Model LMS Article Summaries

TAM Constructs:
Perceived Usefulness (PU); Perceived Ease of Use (PEU); Attitude Towards Using (A); Behavioral Intention to Use (BI); Perceived or Actual Usage (U)

TAM2 Additional Constructs:
Voluntariness (V); Experience (E); Subjective Norm (SN); Image (I); Job/Task Relevance (R); Output Quality (OQ); Result Demonstrability (RD). *Attitude is dropped in TAM2.

	Study Focus	**PU**	**PEU**	**A***	**BI**	**U**		**V**	**E**	**SN**	**I**	**R**	**OQ**	**D**	**Additional Variables**	**Special findings**
Yi & Hwang (2003)	Predicting the use of a web-based class management system	X	X		X	X									Three intrinsic motivation constructs: Enjoyment; Learning Goal Orientation; Application Specific Self-Efficacy	In the presence of Enjoyment, ease of use no longer had a significant effect on usefulness. Application Specific Self-Efficacy had significant effects on ease of use and use.
Landry, Griffeth, & Hartman (2006)	Web-enhanced instruction for students using an LMS	X*	X			X									*Usefulness a combination of Effectiveness & Importance. Assessed Effectiveness and Importance and Usage of 10 LMS elements split into two factors: Content and Support.	Support for TAM in academic setting. Usefulness, more than EoU determines Usage.

	Study Focus	PU	PEU	A*	BI	U		V	E	SN	I	R	OQ	D	Additional Variables	Special findings
Pituch & Lee (2006)	Compared a partially mediated model and a fully mediated model of system characteristics effect on e-learning use.	X	X		X*										External Variables (System Functionality; System Interactivity; System Response; Self Efficacy; Internet Experience). *Use for Supplementary Learning; Use for Distance Education.	Partially mediated model was superior to the fully mediated mode. Important to look at system characteristics
Abdalla (2007)	Student perception of LMS effectiveness	X	X	X											Cognitive Behavior and Technology Effectiveness (similar to Benefits/Impact).	Usefulness and Ease of Use of TAM model confirmed. TAM model extended to include Effectiveness of Technology.
Ngai, Poon, & Chan (2007)	Examination of LMS adoption using TAM	X	X	X	x*	X									Technical Support (availability of technical assistance, specialized instruction, and internal training for the LMS). *Intention removed based on principal component statistical analysis.	Most causal relationships between constructs well supported. PEU and PU were dominant factors affecting attitude. Technical Support had a significant effect on PEU and PU.

	Study Focus	PU	PEU	A*	BI	U		V	E	SN	I	R	OQ	D	Additional Variables	Special findings
Martínez-Torres, Marín, García, Vázquez, Oliva, & Torres (2008)	TAM of e-learning tools of web-based e-learning tools used in practical and laboratory teaching	X	X		X	X									Methodology; Accessibility; Reliability; Enjoyment; User Adaption; Communicativeness; Feedback; Format; Interactivity and Control; Diffusion; User Tools	Consistent with prior studies, all variables except perceived ease of use significantly affected users behavioral intent. Perceived Usefulness had the strongest direct effect on Behavioral Intention.
Van Raaij & Schepers (2008)	Acceptance and use of a Virtual Learning Environment (VLE) designed for an Executive MBA	X	X			X				X					Personal innovativeness in the domain of IT; Computer Anxiety	PU has a direct effect on use; PEU and SN have only indirect effects via PU. Personal innovativeness and computer anxiety have direct effects on PEU only.
Wang & Wang (2009)	Instructor attitudes of web-based learning systems looking at both user intention and IS success	X	X		X	X				X					Combined TAM with D&M (Information Quality, System Quality, Service Quality) and Self-efficacy	Especially Service Quality, but also System Quality, and Self Efficacy increased EOU. Information Quality, PEU, and SN increased PU. Perceived usefulness and Subjective Norm were the dominant factors affecting Intention to Use. Self-Efficacy did not.

	Study Focus	PU	PEU	A*	BI	U		V	E	SN	I	R	OQ	D	Additional Variables	Special findings
Al-Bushaidi & Al-Shihi (2010)	Theoretical Framework for instructor's acceptance of LMS	X	X	X	X										Three D&M technology factors (System Quality, Information Quality, and Service Quality) and other external variables pertaining to Instructor Factors and Organizational Factors.	Did not test the proposal framework.
Sánchez & Hueros (2010)	Motivational factors that influence the acceptance of Moodle using TAM	X	X	X		X									Technical Support (availability of technical assistance, specialized instruction, and internal training for the LMS). Perceived self-efficacy was initially included, but principal component analysis loaded it onto PEU and so the construct was eliminated.	TAM constructs used were confirmed. And technical support has a direct effect on perceived ease of use and perceived usefulness, but not directly on attitude.
Jan & Contreras (2011)	Student use of an academic administrative information system providing content, information and communication	X	X	X	X	X				X					Compatibility (adapted from Rogers): Perceived as compatible with previous values and experiences.	Perceived ease of use and perceived compatibility do not intervene in the model.

	Study Focus	PU	PEU	A*	BI	U		V	E	SN	I	R	OQ	D	Additional Variables	Special findings
Venter, van Rensburg, & Davis (2012)	Drivers of LMS use in South African open and distance learning institution	X	X	*	X	X				*		X	*	*	Facilitating conditions; self-reported frequency of use cross-tabulated with activities performed. * Items for Results Demonstrability, Attitude, Output Quality, and Subjective Norm were, after factor analysis, combined into Performance Enhancement	PU and PEU along with R and Facilitating Conditions are confirmed. "This finding raises questions about the usefulness of TAM2 where usage patterns have already been established over prolonged periods of time." (p. 195)
Chung, Pasquini, and Koh (2013)	LMS for higher education	X	X	X	X										Five categories of LMS features: transmitting course content, evaluating students, evaluating courses and instructors, creating class discussions, creating computer-based instruction.	Adapted TAM model is proposed for LMS design and development, but was not tested.
Fathema & Sutton (2013)	Faculty attitudes towards LMS	X	X	X	X	X									Asked why using or not; extent LMS is understandable; level of skill required to use LMS; strengths; weaknesses; recommendations.	Five TAM constructs were a practical way to code and organize open-ended survey responses about LMS.

	Study Focus	PU	PEU	A*	BI	U		V	E	SN	I	R	OQ	D	Additional Variables	Special findings
Ma, Chao, & Cheng (2013)	Blended e-learning in nursing	X	X		X										Three constructs from Task-technology Fit: TTF with antecedents of Task Characteristics and Technology Characteristics; TTF points to TAM construct Perceived Usefulness. Self-Efficacy. User Satisfaction.	Computer self-efficacy had no significant influence on perceived usefulness. TTF (with its two significant antecedents) had a significant impact on Perceived usefulness that was much stronger than the impact of perceived ease of use.
Alharbi & Drew (2014)	Understanding Academics' Behavioral intention to use LMS in Saudi Arabia	X	X	X					X			X			Lack of LMS availability (considered potentially important because of the local context).	All TAM related constructs were validated. Lack of LMS availability did not negatively affect perceived ease of use and usefulness.
Baleghi-Zadeh, Ayub, Mahmud, & Daud (2014b)	Developing a measurement model for behavior intention to use LMS by pre-service teachers.	X	X		X										Task Technology Fit; Technical Support as an external variable.	Five constructs did fit; factor analysis reduced 39 items to 28.
Baleghi-Zadeh, Ayub, Mahmud, & Daud (2014c)	Developing a measurement model LMS Utilization among Malaysian higher ed students	X	X		X	X*				X					*LMS Use construct was operationalized with "I use" questions for 10 tasks, e.g., I use X to submit my assignments.	A modified measurement model was fit and validated with the data of the present study. 39 items were reduced to 29.

	Study Focus	PU	PEU	A*	BI	U		V	E	SN	I	R	OQ	D	Additional Variables	Special findings
Schoonenboom (2014)	Why instructors in higher education intend to use some LMS tools more than others	X	X		X										For 18 instructional tasks, instructors were asked about task performance, task importance, and three TAM concepts.	"Results seem to suggest that technology acceptance might be influenced by possibly unique combinations of an instructional task, the interface [...] and the context in which the task is performed" (p. 254)

Appendix C: D&M Model LMS Article Summaries

D&M Constructs: System Quality (SysQ); Information Quality (InfoQ); Service Quality (ServQ); Use/Intention to Use (U); Satisfaction (S); Net Benefits (B)

	Study Focus	**SysQ**	**InfoQ**	**ServQ**	**U**	**S**	**B**		**Additional Variables**	**Special findings**
Holsapple & Lee-Post (2006)	To advance the understanding of how to define, evaluate, and promote e-learning success	X	X	X	X	X	X		None	In an action-research context, the IS Success model was useful in defining, assessing, and promoting e-learning success.
Lin (2007)	Examine the determinants for successful use of online learning systems	X	X	X	X*	X	X*		Behavioral Intention (BI) to use. *Actual Use construct expressed in terms of benefits: I use OLS to increase my sense of accomplishment; to improve my status among my peers; to increase my chances of obtaining rewards	InfoQ strong influence on Satisfaction and BI; SysQ and ServQ affect Satisfaction and BI.
Wang, Wang, & Shee (2007)	E-learning system in an organizational context; scale development; validate IS Success model for e-learning	X	X	X	X	X	X		None	IS Success model validated in context of enterprise e-learning systems.
Ozkan & Koseler (2009)	Multi-dimensional students' evaluation of e-learning systems in higher education	X	X*	X		X**			Instructor Quality; Supportive Issues; *InfoQ defined as Content Quality; **S defined as Learner Attitude	Model was validated; correlations between dimensions were out of the scope of the study.

	Study Focus	SysQ	InfoQ	ServQ	U	S	B		Additional Variables	Special findings
Klobas & McGill (2010)	Role of instructor and student involvement on LMS success	X	X	X	X	X	X		Student involvement; Instructor involvement	Perception of Instructor involvement affected use; student involvement did not, though it did affect students' perception of LMS benefits. Confirmed the importance of studying the nature of use rather than just the extent of use.
Almarashdeh, Sahari, Zin, & Alsmadi (2010)	LMS success in Malaysian Universities' distance education	X	X	X	X	X	X		From TAM: Perceived ease of use and Perceived Usefulness	Researchers found empirical support for the model.
Tella (2011)	Scale development and validation in an educational context	X	X*	X	X	X	X		Teaching and Learning Quality; Self-Regulated Learning; *InfoQ defined as Content Quality	All dimensions contributed to measuring course management system success.
Lin & Chen (2012)	Satisfaction and Continuance Intention of E-Learning systems	X	X*			X			*Two constructs: Course Information Quality and Platform Information Quality. Added two TAM constructs: Perceived Usefulness and Perceived Eas of Use. Continuance Intention.	Usefulness and Satisfaction both determined Continuance Intention. Usefulness and Ease of use affected Satisfaction, with ease of use stronger.

	Study Focus	SysQ	InfoQ	ServQ	U	S	B		Additional Variables	Special findings
Lin & Wang (2012)	E-learning system in blended learning instruction	X*	X*			S**			Task Technology Fit; Four constructs from Bhattacherjee's post acceptance model: Perceived Usefulness (from TAM); Confirmation of System Acceptance; **System Satisfaction; and Continued Use Intention. *New variable Knowledge Quality combined with System Quality and Information Quality in the area of System Success Factors	TTF has impacts on the utilization of the learning system. Perceived Usefulness and Satisfaction have high prediction rates in explaining continuance intentions.
Wang, Doll, Deng, Park, & Yang (2013)	Faculty perceived reconfigurability of LMS on effective teaching practices	X*			X**		X		*Adapted as System Configurability (of Interface, Interaction, Content). **Use defined as Faculty Use of LMS to Implement Effective Teaching Practices.	Reconfigurability dimensions have significant impacts on helping faculty use LMS to implement effective teaching practices, with interaction reconfigurability having the strongest relationship.
Mtebe & Raisamo (2014)	LMS Success in higher education in Sub-Saharan countries	X	X*	X	X	X	X		*InfoQ defined as Course Quality	All six constructs were significant; however, service quality and system quality did not impact learner satisfaction, though they did still impact use.

Appendix D: TTF/TPC Model LMS Article Summaries

TTF Constructs: Task Characteristics (TaskC); Technology Characteristics (TechC); Individual Characteristics (IndC); Task Technology Fit (TTF); Performance Impacts (PI)

TCP Additional Constructs: Utilization (U); Expected Consequences (EC); Affect towards Using (A); Social Norms (SN); Habit (H); Facilitating Conditions (FC)

	Study Focus	**TaskC**	**TechC**	**IndC**	**TTF**	**PI**		**U**	**EC**	**A**	**SN**	**H**	**FC**		**Additional Variables**	**Special findings**
McGill & Hobbs (2008)	Student vs instructor perceptions of a LMS/Virtual Learning Environment				X	X		X	X	X	X		X		User Satisfaction	TTF, User Satisfaction, A, and EC were all higher for students than instructors. Structural model not tested.
McGill & Klobas (2009)	Using technology-to-performance chain as a framework to look at how task-technology fit influences students' perceived impacts on learning in LMS				X	X		X	X	X	X		X		Student Grades; Instructor Norms	TPC was found useful in the e-learning context. Common social norms and facilitating conditions were not found to influence Performance Impacts.

	Study Focus	TaskC	TechC	IndC	TTF	PI		U	EC	A	SN	H	FC		Additional Variables	Special findings
Larsen, Sørebø, & Sørebø (2009)	The role of TTF as users' motivation to continue information system use in e-learning				X*			X							*Labeled as Perceived TTF. Constructs from Bhattacherjee's post-acceptance model: Perceived Usefulness (from TAM); Confirmation; Satisfaction; IS Continuance Intention.	Constructs from TTF/TPC (TTF and Utilization) contributed to the model.
Yu & Yu (2010)	Modeling factors that affect individuals' utilization of online learning systems		X	X	X*	X**		X**		X	X***				*TTF labeled as Learner-Technology Fit. **Utilization labeled as Learner Utilization but items ask about impacts; Intended Use labeled Behavioral Intentions; ***Social Norms labeled Social Influences. Perceived Behavioral Control and Behavioral Intentions added.	Combining TPB and TTF constructs provides a better explanation for the variance in electronic learning system utilization than either the TPB or TTF models can provide alone. This corroborates Dishaw and Strong (1999), who combined the TAM and TTF models. The current study proposes a better hybrid technology utilization model to explain students' usage behavior.

	Study Focus	TaskC	TechC	IndC	TTF	PI		U	EC	A	SN	H	FC		Additional Variables	Special findings
McGill, Klobas, & Renzi (2011)	Using technology-to-performance chain as a framework to look at how task-technology fit influences instructors' perceived impacts on learning in LMS.				X	X		X			X		X			Only a single significant path -- from TTF to LMS Performance Impacts. Social Norms and Facilitating Conditions did not impact Utilization. Utilization did not significantly affect LMS Performance Impacts.
Lin (2012)	Web learning performance with a Virtual Learning System				X*	X**									Two constructs from Bhattacherjee's post-acceptance model: Satisfaction; Continuance Intention (in place of Utilization). *Defined as Perceived Fit; **Defined as Positive Impacts on Learning	Perceived Fit and Satisfaction had significant paths to both Continuance Intentions and Perceived Impacts. Perceived Fit is three times more important than Satisfaction to Impact on Learning.
Baleghi-Zadeh, Ayub, Mahmud, & Daud (2014a)	Views of LMS by Malaysian Higher Education Students				X										Internet Experience; Subjective Norms	Comparison of the three means, with Internet Experience being the highest one.

Appendix E: LMS Pilot Study Student Survey

[Note: the system name has been replaced with *X*]

Introduction and Consent

In partnership with [the central IT organization, [we are] conducting an evaluation of the *X* Learning Management System Pilot Program being conducted during [this] semester. You have been invited to participate in this survey because you are enrolled in one or more courses being taught in *X* this semester.

Participation in this survey is completely voluntary. Should you decide to participate your responses will be kept confidential and will be reported only in aggregate in published reports. Comments will not be reported with demographics that would allow for identification of individuals. If you have any questions about the survey, please contact us [survey administrator contact information redacted].

This survey should take approximately 15 minutes to complete. Data collection will close at 5pm (EST) on [Day, Month, Year]. You may terminate your participation in the survey at any time.

Pre-Question 1: If you are 18 years of age or older as of today's date and consent to participate in the survey data collection process, please acknowledge by checking the box below. Then proceed to next page to begin the survey.

If you are NOT 18 years of age or older as of today's date or do not consent, please close the link to the survey now.

I acknowledge that I am at least 18 years of age or older as of today's date and consent to participate in this survey (will be a required check box)

Part I: Student Demographics/Institutional Context

Q1: Age/Consent

Q2: What is your current academic level?
Scale: first-year undergraduate (freshman), second-year undergraduate (sophomore), third-year undergraduate (junior), four or more years undergraduate (senior), master's degree student (MA, MS, MBA, MFA, etc.), doctoral student (EdD, PhD, etc.)

Q3: At which campus are you enrolled as a student? (Choose ONE)
[campus list redacted]

Q4: What is your age? (open text box)

Q5: What is your gender? (open text box)
Q6: Which course were you enrolled in during fall 2013 that used *X*? (If you were enrolled in more than one course that used *X*, please choose one for the purpose of this survey) *Please note: Although we ask you to identify the course in which you were enrolled, this survey is not an evaluation of the course. We will use this information to report aggregate response rates within each course and to create categories of types (disciplinary areas) and levels of courses for reporting purposes.*

(drop down list of pilot courses)

Q7: That course was delivered (Choose one BEST answer)
primarily face-to-face; using a blend of face-to-face and online interaction; online with face-to- face interaction only for exams; exclusively online with no face-to-face interaction; other (please describe)

Part II: Use of Technology

General Level of Experience/Use:

Q8: In terms of my level of comfort in using different types of technology, I am
Scale: very uncomfortable, somewhat uncomfortable, somewhat comfortable, very comfortable

Q9: What type(s) of networked device(s) do you currently use on a regular basis?
mobile phone; portable media player (e.g., iPod Touch); ebook reader (e.g., Kindle); tablet (e.g., iPad, Nexus, Galaxy); laptop/netbook computer; desktop computer; other device (please describe)

Q10: On average, how many *hours per week* have you been spending in *X* for this course?
Scale: none, fewer than 5 hours, 5-10 hours, 11-15 hours, 16-20 hours, more than 20 hours

Part III: Feedback on *X*

Q11: Please rate the usefulness of the following tools and features of *X* in contributing to your learning in this course.
Scale: did not use this feature, not at all useful, slightly useful, moderately useful, highly useful

Note: Some of these tools and features may have a different name in your course.

Q11.1. Announcements (for reading announcements and other timely news and information posted by your instructor or department)
Q11.2. Assignments (for submitting individual or group assignments)
Q11.3. Blog and Wikis (for individual and group writing tasks assigned by your instructor)

Q11.4. Calendar (for managing your personal calendar and viewing course events and due dates)
Q11.5. Chat (for live text messaging with classmates and other Blackboard users)
Q11.6. Content (for viewing course materials and completing activities organized into lessons or modules)
Q11.7. Course Messages (for sending and receiving messages to and from your instructor and other students)
Q11.8. Discussions/Discussion Board (for participating in online discussions with the entire class or in small groups)
Q11.9. Groups (for collaborating with a specific group of students on assignments, discussions, blogs, wikis, or projects)
Q11.10. Journal (for keeping a learning journal shared with your instructor)
Q11.11. Content > My Content (for storing personal files related to your course work)
Q11.12. My Grades (for viewing a list of the graded items in the course and the grades you received)
Q11.13. Quizzes/Tests (for taking and receiving feedback on online quizzes, tests, and self-assessments)
Q11.14. Roster (for viewing a list of the other people in the course)
Q11.15. Rubrics (for understanding how your work will be or was graded)
Q11.16. Send Email (for sending messages to the external email account of other course members).
Q11.17. Surveys (for taking online surveys)
Q11.18. Tasks (for completing a list of tasks prepared by the instructor)

Q12: Please rate the overall <u>ease of use</u> of *X.*
Scale: difficult to use, slightly easy to use, moderately easy to use, very easy to use

Q13: Please rate the overall <u>usefulness</u> of *X's* online documentation for students.
Scale: did not use, not at all useful, slightly useful, moderately useful, highly useful

Q14: What did you like MOST about *X*? Why? (open text box)

Q15: What did you like LEAST about *X*? Why? (open text box)

Q16: <u>Perceived impact on learning</u>
Scale: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree, not applicable

Q16.1. *X* helps me to learn the course materials/content.
Q16.2. *X* helps me to study for exams/tests.
Q16.3. *X* helps me to complete course assignments.
Q16.4. *X* helps me to take quizzes/exams.
Q16.5. *X* helps me to make efficient use of my time in the course.
Q16.6. *X* helps me to be in control of my own learning in the course.
Q16.7. *X* helps me to communicate with my professor.

Q16.8. *X* expands access to learning materials/resources available to me (e.g., print, audio, video, etc.).
Q16.9. *X* was beneficial to my overall learning in the course.

Q17 Overall, compared to [our institution's] current LMS (title), please select the choice that best describes your preference for [current LMS] versus *X*:

I prefer *X* over [current LMS].
I prefer [current LMS] over *X*.
I have no preference.

Q18 Additional Comments
Is there anything else you would like to tell us about your experience using *X* this semester? (open text box)

Appendix F: Glossary of PLS-SEM Terms (Hair et al., 2014)

Adjusted R^2 value (R^2_{adj}): is a modified measure of the *coefficient of determination* that takes into account the number of predictor constructs. The statistic is useful for comparing models with different numbers of predictor constructs, different sample sizes, or both. (p. 200-201)
Average variance extracted (AVE): a measure of convergent validity. It is the degree to which a latent construct explains the variance of its indicators. (p. 114)
Blindfolding: is a sample reuse technique that omits part of the data matrix and uses the model estimates to predict the omitted part. (p. 201)
Bootstrapping: is a resampling technique that draws a large number of subsamples from the original data (with replacement) and estimates models for each subsample. It is used to determine standard errors of coefficient estimates to assess the coefficient's statistical significance without relying on distributional assumptions. (p. 163)
Coefficient of determination: see R^2 values.
Collinearity: arises in the context of structural model evaluation when two constructs are highly correlated. (p. 201)
Composite reliability: a measure of internal consistency reliability, which, unlike […] does not assume equal indicator loadings. Should be above 0.70 (in exploratory research, 0.60 to 0.70 is considered acceptable). (p. 115)
Constructs (also called latent variables): measure concepts that are abstract, complex, and cannot be directly observed by means of (multiple) items. Constructs are represented in path models as circles or ovals. (p. 29)
Convergent validity: is the extent to which a measure correlates positively with alternative measures of the same construct. (p. 115)
Cross loadings: an indicator's correlation with other constructs in the model. (p. 115)
Discriminant validity: extent to which a construct is truly distinct from other constructs, in terms of how much it correlates with other constructs, as well as how much indicators represent only a single construct. (p. 115)
Endogenous latent variables: are constructs considered as dependent in a structural model. (p. 70)
Exogenous latent variables: are constructs that only act as independent variables in a structural mode. (p. 70)
f^2 effect size: is a measure used to assess the relative impact of a predictor construct on an endogenous construct. (p. 201)
Finite Mixture Partial Least Squares (FIMIX-PLS): is a latent class approach that allows for identifying and treating unobserved heterogeneity in PLS path models. (p. 278)
Fornell-Larcker criterion: a measure of discriminant validity that compares the square root of each construct's average variance extracted with its correlations with all other constructs in the model. (p. 115)
Indicators: are directly measured observations (raw data), generally referred to as either *items* or *manifest variables*, represented in path models as rectangles. (p. 29)
Indicator reliability: is the square of a standardized indicator's outer loading. It represents how much of the variation in an item is explained by the construct and is referred to as the variance extracted from the item. (p. 115-116)

Indirect effect: is a relationship that involves a sequence of relationships with at least one intervening construct involved. (p. 70).
Measurement model: is an element of a path model that contains the indicators and their relationships with the constructs and is also called the *outer model* in PLS-SEM. (p. 29)
Outer loadings: are the results of a single regression of each indicator variable on their corresponding construct. Loadings are of primary interest in the evaluation of reflective measurement models. (p. 92)
Path coefficients: are the relationships between the latent variables in the structural model. (p. 93)
Partial least squares structure equation modeling: is a variance-based method to estimate structural equation models. The goal is to maximize the explained variance of the endogenous latent variables. (p. 30)
Predictive relevance: when PLS-SEM exhibits predictive relevance, it accurately predicts the data points of indicators in reflective measurement models endogenous constructs and endogenous single-item constructs. (p. 178)
Q^2 value: is a measure of predictive relevance based on the *blindfolding* technique. (p. 203)
q^2 effect size: is a measure used to assess the relative predictive relevance of a predictor construct on an endogenous construct. (p. 203)
R^2 values: are the amount of explained variance of endogenous *latent variables in the structural model.* The higher the R^2 values, the better the construct is explained by the latent variables in the structural model that point at it via structural model path relationships. High R^2 values also indicate that the values of the construct can be well predicted via the PLS path model. (p. 93)
Reflective measurement model: is a type of measurement model setup in which the direction of the arrows is from the construct to the indicator variables, indicating the assumption that the construct causes the measurement (more precisely, the covariation) of the indicator variables. (p. 30)
Structural model: is an element of a PLS path model that contains the constructs as well as the relationships between them. It is also called the *inner model* in PLS-SEM. (p. 31)
Testing for statistical significance: see *Bootstrapping.*
Unobserved heterogeneity: occurs when the sources of heterogeneous data structures are not (fully) known. (p. 203)
Variance inflation factor (VIF): quantifies the severity of collinearity. (p. 165)

Appendix G: Results of Practice Coding of Sample Open-Ended Responses

Unit #	TAM	D&M	TPC	***Q 14 What did you like MOST about [the pilot system]? Why?***
1	-	SysQ	-	Clean look,
1.1	PEU	SysQ	TTF	*easy to navigate,
1.2	PU	InfoQ	TTF	*and integrated assignment submission confirmation.
2	PU	SysQ	FC	Fits my schedule and I am able to use it whenever I am not working.
3	PEU	SysQ	TTF	I like the organization of Course Tools to group together some of the most important features of the site such as grades and quizzes.
3.1	PU	InfoQ	TTF	*I like that an overall grade for the course is shown for grades.
4	PEU	SysQ	TTF	I liked how it hard [sic] a lot of ways to like breakdown class things like grades, content, quizzes and so on.
5	OQ	InfoQ	TTF	I liked the grades always being up to date,
5.1	PU	SysQ	TTF	*the list of home works,
5.2	PEU	InfoQ	TTF	*the files labeled with course subjects.
5.3	A	S	A	*I love [the pilot system]!
6	PEU	SysQ	-	It has a clean layout
6.1	PEU	SysQ	TTF	*and is user friendly.
7	PEU	SysQ	TTF	It was easy to use and understand
8	A	S	A	NOTHING
9	PEU	SysQ	TTF	straight forward and easy to navigate
9.1	PEU	SysQ	TTF	*but was hard learning it to begin with. /
10	PEU	SysQ	FC	The relative ease of access.
10.1	PEU	SysQ	TTF	*I liked how simple and straight forward the navigation was within the class.
11	PU	SysQ	TTF	The chat tool

Legend:

TAM: (PU) Perceived Usefulness; (PEU) Perceived Ease of Use; (A) Attitude Towards Using; (BI) Behavioral Intention to Use; (U) Perceived or Actual Usage; (V) Voluntariness; (E) Experience; (SN) Subjective Norm; (I) Image; (R) Job/Task Relevance; (OQ) Output Quality; (RD) Result Demonstrability

D&M: (SysQ) System Quality; (InfoQ) Information Quality; (ServQ) Service Quality; (U) Use/Intention to Use; (S) Satisfaction; (NB) Net Benefits

TPC: (TaskC) Task Characteristics; (TechC) Technology Characteristics; (IndC) Individual Characteristics; (TTF) Task-Technology Fit; (PI) Performance Impacts; (U) Utilization; (A) Affect towards Using; (SN) Social Norms; (FC) Facilitating Conditions

Unit #	TAM	D&M	TPC	***Q 15. What did you like LEAST about [the pilot system]? Why?***
1	OQ	InfoQ	TTF	I think there needs to be a confirmation of something being posted on the discussion board. It wouldn't do anything, just stay on the page I was on. I just hoped it went through every time.
2	PEU	SysQ	TTF	too many access points for similar things made it difficult to make sure that things were submitted and to find descriptions for assignments /
2.1	PU	SysQ	TTF	*also, the fact that it doesn't send emails through the [university] email system was a big downside, as it meant that in addition to checking umail, I had to check [the pilot system's] mailbox as well
3	PEU	SysQ	TTF	It was almost too complex. Sometimes I would just want to view an assignment or something small and I would have difficulty getting there and would have to click multiple buttons until I would find it.
4	U	U	U	I think if the instructor had used more of the features it would have been great, but she does not use the grade book or the assignment tab. Makes it very difficult to evaluate.
5	PEU	SysQ	TTF	I found the organization of the site made things hard to find. When I began using the site I had trouble finding the specific content. As an example, on the home screen the content browser still displays Chapter 4 content despite the fact that we are now on Chapter 9 and that is the content I have most recently accessed. Since the home page doesn't keep up with current material I have to manually access the content from the content tab at the top of the page. /
6	PEU	U	TTF	It was too hard to learn how to use it. We tried the first two weeks and then our teacher gave up.
6.1	A	S	A	*Stick with [current system] and other websites.
6.2	PEU	SysQ	TTF	*They are more user friendly.

Unit #	TAM	D&M	TPC	***Q18. Please share anything else you would like to tell us about your experience using [the pilot system] this semester***
1	PEU	SysQ	TTF	[The current system] is so much easier to use and easier to navigate.
1.1	-	-	FC	*I did not like going to all the different sites for one class.
2	PEU	SysQ	-	Overall, I prefer the layout
2.1	PU	SysQ	TTF	*and functionality of [the current system] to [the pilot system].
3	U	U	U	We never even used it. It set us behind in the class at least three weeks.
3.1	A	S	A	*Strongly do not reccomend [sic] this to anyone
4	A	S	A	[The current system] is much better than [the pilot system]
5	-	-	FC	It was a real hassle to use [the pilot system] for one class while all my other classes used [the current system]

Appendix H: Measurement Model Indicator Crossloadings

Adapted TAM Indicator Cross Loadings

(Note: a construct's indicators are in bold)	Attitude	Perceived Ease of Use	Perceived Usefulness	Perceived or Actual Usage
Q10	0.151	0.215	0.178	**single item**
Q11_avg_PU	0.361	0.594	**0.776**	0.192
Q12	0.473	**single item**	0.667	0.215
Q13	0.448	0.704	**0.742**	0.160
Q16_1	0.377	0.499	**0.852**	0.081
Q16_2	0.399	0.462	**0.790**	0.054
Q16_3	0.326	0.537	**0.824**	0.181
Q16_4	0.323	0.435	**0.780**	0.203
Q16_5	0.443	0.588	**0.886**	0.176
Q16_6	0.473	0.559	**0.886**	0.192
Q16_7	0.304	0.434	**0.775**	0.086
Q16_8	0.408	0.479	**0.823**	0.092
Q16_9	0.514	0.637	**0.916**	0.171
Q17 Recoded	**single item**	0.473	0.491	0.151

Adapted D&M Indicator Cross Loadings

(Note: a construct's indicators are in bold)	Net Benefits	Service Quality	System Quality	Use	User Satisfaction
Q10	0.171	0.160	0.203	**single item**	0.151
Q11_avg_PU	0.696	0.647	**0.853**	0.192	0.361
Q12	0.616	0.704	**0.855**	0.215	0.473
Q13	0.646	**single item**	0.765	0.160	0.448
Q16_1	**0.867**	0.550	0.695	0.081	0.377
Q16_2	**0.810**	0.518	0.632	0.054	0.399
Q16_3	**0.833**	0.499	0.719	0.181	0.326
Q16_4	**0.802**	0.438	0.639	0.203	0.323
Q16_5	**0.910**	0.592	0.730	0.176	0.443
Q16_6	**0.903**	0.595	0.738	0.192	0.473
Q16_7	**0.782**	0.491	0.636	0.086	0.304
Q16_8	0.784	0.555	**0.802**	0.092	0.408
Q16_9	**0.910**	0.669	0.821	0.171	0.514
Q17 Recoded	0.474	0.448	0.500	0.151	**single item**

Adapted TPC Indicator Cross Loadings

(Note: a construct's indicators are in bold)	Affect towards Using	Individual Character-istics	Performance Impacts	Task-Technology Fit	Utilization
Q10	0.151	0.118	0.163	0.216	**single item**
Q11_avg_PU	0.361	0.099	0.701	**0.855**	0.192
Q12	0.473	0.130	0.611	**0.874**	0.215
Q13	0.448	0.020	0.647	**0.895**	0.160
Q16_1	0.377	0.139	**0.865**	0.628	0.081
Q16_2	0.399	0.067	**0.800**	0.582	0.054
Q16_3	0.326	0.159	**0.839**	0.630	0.181
Q16_4	0.323	0.155	**0.805**	0.543	0.203
Q16_5	0.443	0.181	**0.898**	0.675	0.176
Q16_6	0.473	0.123	**0.895**	0.669	0.192
Q16_7	0.304	0.090	**0.787**	0.577	0.086
Q16_8	0.408	-0.005	**0.830**	0.617	0.092
Q16_9	0.514	0.117	**0.910**	0.753	0.171
Q17 Recoded	**single item**	0.050	0.472	0.488	0.151
Q8	0.050	**single item**	0.135	0.095	0.118

Appendix I: Measurement Model Summary Results

Adapted TAM Measurement Model Results

Latent Variable	*Indicators*	*Loadings > 0.708 at least >0.4 & stat. sig.*	*Indicator Reliability*	*Composite Reliability > 0.708 at least > 0.60*	*Convergent Validity AVE > 0.50*	*Discriminant Reliability*
Perceived Usefulness	*Q11 avg PU*	0.776***	0.602	0.959	0.680	Yes
	Q13	0.742***	0.551			
	Q16.1	0.852***	0.726			
	Q16.2	0.790***	0.624			
	Q16.3	0.824***	0.679			
	Q16.4	0.780***	0.608			
	Q16.5	0.886***	0.785			
	Q16.6	0.886***	0.785			
	Q16.7	0.775***	0.601			
	Q16.8	0.823***	0.677			
	Q16.9	0.916***	0.839			
Perceived Ease of Use	*Q12*		Single indicator			
Perceived Usage	*Q10*		Single indicator			
Attitude	*Q17 recoded*		Single indicator			

*** *p*<.001

Adapted D&M Measurement Model Results

Latent Variable	*Indicators*	*Loadings > 0.708 at least >0.4 & stat. sig.*	*Indicator Reliability*	*Composite Reliability > 0.708 at least > 0.60*	*Convergent Validity AVE > 0.50*	*Discriminant Reliability*
System Quality	*Q11 avg PU*	0.853***	0.728	0.875	0.700	Yes
	Q12	0.855***	0.731			
	Q16.8	0.802***	0.643			
Service Quality	*Q13*	Single indicator				
Use	*Q10*	Single indicator				
Satisfaction	*Q17 recoded*	Single indicator				
Net Benefits	*Q16.1*	0.867***	0.752	0.955	0.728	Yes
	Q16.2	0.810***	0.656			
	Q16.3	0.833***	0.694			
	Q16.4	0.802***	0.643			
	Q16.5	0.910***	0.828			
	Q16.6	0.903***	0.815			
	Q16.7	0.782***	0.612			
	Q16.9	0.910***	0.828			

*** *p*<.001

Adapted TPC Measurement Model Results

Latent Variable	*Indicators*	*Loadings > 0.708 at least >0.4 & stat. sig.*	*Indicator Reliability*	*Composite Reliability > 0.708 at least > 0.60*	*Convergent Validity AVE > 0.50*	*Discriminant Reliability*
Individual Characteristics	*Q8*	Single indicator				
Affect towards Using	*Q17 recoded*	Single indicator				
Task-Technology Fit	*Q11 avg PU*	0.855***	0.731	0.907	0.766	Yes
	Q12	0.874***	0.764			
	Q13	0.895***	0.801			
Utilization	*Q10*	Single indicator				
Performance Impacts	*Q16.1*	0.865***	0.748	0.959	0.720	Yes
	Q16.2	0.800***	0.640			
	Q16.3	0.839***	0.704			
	Q16.4	0.805***	0.648			
	Q16.5	0.898***	0.806			
	Q16.6	0.895***	0.801			
	Q16.7	0.787***	0.619			
	Q16.8	0.830***	0.689			
	Q16.9	0.910***	0.828			

*** $p<.001$

Appendix J: Structural Model Collinearity Assessments

Adapted TAM Collinearity Assessment

	Attitude
Constructs	*VIF < 5.00*
Perceived Ease of Use	1.800
Perceived Usefulness	1.800

Adapted D&M Collinearity Assessment

	Net Benefits	*Use*	*User Satisfaction*
Constructs	*VIF < 5.00*	*VIF < 5.00*	*VIF < 5.00*
Service Quality		2.407	2.407
System Quality		2.407	2.446
Use	1.023		1.043
User Satisfaction	1.023		

Adapted TPC Collinearity Assessment

	Performance Impacts
Constructs	*VIF < 5.00*
Task-Technology Fit	1.049
Utilization	1.049

Appendix K: FIMIX Results for Unobserved Heterogeneity

Adapted TAM

	1 Segment	*2 Segments*	*3 Segments*
LnL	-654.20	2757.08	3595.09
AIC	1322.40	-5484.16	-7144.18
CAIC	1351.50	-5421.86	-7048.66
BIC	1344.47	-5436.86	-7071.66

Adapted D&M

	1 Segment	*2 Segments*	*3 Segments*
LnL	-683.77	2844.54	2879.57
AIC	1387.55	-5647.08	-5663.141
CAIC	1429.08	-5559.86	-5562.236
BIC	1419.08	-5580.86	-5594.236

Adapted TPC

	1 Segment	*2 Segments*	*3 Segments*
LnL	-886.071	2508.857	2498.72
AIC	1790.142	-4979.715	-4939.44
CAIC	1827.522	-4900.802	-4819.00
BIC	1818.522	-4919.802	-4848.00

Appendix L: Analysis of Effect Sizes in the Structural Models

TAM Effect Sizes: In evaluating contributions to the explained variance of an endogenous latent construct, the effect size f^2 of the exogenous latent construct Perceived Ease of Use has a large (0.800) contribution to Perceived Usefulness, and both Perceived Ease of Use and Perceived Usefulness have a small (0.053 and 0.077, respectively) contribution to Attitude. In evaluating contributions to the predictive relevance of an endogenous latent construct by exogenous latent constructs, the effect size q^2 (0.406) indicated that Perceived Ease of Use has a large (0.406) contribution to Perceived Usefulness, and both Perceived Ease of Use and Perceived Usefulness have a small (0.048 and 0.072, respectively) contribution to Attitude. See a summary of effect sizes below:

Adapted TAM Summary of Effect Sizes for Explained Variance and Predictive Relevance

	f^2 Effect Size	*q^2 Effect Size*
Perceived Ease of Use -> Perceived Usefulness	0.800	0.406
Perceived Ease of Use -> Attitude	0.053	0.048
Perceived Usefulness -> Attitude	0.077	0.072
Attitude -> Perceived or Actual Use	0.023	-0.025

Effect sizes: 0.02 small, 0.15 medium, 0.35 large

D&M Effect Sizes: In evaluating contributions to the explained variance of endogenous latent constructs, the effect size f^2 of the exogenous latent construct System Quality has a small (0.075) contribution to User Satisfaction and User Satisfaction has a medium (0.268) contribution to Net Benefits. In evaluating contributions to the predictive relevance endogenous latent constructs by exogenous latent constructs, the effect size q^2 (0.055), indicated that System Quality has a small effect on User Satisfaction, and User Satisfaction has a medium (0.172) contribution to Net Benefits. See a summary of effect sizes below.

Adapted D&M Summary of Effect Sizes for Explained Variance and Predictive Relevance

	f2 Effect Size	*q2 Effect Size*
System Quality -> Use	0.016	0.011
Service Quality -> Use	0.000	-0.012
System Quality -> User Satisfaction	0.075	0.055
Service Quality -> User Satisfaction	0.014	-0.005
Use -> User Satisfaction	0.003	-0.017
Use -> Net Benefits	0.013	0.007
User Satisfaction -> Net Benefits	0.268	0.172

Effect sizes: 0.02 small, 0.15 medium, 0.35 large

TPC Effect Sizes: In evaluating contributions to the explained variance of endogenous latent constructs, the effect size f^2 of the exogenous latent construct Affect towards Using has a small (0.023) contribution to Utilization, and Task-Technology Fit has a nearly large contribution to Affect Towards Using and a large contribution to Performance Impacts (1.202). In evaluating contributions to the predictive relevance of endogenous latent constructs by exogenous latent constructs, the effect size q^2 (0.305) indicates that Task-Technology Fit nearly has a large effect on User Satisfaction and has a large (0.627) contribution to Performance Impacts. See a summary of effect sizes below.

Adapted TPC Summary of Effect Sizes for Explained Variance and Predictive Relevance

	f2 Effect Size	*q2 Effect Size*
Individual Characteristics -> Task Technology Fit	0.009	0.002
Task-Technology Fit -> Affect towards Using	0.313	0.305
Affect towards Using -> Utilization	0.023	-0.006
Utilization -> Performance Impacts	0.000	-0.002
Task-Technology Fit Utilization -> Performance Impacts	1.202	0.627

Effect sizes: 0.02 small, 0.15 medium, 0.35 large

Appendix M: Common Points of Comparison with Other LMS Studies Using TAM

	Variance Explained				*Path Coefficients*						*Analysis*
	PU	A	BI	Use	PEOU -> PU	PU -> A or BI	PEOU -> A or BI	BI or A -> Use	PU -> Use	PEOU -> Use	
Ma et al. (2013)	65%	36%	53%		0.10	0.50	0.53				CB-SEM
Venter et al. (2012)	84%				0.54	0.49	n.s.	0.27	0.22	n.s.	CB-SEM
Sánchez et al. (2010)	54%	77%		41%	0.66	0.63	0.29	0.37	n.a.	0.30	CB-SEM
Wang & Wang (2009)	82%		69%	56%	0.48	0.45	n.s.	0.75			CB-SEM
Van Raaij et al. (2008)	54%			31%	0.69				0.67	n.s.	PLS-SEM
Martínez-Torres et al. (2008)	26%	32%	32%	12%	0.37	0.50	0.12	0.34			PLS-SEM
Ngai et al. (2007)	27%	60%		12%	0.23	0.75	0.37	n.s.	0.18	n.s.	CB-SEM
Pituch & Lee (2006)	48%			64%	0.24	0.38	0.28		0.38	0.29	CB-SEM
Yi & Hwang (2003)	26%		32%	15%	n.s.	0.46	0.22	0.19			PLS-SEM
Average	52%	51%	47%	33%	0.41	0.52	0.30	0.38	0.36	0.30	
	44%	28%		2%	0.67	0.32	0.26	n.s.			PLS-SEM

Abbreviations: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (A), Behavioral Intention (BI), Perceived or Actual Use (Use). For Variance Explained, blank cells indicate the construct was not included and/or was not endogenous; for Path Coefficients, blank cells indicate the relation was not measured.

Appendix N: Common Points of Comparison with Other LMS Studies using D&M

	Variance Explained			*Path Coefficients*								*Analysis*
	Use	S	NB	ServQ -> Use	ServQ -> S	SysQ -> Use	SysQ -> S	S -> Use	Use -> S	Use -> NB	S-> NBs	
Mtebe et al. (2014)				0.25	n.s.	0.28	n.s.	0.31		0.35	0.23	CFA
Wang et al. (2013)	35%		49%							0.33		CB-SEM
Lin & Chen (2012)								0.57				CB-SEM
Almarashdeh et al. (2010)				0.13	0.24	0.15	0.24	0.15		0.14	0.48	CB-SEM
Klobas & McGill (2010)	17%	57%	58%		0.31		0.15		n.s.	n.s.	0.29	regres-sion analysis
Lin 2007				0.26	0.42	0.13	0.18			0.25	0.36	CFA
Average	26%		54%	0.21	0.32	0.19	0.19	0.34		0.27	0.34	
This Study	4%	26%	23%	n.s.	n.s.	0.20	0.37		n.s.	n.s.	0.46	PLS-SEM

Abbreviations: User Satisfaction (S), Net Benefits (NB), Service Quality (ServQ), System Quality (SysQ). For Variance Explained, blank cells indicate the construct was not included and/or was not endogenous; for Path Coefficients, blank cells indicate the relation was not measured.

Appendix O: Common Points of Comparison with Other LMS Studies using TPC

	Variance Explained				*Path Coefficients*					*Analysis*
	TTF	A	Util.	PI	IndChar -> TTF	TTF -> A	A -> Util.	TTF -> PI	Util. -> PI	
Lin (2012)		35%		57%		0.60		0.73		PLS-SEM
McGill et al. (2011)			8%	32%				0.52	n.s.	PLS-SEM
Yu & Yu (2010)	50 %	26%	57%	66%	0.36	0.51	57%	0.30	0.62	CB-SEM
Larsen et al. (2009)		58%	37%							PLS-SEM
McGill & Klobas (2009)		61%	22%	45%		0.78	0.26	0.53	0.30	PLS-SEM
Average		45%	31%	50%		0.63	0.42	0.52	0.46	
This Study	0%	24%	2%	56%	n.s.	0.49	n.s.	0.75	n.s.	PLS-SEM

Abbreviations: Task-Technology Fit (TTF), Affect towards Using (A), Utilization (Util), Performance Impacts (PI), Individual Characteristics (IndChar). For Variance Explained, blank cells indicate the construct was not included and/or was not endogenous; for Path Coefficients, blank cells indicate the relation was not measured.

Appendix P: Summary of Suggested Survey Questions for LMS-PM Core Constructs

LMS-PM Constructs	*Suggested Questions for Demo & Short Hands-On Experience*	*Suggested Questions for LMS Full Pilot*
LMS Quality		(Adapted from Jan & Contreras, 2011) I have no problem with the overall quality of X. (Adapted from Lin, 2007) The operation of X is reliable. (Adapted from Klobas & McGill, 2010) X is available when I need it. Output is in the needed form. (new question in draft form) I frequently encounter glitches and errors while using X.
LMS Pilot Conditions		(new questions in draft form) I understand why this course was trying out X. It was not a problem to use X for only one course this semester. Help was available when I had difficulties using X.
Perceived Ease of Use	(new questions in draft form) It would be easy to navigate around X. Finding things in X would not a problem. I would find using X very confusing. (Adapted from Yi & Hwang, 2003) Learning to use X would be easy for me. Overall, I would find X easy to use.	(new questions in draft form) It is easy to navigate around X. Finding things in X is not a problem. Using X is very confusing. (Adapted from Yi & Hwang, 2003) Learning to use X is easy for me. Overall, I find X easy to use.

LMS-PM Constructs	*Suggested Questions for Demo & Short Hands-On Experience*	*Suggested Questions for LMS Full Pilot*
Perceived Usefulness	(adapted from this study) Please rate the usefulness of the following tools and features of *X* in contributing to your work in courses Scale: would not use this feature, not at all useful, slightly useful, moderately useful, highly useful: [list of specific tools and features] (Adapted from Yi & Hwang, 2003) Using X would improve my performance in courses. Using X would increase my productivity in courses. Using X would enhance my effectiveness in courses. Overall, I would find X useful in courses.	(from this study) Please rate the usefulness of the following tools and features of *X* in contributing to your work in this course. Scale: did not use this feature, not at all useful, slightly useful, moderately useful, highly useful: [list of specific tools and features]. (Adapted from Yi & Hwang, 2003) Using X improves my performance in this course. Using X increases my productivity in this course. Using X enhances my effectiveness in this course. Overall, I find X useful in this course.
Perceived/ Anticipated Impact on Learning	(adapted from this study) Perceived impact on learning Scale: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree, not applicable *X* would help me to learn the course materials/content. X would help me to study for exams/tests. *X* would help me to complete course assignments. *X* would help me to make efficient use of my time in the course. *X* would help me to be in control of my own learning in the course. *X* would help me to communicate with my professor. X would help me to communicate with my fellow students. X would help me to know how I am doing in the course. *X* would be beneficial to my overall learning in the course.	(adapted from this study) Perceived impact on learning Scale: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree, not applicable *X* helps me to learn the course materials/content. *X* helps me to study for exams/tests. *X* helps me to complete course assignments. *X* helps me to make efficient use of my time in the course. *X* helps me to be in control of my own learning in the course. *X* helps me to communicate with my professor. X helps me to communicate with my fellow students. X helps me to know how I am doing in the course. *X* was beneficial to my overall learning in the course.

LMS-PM Constructs	*Suggested Questions for Demo & Short Hands-On Experience*	*Suggested Questions for LMS Full Pilot*
Feedback: LMS Preference	(new question in draft form) I would recommend X for use in courses at [our institution]. (revised from this study) Overall, compared to [our institution's] current LMS (title), please select the choice that best describes your preference for [current LMS] versus *X*: I would prefer [current LMS] over *X*. I have no preference. I would prefer *X* over [current LMS].	(new questions in draft form) In the future, my professor/instructor should continue to use X in this course. I would recommend X for use in other courses at [our institution]. (revised from this study) Overall, compared to [our institution's] current LMS (title), please select the choice that best describes your preference for [current LMS] versus *X*: I prefer [current LMS] over *X*. I have no preference. I prefer *X* over [current LMS].
Open-Ended Questions	(from this study) What did you like *most* about X? Why? What did you like *least* about X? Why? Additional Comments: Is there anything else you would like to tell us about your experience getting a demonstration/brief hands-on experience with X?	(from this study) What did you like *most* about X? What did you like *least* about X? Additional Comments: Is there anything else you would like to tell us about your experience using *X* this semester?

CURRICULUM VITAE

DAVID A. GOODRUM
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EDUCATION

Ed.D. Instructional Systems Technology, School of Education, Indiana University, Bloomington, Indiana, 2016.

Dissertation: Relative Utility of Three Models for User Evaluations of Learning Management Systems: A Higher-Ed Institution Decision Context. Advisor: Thomas Brush (tbrush@indiana.edu).

M.A.T., Germanic Languages, Indiana University, Bloomington, Indiana, 1982.

A.B., with Distinction, Germanic Languages, Indiana University, Bloomington, Indiana, 1980.

A.B., with Distinction and Departmental Honors, English, Indiana University, Bloomington, Indiana, 1977.

PROFESSIONAL POSITIONS

Director, Teaching and Learning Technologies, Learning Technologies division, University Information Technology Services, Indiana University, January 2014 to present.
Teaching and Learning Technologies is comprised of 42 full-time professional staff (online instructional designers and developers, IT training specialists, learning management system business analysts, collaboration technology system administrators, assistive technology and accessibility center staff, and educational research and evaluation specialists) -- plus additional hourly and graduate students -- across multiple locations on multiple campuses.

Director, Instructional Technology Systems and Services (ITSS), Learning Technologies division, University Information Technology Services, Indiana University, February 2011 to January 2014.
ITSS was comprised of 45+ full-time professional staff (teaching centers consultants, student technology center consultants, IT training specialists, learning management system business analysts, and adaptive technology and accessibility center staff) -- plus additional hourly and graduate students -- across multiple locations on multiple campuses.

Director, Academic and Faculty Services (AFS), Learning Technologies division, University Information Technology Services, Indiana University, December 2007 to February 2011.
AFS was comprised of 35 full-time professional staff (teaching centers consultants, IT training specialists, and learning management system business analysts) -- plus additional hourly and graduate students -- across multiple locations on two campuses.

Director, Teaching & Learning Technologies Centers, University Information Technology Services, Indiana University Bloomington, June 2002 to December 2007.
A particular challenge of this position was successfully transitioning the unit from academic affairs to the university technology organization. With the beginning of IU's involvement in Sakai in 2003, responsibilities included faculty support for the collaboration and learning system, requirements gathering and definition, and overseeing functional quality assurance testing.

Director, e-Learning Solutions, Kelley Executive Partners (KEP), IU's Advance Research & Technology Institute, Bloomington, Indiana, January 2001 to June 2002.
Responsibilities in creating this unit included strategic direction for online executive education for KEP, development of online modules, coordination with a web development vendor, functional requirements for a module delivery system, and partnering with the delivery system development vendor.

Director, Instructional Consulting & Technology, Instructional Support Services, Indiana University Bloomington, May 1996 to January 2001.
Responsibilities included supervision and direction of teaching consultants on the Bloomington campus as well as continuing as director of the Teaching & Learning Technologies Lab.

Director, Teaching & Learning Technologies Lab, Instructional Support Services & University Information Technology Services Partnership, Indiana University Bloomington, February 1994 to January 2001.
A particular challenge in the initial formation of this unit required successfully integrating teams from different organizations into a single entity, defining and implementing a new service and approach, and communicating effectively with faculty and various campus administrators on progress and results.

Co-Director, Instructional Consulting & Technology, Instructional Support Services, January 1992 to May 1996. Responsibilities included supervision and direction of teaching consultants on the Bloomington campus.

Co-Director, Enriched Learning and Information Environments (ELIE) /Just-In-Time Knowledge (JITK) Project, joint project of Indiana University Bloomington and AT&T, Center for Media & Teaching Resources, July 1991 to July 1992.

Project Leader, Just-In-Time Knowledge (JITK) Project, joint project of Indiana University Bloomington and AT&T, Center for Media & Teaching Resources, Indiana University Bloomington, July 1990 to July 1991.

ADDITIONAL RELEVANT PROFESSIONAL EXPERIENCE

Member, CIC Chief Academic Technology Officers committee, representing Indiana University. Committee on Institutional Cooperation, October 2015 to present.

Member, Unizin Learning Technologies Group, representing Indiana University. April 2015 to present.

Chair, Learning Technologies Support and Implementation Team (SIT), University Information Technology Services, Indiana University, May 2013 to present.
IU's Learning Technologies SIT brings together personnel across development and support divisions involved in the IU's LMS implementation and other teaching and learning technologies, for discussion, coordination, communication, and implementation decisions.

Chair, Next.IU Strategy Team August 2012 to present. Next.IU is an initiative to discover what might be next for teaching and learning technologies at Indiana University.

Chair, Sakai Open Academic Environment Project Steering Group, Sakai Foundation, June 2011 to May 2012.

Co-Chair, Advisory Board, Center for Teaching and Learning, Indiana University - Purdue University Indianapolis, August 2010 to January 2014.

Chair, University Information Technology Services (UITS) Operations Committee (OC), Indiana University, January 2010 through June 2010.
The OC brings together directors across all UITS divisions for discussion, coordination and communication of university IT operations and strategic initiatives.

Ex Officio Member, Learning Technologies Steering Committee, Indiana University, August 2006 to present.

Member, Sakai Product Council, June 2009 to February 2011.

Participant, Indiana University IT Leadership Program, cohort for 2009. Conducted by MOR Associates.

Chair, Oncourse Support and Implementation Team (SIT), University Information Technology Services, Indiana University, December 2007 to April 2013.
IU's Oncourse SIT brought together personnel across development and support divisions involved in the IU's Sakai LMS implementation, called Oncourse, for discussion, coordination, communication, and implementation decisions.

Chair, Oncourse Functional Requirements Committee (FRC), University Information Technology Services, Indiana University, August 2006 to May 2012.
The Oncourse FRC compiled and analyzed suggestions for Oncourse from seven campuses and made reports and recommendations to the faculty and student priorities committee for development. Through an iterative process, these suggestions were then passed to the faculty Oncourse Priorities Committee which made development recommendations to the Office of the Vice President for Information Technology.

Ex Officio Member, Faculty and Student Oncourse Priorities Committee, Indiana University, August 2006 to present.

UNIVERSITY & HIGH SCHOOL TEACHING EXPERIENCE

Adjunct Instructor, R505: Workshop in Instructional Systems Technology – Instructional Design for Hypermedia, Indiana University-East, Fall 1988.

Instructor, R566: Instructional Development Basics, Department of Instructional Systems Technology, Indiana University-Bloomington, Summer 1988.

Adjunct Faculty, W131 Beginning Composition, Advance College Project, Indiana University-South Bend, August 1985-December 1985.

Instructor, Language Arts Department, Wawasee High School, Syracuse, Indiana, August 1982 to June 1986.

Coordinator, G091 Inter-Language Concepts, Groups Program, Indiana University-Bloomington, Summers, 1981-1982.

Associate Instructor, Department of Germanic Languages, Indiana University Bloomington, August 1980 – August 1982.

PUBLICATIONS

Goodrum, D. A., Abaci, S., & Morrone, A. S. (2016). Learning technologies badges for faculty professional development. In L. Y. Muilenburg and Z. L. Berge (Eds.) *Digital Badges in Education: Trends, Issues, and Cases*. Routledge.

Goodrum, D. A., Holloway, J. R., Morrone, A. S., Speelmon, L., & Van Gordon, E.A. (2008). "Dynamics of Supporting Sakai Through Local and Global Collaboration" (Research Bulletin, Issue 11). Boulder, CO: EDUCAUSE Center for Applied Research, 2008.

Dorsey, L. T., Goodrum, D. A., & Schwen T. M (1997). Rapid collaborative prototyping as an instructional development paradigm. In C. Dills & A. Romiszowski (Eds.), *Instructional Development: The State of the Art, III. The paradigms, models, metaphors & viewpoints*. Englewood Cliffs, New Jersey: Educational Technology.

Goodrum, D. A., Pearce, C. R., & Rathbun, G. A. (1997). Turning *tech*nologies into *teach*nologies: The Teaching & Learning Technologies Lab at Indiana University*. College & University Media Review, 3*(2), 11-29.

Rathbun, G.A., Saito, R.S., & Goodrum, D.A. (1997). Reconceiving ISD: Three perspectives on rapid prototyping as a paradigm shift. In O. Abel, N.J. Maushak & K.E. Wright (Eds.),*19th Annual Proceedings of Selected Research and Development Presentations at the 1997 National Convention of the Association for Educational Communications and Technology* (pp. 291–296). Ames, IA: Iowa State University.

Goodrum, D. A., Dorsey, L. T., & Schwen, T. M. (1994). A socio-technical perspective of instructional development: A Change in paradigms. *Proceedings of Selected Research and Development Presentations at the 1994 National Convention of the Association for Educational Communications and Technology Sponsored by the Research and Theory Division*. Association for Educational Communications and Technology, Annual Convention, Nashville, February 1994.

Goodrum, D. A., Dorsey, L. T., & Schwen, T. M. (1993). Defining and building an enriched learning and information environment. *Educational Technology, 33*(11), 10-20.

Dorsey, L. T., Goodrum, D. A., & Schwen, T. M.(1993). Just-in-time knowledge performance support. *Educational Technology, 33*(11), 21-29.

Schwen, T. M., Goodrum, D. A., Dorsey, L. T. (1993). On the design of an enriched learning and information environment (ELIE). *Educational Technology, 33*(11), 5-9.

Welsh, T., Murphy, K., Goodrum, D. A., & Duffy, T. (1993). Accessing elaborations on core information in a hypermedia environment. *Educational Technology Research and Development, 41*(2), 19-34.

Dalton, D.W., & Goodrum, D.A. (1991). The effects of computer programming on problem-solving skills and attitudes. *Journal of Educational Computing Research, 7*(4), 483-506.

Dalton, D.W., and Goodrum, D.A. (1991). The effects of computer-based pretesting strategies on learning and continuing motivation. *Journal of Research on Computing in Education, 24*(2), 204-213.

Goodrum, D. A., & Knuth, R. A. (1991). Supporting learning with process tools: Theory and design issues. *Proceedings of Selected Research Presentations at the Annual Convention of the Association for Educational Communications and Technology*. Association for Educational Communications and Technology, Annual Convention, Orlando, February 1991.

SELECTED PRESENTATIONS
& INVITED TALKS

Lee, D., Goodrum, D. A. (2015). Does users' comfort level with technology bring bias in measuring the users' satisfaction with LMS? Association for Educational Communications and Technology (AECT) Annual Meeting, Indianapolis, November 2015.

Murday, K., Gosney, J, Newbrough, J. R., Goodrum, D. A. (2015). Embrace the Change: Successfully Moving to a New LMS. EDUCAUSE Annual Meeting, Indianapolis, October 2015.

Gunkel, M., Ricci, M., Goodrum, D. A. (2015). IU Online Virtual PC: Provisioning Tools/Data Files with Zero Logistical Overhead. EDUCAUSE Annual Meeting, Indianapolis, October 2015.

Goodrum, D. A., Demoner, S., Gunkel, M. (2015). What does Unizin mean for digital education? InstructureCon 2015, Park City, UT, June 2015.

Morrone, A., Goodrum, D. A., Demoner, S., (2015). What does Unizin mean for digital education? EDUCAUSE Learning Initiative (ELI) 2015 Annual Meeting, Anaheim, CA, February 2015.

Morrone, A., Goodrum, D. A., Gunkel, M., Lynch, A. (2014). Faculty learning technologies badges: A new addition to the faculty development arsenal. EDUCAUSE Annual Meeting (Virtual Conference), Orlando, September 2014.

Goodrum, D. A., Gunkel, M., Ward, L. (2014). Using data to support technology selection and course design. EDUCAUSE Learning Initiative (ELI) Annual Meeting, New Orleans, February 2014.

Goodrum, D. A., Gunkel, M., Ward, L. (2014). New directions for teaching and learning technologies: Strategy and results of Next.IU. EDUCAUSE Learning Initiative (ELI) Annual Meeting (Virtual Conference), February 2014.

Appert, L., Baron, J., Goodrum, D. A., Squillace, R., Ward, L. (2011). The Sakai Open Academic Environment: Envisioning learning, curriculum in a global context. EDUCAUSE 2011 Annual Meeting, Philadephia, PA, October 2011.

Goodrum, D. A. (2011). The Sakai OAE year two development roadmap. EuroSakai Conference, Amsterdam, September 2011.

Goodrum, D. A. (2011). Invited Keynote – Sakai engaged in the 21st century: Community, collaboration, classroom. AuSakai Conference, Canberra, Australia, September 2011.

Goodrum, D. A. (2011). Sakai and the Engaged University in the 21st Century: Community, Collaboration, Classroom. Miami University, Oxford, OH, April 2011. I was invited by Miami University to represent Sakai and Indiana University at a half-day event including a keynote presentation for faculty and meetings with their Sakai implementation team and faculty steering group.

Goodrum, D. A., Ward, L. (2011). Teaching and Learning Design Lenses for the Sakai Open Academic Environment. EDUCAUSE Learning Initiative (ELI) 2011 Annual Meeting, Washington, D. C., February 2011.

Sakai Teaching & Learning Community (2010). Sakai Learning Capabilities v 1.0. http://bit.ly/sakai-lenses . I was both a champion and a thought-leader of this work in the Sakai community for over a year.

Duke University Sakai Day, March 2010.
I was invited by Duke University to represent Sakai at a daylong event (conducted with colleagues from rSmart) including presentations, meetings with small groups of faculty, and interaction with Duke's LMS roadmap committee. Duke was in the process of comparing Sakai, Moodle, and Blackboard 9.

Learning Management Systems Summit, December 2009.
I organized a daylong event (conducted with colleagues from IU's University Information Technology Services (UITS) and the Sakai Executive Director) with functional and technical participants from Penn State University, Ball State University, IU Kelley School of Business, and IU School of Medicine, all of which were considering Sakai as a replacement for Angel and Blackboard.

Goodrum, D. A., & Walsh, B. (2008). Enhancing the Enhancements Process at Indiana University. 9th Sakai Conference, Paris, July 2008.

Goodrum, D. A. (2007). Engaging an open source course management system: Potential and challenges. Featured presentation, Summer Faculty Institute, University of Delaware, June 2007. A keynote presentation that was a part of Delaware's official kick-off for Sakai.

Morrone, A. S., Goodrum, D. A., & Speelmon, L. (2006). A behind-the-scenes look at the suggestions enhancement process at IU. 6th Sakai Conference, Atlanta, GA, December 2006.

Carter, M. S., & Goodrum, D. A., (2002). Strategies for developing online courses with faculty: How to herd cats. National Conference on Teaching & Learning Online, Madison, WI, August 2002.

Dorsey, L. T., Goodrum, D. A., Knuth, R. A., Cascardo, L., & Schwen, T. M. (1991). Enriched learning and information environments: Towards an architectural model. Association for Educational Communications and Technology, Annual Convention, Orlando, February 1991.

SELECTED INTERNET & MULTIMEDIA DEVELOPMENT

Acito, F. (2002). *Managing Marketing Profitability* (4 online modules). [Role: Director, e-Learning Solutions]. Kelley Executive Partners, Bloomington, Indiana.

Acito, F. (2002). *Marketing Fundamentals* (10 online modules) . [Role: Director, e-Learning Solutions]. Kelley Executive Partners, Bloomington, Indiana.

Hustad T. (2002). *Effective Marketing Management* (3 online modules). [Role: Director, e-Learning Solutions]. Kelley Executive Partners, Bloomington, Indiana.

Boquist, J. (2001). *Finance Fundamentals* (8 online modules). [Role: Director, e-Learning Solutions]. Kelley Executive Partners, Bloomington, Indiana.

Winston, W. (2001). *Business Modeling* (5 online modules). [Role: Director, e-Learning Solutions]. Kelley Executive Partners, Bloomington, Indiana.

Winston, W. (2001). *Data Analysis* (4 online modules). [Role: Director, e-Learning Solutions]. Kelley Executive Partners, Bloomington, Indiana.

Archive of Traditional Music (2001*). Music and Culture of West Africa: The Straus Expedition* (CD-ROM; partial funding by National Endowment for the Humanities). [Role: Director, Teaching & Learning Technologies Lab]. Indiana University Press, Bloomington, Indiana.

Gieryn, T. & Capshew, J. (2000-2001). *X-112: Traditions and Cultures of Indiana University* (online course) [Role: Director, Teaching & Learning Technologies Lab]. Indiana University, Bloomington, Indiana.

McNaughton, Patrick, et al. (2000). *Five Windows into Africa* (CD-ROM; partial funding by National Endowment for the Humanities). [Role: Director, Teaching & Learning Technologies Lab]. Indiana University Press, Bloomington, Indiana.

Sept, Jeanne (1997). *Investigating Olduvai: Archeology of Human Origins* (CD-ROM) [Role: Director, Teaching & Learning Technologies Lab]. Indiana University Press, Bloomington, Indiana.

**RECOGNITION &
HONORARY SOCIETIES**

Sakai Foundation Fellow, 2010, in recognition of service to the Sakai community.

Kappa Delta Pi, Rho Nu Chapter, Bloomington, Indiana, 1988.

Phi Beta Kappa, Indiana University, 1977.

COMMUNITY SERVICE

President, Fourth Street Festival of the Arts & Crafts, Inc. (501c nonprofit), Bloomington, Indiana, January 2006 to December 2010.

Treasurer, Fourth Street Festival of the Arts & Crafts, Inc. (501c nonprofit), Bloomington, Indiana, January 2004 to December 2005.

CREATIVE ACTIVITY

MyOptics Photography, www.davidgoodrum.com, 2003 to present.