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Factors In uencing Curriculum Adoption in 2- and 4-year Undergraduate Cybersecurity Programs

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Factors Influencing Curriculum Adoption in 2- and 4-year Undergraduate Cybersecurity Programs

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It's wonderful to write a section of this work in the first person active voice. Academic writing – while useful in its own way – is horribly painful to compose and equally dull to read.

Being a man of faith, I must first acknowledge my creator and savior Jesus Christ. Since He made the universe and all that is in it, it'd be pretty hard for me to study information systems phenomena without Him. Also, since He tends to work a lot through human agency, that brings me to the rest of this very important list.

- First, I offer my thanks for my patient wife, Susan, and our children, Rebekah and Nathaniel – you gave up a lot to let me spend the time over the majority of a decade to complete this work. Maybe we'll go camping more, now.
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ABSTRACT

Increased demand in the cybersecurity workforce requires a significant response from colleges and universities in order to meet that demand. The federal government has emphasized cybersecurity education at all levels as a way to meet that demand, yet there is wide variance in curriculum defined by academics, industry, and government organizations. While there are many curriculum standards, little research has been conducted to investigate the drivers for curriculum adoption. This study aims to discover what factors influence the adoption of new curriculum at the undergraduate level through a quantitative adaptation and application of existing technology adoption models (e.g UTAUT, UTAUT2, TRA, TPB, TAM) to the domain of curriculum adoption. It is hypothesized that many of the same factors that drive technology adoption also drive curriculum adoption with the addition of altruistic motivation of the faculty member on behalf of the student. The survey-based study employs a path model analyzed using partial least squares structural equation modeling. Of the nine hypotheses derived from technology adoption, three were directly supported and one was partially supported with student performance expectancy and facilitating conditions standing out as the most influential exogenous constructs. If it is desirable to drive toward standardized cybersecurity curriculum, this work will benefit standards bodies, accreditors, university leaders, and the federal government to determine the factors that drive adoption to direct resources appropriately.

DECLARATION

I hereby certify that this dissertation constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the dissertation describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,

Todd A. Whittaker

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CHAPTER 1

INTRODUCTION

The US federal government is investing millions of dollars in building a strong cyber workforce capable of meeting the demands of industry and government for highly educated and effective security professionals. Initiatives such as the National Initiative for Cybersecurity Education (National Institute of Standards and Technology, 2016), the NICE Cybersecurity Workforce Framework (Newhouse, Keith, Scribner, & Witte, 2016), and the joint DHS/NSA National Centers for Academic Excellence in Cybersecurity (National Security Agency, n.d.) are just a few of the ways the federal government is attempting to meet that need. Further, former President Obama and the 114th Congress pressed for additional STEM-based funding for colleges, especially at the community college level (American Association of Community Colleges, n.d.). President Obama, in particular, singled out cybersecurity for college loan forgiveness initiatives for those joining the federal workforce (Office of the Press Secretary, 2016). Combined with increased emphasis on free college tuition, the federal government is heavily invested in cyber education at the two and four year levels.

Further, a recent executive order by President Trump mandates the alignment of "education and training with employers' cybersecurity workforce needs, improve coordination, and prepare individuals for lifelong careers... [and] recommends curricula for closing the identified skills gaps... through the development of similar curricula by education or training providers," (Trump, 2019). There are several challenges associated with cybersecurity in colleges. Among these are the dearth of cybersecurity programs, the numerous competing standards for curriculum that need to be considered for adoption, and the constantly evolving landscape that makes it difficult to keep curriculum up to date.

The first challenge is that there aren't that many community colleges offering degrees in cybersecurity. In 2017, only 124 community colleges out of more than 1500 (8%) in the nation had graduates under the Integrated Postsecondary Education Data System (IPEDS), Classification of Instructional Programs (CIP) code 11.1003 – Computer and Information Systems Security/Information Assurance – with a total of 1490 degrees conferred. Only 48 of those had 10 or more graduates. While more community colleges offer a course or a certificate in cybersecurity, this is a very small percentage of institutions. Although four-year programs are more plentiful, the lack of two-year programs hurts workforce preparedness.

The second challenge is that there have been many competing guidelines for curriculum in cybersecurity. The NSA guidelines for their Centers of Excellence describes high-level topics and outcomes. The Association for Computing Machinery (ACM) Joint Task Force on Cybersecurity Education has recently developed its own guide, as has the Accreditation Board for Engineering and Technology (ABET). Industry certifications such as $(ISC)^2$'s SSCP and CISSP and CompTIA's Security+ body of knowledge documents represent yet another source of curricular guidance. While there is substantial overlap among the standards, it is cumbersome for faculty to juggle so many competing criteria.

By way of example, only 17 of the top 100 community colleges (by full time equivalent enrollment) hold the NSA Center of Academic Excellence credential. Many of those 100 have no security program, while others have a major, a certificate, or a track within an existing major such as Information Technology. As a result, curriculum varies widely. With so many options available, community colleges must choose what kinds of topics to include and what topics to defer to 4-year or graduate-level institutions. But what kinds of factors drive college faculty in making those decisions? Little has been written concerning their curricular decision making process.

The third challenge is keeping curriculum up-to-date in a rapidly changing environment. New security vulnerabilities and new attacks are becoming more and more common, such as the recent hardware and firmware flaws (Spectre and Meltdown) discovered in Intel and AMD processors, or the growing prevalence of smart devices – the Internet of Things (IoT) – and the lack of security in a rush to market. Ransomware, self-propagating malware, and fileless attacks are becoming increasingly common (Cisco Systems, 2018). While many principles in curriculum may stay the same, the specific examples and exercises are difficult to keep current.

College faculty members are critical to keeping curriculum current as regional accrediting bodies require substantive faculty oversight of curriculum in a shared governance model (MSCHE, 2018; HLC, 2018; SACSCC, 2017; NEASC-CIHE, 2016; ACCJC-WASC, 2014). At a time when many colleges are adding some small cyber-related topics to existing networking programs and re-branding them, understanding the factors that drive changes in existing curriculum will help government, academic, and industry standardization efforts to direct resources appropriately.

The research question investigated is: what factors influence the cybersecurity curricular decisions of faculty at two-year institutions? By surveying faculty with current cybersecurity curriculum, and using an adaptation of the Unified Theory of Acceptance and Use of Technology version 2 (UTAUT2), the goal of this research is to identify and quantify the precursors of curriculum adoption behavior of faculty in two- and four-year colleges.

CHAPTER 2

LITERATURE REVIEW

Cybersecurity curriculum

There have been many calls for cybersecurity curriculum standards in the past decade and much has been published about the need for a common body of knowledge and what the elements should be. Most, if not all, standards focus on the bachelors or graduate levels.

But what is curriculum? Defining curriculum is a difficult task fraught with confusion. As noted by Egan (1978)

> At a superficial level, confusion about what curriculum is, and thus what people concerned with it should do, involves argument about whether curriculum subsumes instruction—and thus whether a student of curriculum should also be a student of instructional methods—or whether curriculum involves all learning experiences, or refers simply to a blueprint for achieving restricted objectives in a school setting, or includes the statement of objectives as well, or also the evaluation of their achievement, and so on. The field seems to have no clear logical boundaries.

Thus, curriculum could be narrowly defined to outcomes or broadly defined to include all aspects of the program of study with which a student engages. However, for the purpose of this research, curriculum will be defined as any designed set of educational experiences. Within the context of cybersecurity, this could range from a set of lab exercises, readings from textbooks, a course, certificate, minor, or up to an entire program of study for a degree. Much of the existing literature on cybersecurity curriculum is devoted to developing and understanding the body of knowledge that should be taught.

Theoharidou and Gritzalis (2007) developed a framework for cybersecurity curriculum based on a study of undergraduate and graduate programs and syllabi at 135 institutions. Course content was found to map into seven categories of access control, risk, cryptography, networks, design, business, and legal considerations. They then used a mind-mapping technique to classify the content into ten basic domains that encompassed both technical and soft skills. A stated goal was to employ their framework to develop a comprehensive cybersecurity curriculum. However, no evaluation of the framework was present (or later published), nor were the domains tied to levels of degree (associates, bachelors, or graduate levels).

Manson, Curl, and Torner (2009) conducted a study of NSA CAE institutions to determine which existing standards were being employed in course and curriculum decisions. They examined standards produced by the federal government (e.g. the NSA CAE, and the Department of Homeland Security Essential Body of Knowledge) as well as industry standards (e.g. Certified Information Systems Security Professional). Using a survey-based approach, the various categories within each standard were measured for their perceived importance and the number of courses that covered those topics. However, the study had a very low response rate and was limited to institutions that were already accredited by the NSA. Further, the study described what *was* instead of the decision-making process for faculty.

Maconachy, Duryea, and Starland (2009) performed an extensive review of available literature (government, industry, and academic) on the topic of cybersecurity education in the US. Their conclusion was that while many other technical fields had "a clear set of expectations regarding the… knowledge set," there was no such set of expectations for cybersecurity professionals. Government sources were predominantly concerned about job descriptions and training. Industry sources were concerned with certifications and testing. There was "no national effort to formalize the content of information assurance," and formal academic body of knowledge sources were lacking.

Bishop and Taylor (2009) analyzed the NSA CAE designation and identified a number of significant weaknesses in using it as a benchmark of quality for academically-based cybersecurity education. In particular, they state the curriculum mapping against federal standards was opposed to academic goals in that the federal standards "ensure students are trained in specific topic areas related to the job," whereas academic goals "emphasize fundamental understanding of principles and concepts," that can then be transferable to specific situations. Their suggested reconciliation was to replace the federal training standards with academic ones, yet no academic standard exists to date.

Finally, there are two recent efforts to determine cybersecurity education curricular guidelines. The first has been developed by the ACM Joint Task Force on Cybersecurity Education. Its goal is to provide "comprehensive guidance in cybersecurity education that will support future program development and associated educational efforts," (McGettrick, Cassel, Dark, Hawthorne, & Impagliazzo, 2014). Their work was published in late January but they did not separate curricular guidance into 2-year and 4-year undergraduate categories. Previous ACM curricular guides do not establish evaluation criteria to measure programs. Again, the process of decision-making and factors are not considered.

The second effort to develop curricular evaluation criteria for cybersecurity education is under the Accreditation Board for Engineering and Technology (ABET) as part of the Cyber Education Project. They have developed program criteria based on student outcomes, curriculum, and faculty qualifications (Phillips et al., 2016). Their evaluation model identifies nine topic areas in cyber defense, operations, forensics, physical systems, software, ethics, policy, risk, and human factors. While ABET may be common in 4-year engineering schools, interest in this accreditation is waning: ABET accreditation is expensive, time consuming, and requires extensive internal documentation.

Behavioral Theory and Technology Adoption Models

To identify factors influencing intention toward a particular behavior, it is appropriate to discuss a number of relevant information systems theories that have aimed at technology adoption. These can then be adapted toward curriculum adoption. The four most relevant theories for this proposed study are the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (TPB) (Ajzen, 1985), the Technology Acceptance Model (TAM) (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012).

Theory of Reasoned Action (TRA)

First proposed by Fishbein and Ajzen (1975), the Theory of Reasoned Action consists of four constructs: behavior, behavioral intention, attitude toward behavior, and the subjective norms about the behavior. As a causal model, attitudes and norms drive intention, and intention drives behavior; see Figure 1.

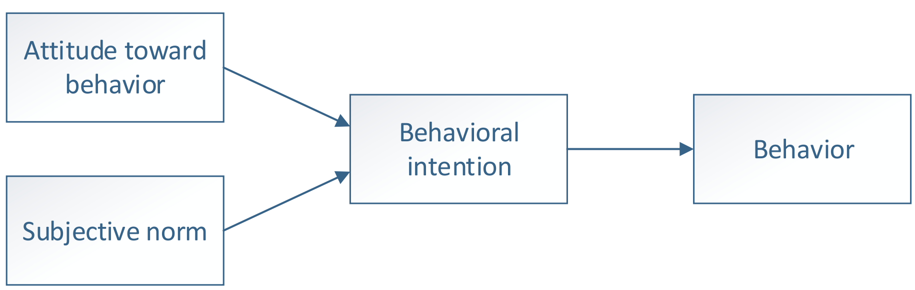

Figure 1: Theory of Reasoned Action, adapted from Madden, Ellen, and Ajzen (1992)

The construct of "attitude toward behavior" describes the beliefs a person holds through personal experience. Both positive outcomes and consequences are part of the consideration of attitude. Relative to this proposed study, the attitudes towards and importance associated with a particular curricular element is expected to influence the decisions in adopting that curricular element. Likewise, "subjective norm" describes the influence of other people deemed important by that particular person. In the context of this study, peer and supervisor influences would be likely to influence the decisions made about curriculum. Attitude and norms are not necessarily weighted equally either for a given person in all situations, but are dependent on context.

Under TRA, both attitude and subjective norms influence the intention of a person to carry out a specific action. Not surprisingly, meta-analyses of TRA have indicated that "the model performed extremely well in the prediction of goals and in the prediction of activities involving explicit choice among alternatives," (Sheppard, Hartwick, & Warshaw, 1988). However, intent is not a guarantee of the behavior occurring. External constraints (e.g. resources, time, training, etc.) will further impact the probability of carrying out the actual behavior. It was precisely this limitation that drove the development of the Theory of Planned Behavior.

Theory of Planned Behavior (TPB)

Proposed by Ajzen (1985), the Theory of Planned Behavior attempts to address the external influences not accounted for in TRA by adding the additional construct of "Perceived Behavioral Control," (see Figure 2).

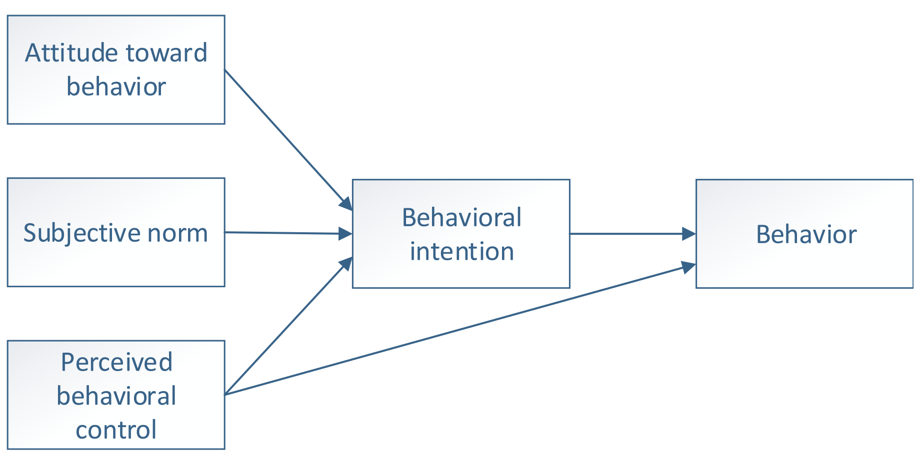

Figure 2: Theory of Planned Behavior, adapted from Madden et al. (1992)

The construct of "Perceived Behavioral Control," (e.g. self-efficacy, or a person's belief about being successful in executing a particular behavior), encapsulates not just the belief as it influences intention, but actual behavioral control as it directly influences the behavior. That is, "perceived behavioral control reflects motivational factors that have an indirect effect on behavior through intentions... [and] reflects actual control and has a direct link to behavior not mediated by intentions," (Madden et al., 1992). The additional construct of perceived behavioral control is apropos to this study because external constraints of technology resources, training, publisher resources, etc. are all expected to influence curricular adoption.

Technology Acceptance Model (TAM)

The Technology Acceptance Model was another attempt to improve on TRA. Developed by Davis (1989), the TAM and its subsequent revisions employ the constructs of perceived usefulness and perceived ease of use as antecedents to attitude and behavioral intention and finally actual system use. See Figure 3.

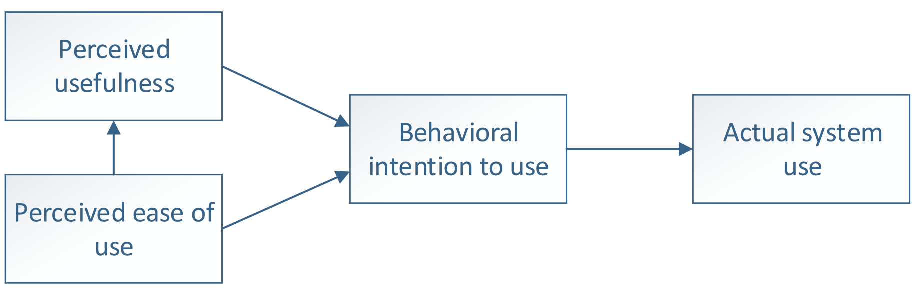

Figure 3: Technology Acceptance Model, adapted from Davis (1989).

Contrasted against TRA, TAM removes the attitude constructs and focuses on system-specific attributes. Perceived ease of use is "the degree to which a person believes that using a particular system would be free of effort," (Davis, 1989). Likewise, perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance," (Davis, 1989). However, ease of use is also a potential system feature and would influence perceived usefulness. Actual ease of use would also directly influence intention to use.

In the context of this research, these two additional constructs are relevant, but from an altruistic perspective. Instead of usefulness to the job performance of the faculty member adopting curriculum, it is expected that the instructor would act as a proxy for the usefulness of the curricular element to the job performance of the student. Faculty are experts in the field of study and should know what will best serve students' interests. This topic will be further addressed below in the section "Student Performance Expectancy." Again, perceived ease of use would be a factor in curricular adoption as well both personally (for the instructor) and altruistically (for the student).

Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) was an attempt to unify many of the existing theories of technology acceptance into a single unified theory. It built on the aforementioned TRA, TPB, and TAM models and also incorporated a number of additional information systems and social science models. Venkatesh et al. (2003) built the model by first empirically measuring each of the eight models on data from four organizations. Using partial least squares (PLS), they tested for convergent and discriminant validity and determined loading factors for each of the constructs, including moderating variables such as gender, age, etc. The best of the individual models (TAM2) was able to account for approximately 53% of variance in actual system use.

By grouping similar constructs from the eight separate models, Venkatesh et al. was able to narrow the number of constructs down to seven which were used in an exploratory analysis. The four highest loading indicators from the previous measurement model were used in their survey. However, only four of the seven exogenous variables and the sole endogenous variable was were used to build the final model, the analysis having revealed that the additional three did not add explanatory power.

The final model, shown in Figure 4, shows the five independent variables, the dependent variable, and their mediators. The constructs are further described in Table 1.

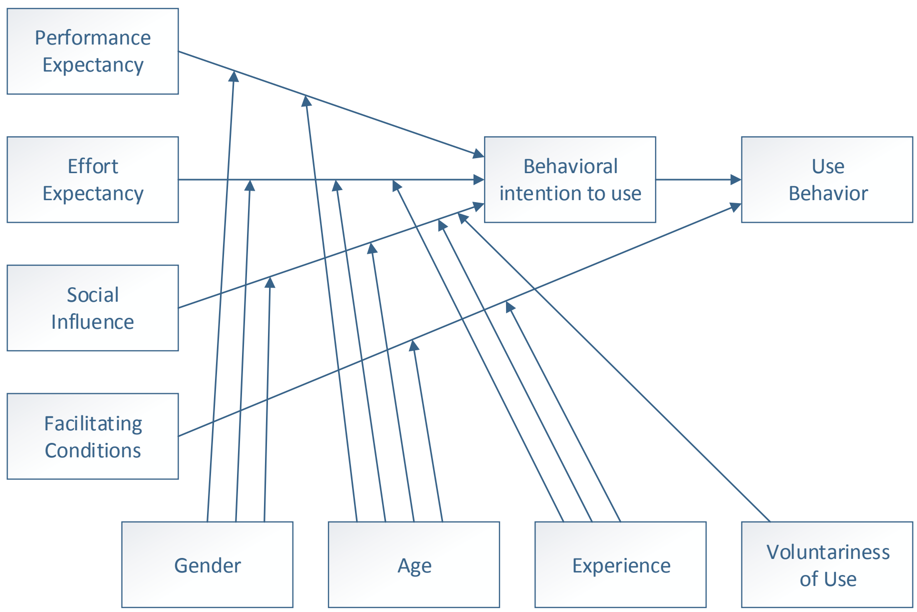

Figure 4: UTAUT model, adapted from Venkatesh et al. (2003).

Table 1: Constructs in UTAUT from Venkatesh et al. (2003).

Construct	**Definition**
Performance expectancy	"The degree to which an individual believes that using the system will help him or her to attain gains in job performance."
Effort expectancy	"The degree of ease associated with the use of the system."
Social influence	"The degree to which an individual perceives that important others believe he or she should use the new system."
Facilitating conditions	"The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system."
Behavioral intention to use	The degree to which an individual intends to make use of the new system.

Using this model Venkatesh et al. was able to explain 70% of variance — far more than any other single model of technology acceptance.

Venkatesh et al. (2012) extended the earlier UTAUT model to UTAUT2 in order to study consumer behaviors related to technology acceptance. In the second iteration, constructs of "Hedonic Motivation," "Price Value," and "Habit" — the definitions for which are given in Table 2. Hedonic and price value were exogenous construct posited to influence behavioral intention to use while habit was an exogenous construct posited to influence actual use behavior.

Table 2: Additional constructs in UTAUT2 from Venkatesh et al. (2012).

Construct	**Definition**
Hedonic Motivation	"The fun or pleasure derived from using a technology."
Price Value	"The consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them."
Habit	"The extent to which people tend to perform behaviors automatically because of learning."

The additions of the three constructs "produced a substantial improvement in the variance explained in behavioral intention (56 percent to 74 percent) and technology use (40 percent to 52 percent)," (Venkatesh et al., 2012).

UTAUT in Higher Education

UTAUT has been studied in the context of higher education as an acceptance model for learning technologies. Thomas, Singh, and Gaffar (2013) employed a modified version of UTAUT to measure mobile learning among higher education faculty in Guyana. A distinct feature was the incorporation of an "Attitude" construct that is very similar to the "Hedonic Motivation" construct of UTAUT2. The authors were able to explain about 40% of the variance in the behavioral intention to use mobile learning using their model. However, they used "attitude" as an endogenous variable rather than exogenous as with UTAUT2.

A similar study about mobile learning in Chinese higher education was published by Yang (2013). Yang employed the UTAUT2 model, but completely from the perspective of undergraduate students instead of faculty. Hedonic motivation was statistically significant at the $p < 0.001$ level, although the overall study could only account overall for 33% of variance in intention to use mobile learning technologies.

Curriculum Adoption and Curriculum as Technology

As mentioned previously, motivations for curriculum adoption has not been widely studied. However, one effort by Ni (2009) did consider factors influencing adoption of "curriculum innovation." Using other fields as a basis, Ni states that

> . . . change in teaching practice relies on the change of teachers' knowledge and beliefs. No change can occur without the teacher believing that the change is worth making. From this perspective, teachers' knowledge and beliefs could serve as critical factors that impact teachers' decisions about whether to adopt a new curriculum, especially at the post-secondary level where teachers have significant influence (if not the final decision) over adoption.

Data were collected from workshops where new curricular innovations in the teaching of computer science were discussed. Using the post-workshop surveys, Ni collected data about attitudes and beliefs of teachers regarding curriculum adoption. After careful analysis using a mixed-methods approach, Ni concluded that among the many factors influencing adoption (such as fit with existing curriculum, confidence levels of faculty, and organizational resources to support adoption), the largest single predictor was teachers' excitement about the new approach, which "could predict 70.8% of actual adoption." Again, the concept of excitement is related to the UTAUT2 construct of hedonic motivation.

But, is it legitimate to apply technology adoption models to curriculum adoption? Curriculum has been studied as if it were technology (Johnson, 2015; Zuga, 1989;

Jenkins, 2009; Cheung & Wong, 2002). A behavioral model adapted from psychology, curriculum-as-technology forms a system in which the student-teacher feedback loop is employed to transmit knowledge and skills from teacher to student (Johnson, 2015; Jenkins, 2009). As an information system, curriculum consists of the people involved (students, teachers), the processes followed (instruction, assessment), the data that is processed (instructional content), and communications (student-teacher interactions). Thus the adoption of curriculum is consistent with the adoption of an information system or technology and the models can be legitimately applied.

Student Performance Expectancy

Performance expectancy has long been a part of most technology adoption models — whether captured as "attitude toward behavior," in TRA "perceived usefulness," in TAM or by the directly named "performance expectancy," construct in UTAUT and UTAUT2. However all technology acceptance models and associated studies interpret performance expectancy from the perspective of the user of the system. This is "first person" performance expectancy. However, in teaching and learning situations (as is the case with curriculum), it isn't the instructor's expectation of improved instructor performance that is at issue. Instead, it is concern about the students' performance that is paramount. Allen (2016, p. 88) makes this instructor focus on student performance clear — in this context, about e-learning:

> It's easy to assume that e-learning is only about teaching things, but success isn't the result when people know the right things to do, yet continue to do the wrong things. Both the e-learning and the environment in which it is applies must be designed to enable, facilitate, and reward good performance in order to achieve maximum success.

Allen proceeds to contrast "typical e-learning" with "serious e-learning" in that typical learning experiences focus on content, information presentation, and knowledge acquisition whereas serious learning experiences target "performance outcomes," (2016, p. 112.).

Again, this sentiment that faculty are driven by the performance expectation of their students is echoed by Mager (1997)

> Why do we teach? Why do we go to the trouble of analyzing, designing, developing, and delivering instruction? What do we hope to accomplish by these efforts? Don't we instruct because we hope that through our instruction our students will somehow be different than they were before the instruction? Don't we teach in order to increase the capabilities of our students?

Although much literature in education, curriculum, and instruction assumes a motive for student performance expectancy, can the same case be made in information systems research and technology adoption models? While there is no direct theory to answer this question, there are ways to triangulate on a reasonable theoretical basis through the Multimotive Information Systems Continuance Model (Lowry, Gaskin, & Moody, 2015) and Stakeholder Theory (Freeman & McVea, 2001).

Multimotive Information Systems Continuance Model

Pioneered by Lowry et al. (2015), the multimotive information systems continuance model seeks to add to the existing theory of user acceptance (or in this case continuation of use) of information systems. Lowry et al. state that "most extant models of user perceptions and evaluations of information systems focus on fulfilling users' extrinsic motivations such as desires for productivity, efficiency, and general utility. These models, however, do not fully explain the range of intrinsic and extrinsic motivations that influence these outcome variables," (2015). The authors use several modifications to technology acceptance models, one of which focuses on the differing motivations for acceptance, including intrinsic, extrinsic, and hedonic motivations. UTAUT2 already includes some extrinsic (performance expectancy) and hedonic motivations. Intrinsic motivations then become a missing component from the current model.

Extrinsic motivations are generally easy to describe in terms of externally imposed rewards or punishments for a given behavior. These are captured in existing models as first-party performance expectancy — "the degree to which an individual believes that using the system will help him or her to attain gains in job performance," (Venkatesh et al., 2003). Intrinsic motivations, however are internal rewards (e.g. personal satisfaction) for carrying out an action for its own sake and are more concerned with the process that leads to the outcome than the outcome itself (Lowry et al., 2015). Examples of intrinsic motivation are "accomplishment, learning or enlightenment, and socialization," (Lowry et al., 2015).

Lowry et al. further produce a taxonomy of intrinsic motivations. Some of the elements relevant to faculty motives for student performance are:

- **Influencing others:** "to engage in a system activity to influence other people," (Lowry et al., 2015). Faculty would engage in a curriculum adoption activity in order to influence their students.
- **Altruism:** "to engage in a system activity for altruistic service purposes, such as helping others learn," (Lowry et al., 2015). Faculty would engage in a curriculum adoption activity in order to help their students learn. This makes explicit in information systems the assumption from educational literature that faculty are motivated for the good of their students.
- **Improving reputation/receiving approval:** "to engage in a system activity to improve one's reputation or gain approval from others," (Lowry et al., 2015). While this also involves aspects of social influence (e.g. reputation with peers), faculty would engage in a curriculum adoption activity in order to improve their own reputation in the eyes of or to gain approval from their students. This could be connected to extrinsic motivation through student evaluations.

- **Leadership:** "to engage in a system activity to lead others," (Lowry et al., 2015). Faculty would engage in a curriculum adoption activity in order to lead students in their field of expertise.
- **Knowledge sharing:** "to use a system for learning through mutual knowledge sharing," (Lowry et al., 2015). Faculty would engage in a curriculum adoption activity in order to share their knowledge with students.

Finally Lowry et al. specifically identifies Venkatesh et al. and the UTAUT model as an example "of how differentiation between types of intrinsic motivation can influence future research... on system adoption," (2015) beyond "simple extrinsic motivations based on usefulness."

Stakeholder Theory

First published by R.E. Freeman in 1984 as an alternative to the input/output theory of the firm, stakeholder theory states that strategic management decisions should address the key interests of all stakeholders of that firm, including investors, suppliers, customers, governments, trade associations, communities, etc. (Freeman & McVea, 2001). Moreover, those interests are relational — the firm has an interest in the needs of stakeholders and stakeholders have an interest in the needs of the firm: "each of these groups can be seen as supplying the firm with critical resources (contributions) and in exchange each expects its interests to be satisfied," (Hill & Jones, 1992).

While colleges and universities are not "firms" in the sense that they are publicly held corporations that must maximize shareholder value, they still do fit well within the framework of stakeholder theory — "meeting the needs of individuals or groups is an important competitive factor" for higher education institutions (Alves, Mainardes, & Raposo, 2010). The survey of higher education stakeholders in Alves et al. (2010) stated that all examined studies considered students, faculty, staff, alumni, government, and employers as significant stakeholders whose interests must be considered. What are student interests as stakeholders?

One study of accounting students by Byrne and Flood (2005) concluded that "career and educational aspirations are the main reasons why these students choose to go to university." The highest scoring indicators were:

1. A degree will open up new opportunities in the future
2. This degree will enable me to get a good job
3. To develop my mind and intellectual abilities
4. Completing this degree will increase my earning power
5. Develop knowledge and skills which will be useful

If generalizing from accounting students to overall student population is valid, this demonstrates that students are attending universities for their own future performance expectancy. Under stakeholder theory, this is sufficient reason for faculty, as agents of the institution, to consider student performance expectancy as part of their curriculum adoption intent.

CHAPTER 3

METHODOLOGY

Overview

The study employed a quantitative approach using a survey instrument based on UTAUT2. Faculty, staff, and administrators with responsibility for cybersecurity-related curriculum were surveyed based on the instrument detailed in "Appendix A: Survey Instrument," on page 92. The instrument and model (see Figure 5) was checked for convergent and discriminant validity as well as significance. Composite reliability of each construct was measured through Chronbach's Alpha measures. The path model was analyzed using partial-least squares structural equation modeling (PLS-SEM) to determine path coefficients and T-statistics for each path to validate hypotheses. Overall variance (R^2) in behavioral intention to adopt was determined, as well.

Design and Model

The constructs for the model are drawn from Venkatesh et al. (2003, 2012) and influenced by Thomas et al. (2013) and Ni (2009). The overall structure of the model is given in Figure 5. In particular, it is Thomas et al. that first set the construct of performance expectancy to that of a third party, in this case the student. However, first-person performance expectancy is part of Venkatesh et al. (2003). Therefore student and faculty performance expectancy are measured separately.

Further, from Ni (2009), it is clear that some form of hedonic motivation (in this case, "excitement") also motivates faculty. Therefore, the hedonic motivation construct from Venkatesh et al. (2012) is imported into the model. Thomas et al. (2013) also used a form of hedonic motivation, naming his construct "attitude." However, Thomas et al. saw attitude as endogenous, while Venkatesh et al. saw hedonic motivation as exogenous. The proposed model adopts the latter perspective. The operationalized constructs are defined in Table 3.

Table 3: Operationalized constructs in proposed model.

Construct	**Definition**	**From**
Student Performance Expectancy (SPE)	The degree to which an individual believes that adopting the curriculum will help his or her students to attain gains in job performance.	Allen (2016), Lowry et al. (2015), Freeman and McVea (2001), Byrne and Flood (2005)
Faculty Performance Expectancy (FPE)	The degree to which an individual believes that adopting the curriculum will help him or her to attain gains in job performance.	Venkatesh et al. (2003)
Effort Expectancy (EE)	The degree of ease associated with the adoption of the curriculum.	Venkatesh et al. (2003)
Social Influence (SI)	The degree to which an individual perceives that important others believe he or she should adopt the curriculum.	Venkatesh et al. (2003)
Facilitating Conditions (FC)	The degree to which an individual believes that an organizational and technical infrastructure exists to support the adoption of the curriculum.	Venkatesh et al. (2003)
Hedonic Motivation (HM)	The degree to which an individual believes that the adoption of the curriculum will be enjoyable.	Venkatesh et al. (2012), Thomas et al. (2013), and Ni (2009)
Behavioral Intention to Adopt (BIA)	The degree to which an individual intends to adopt the new curriculum.	Venkatesh et al. (2003)

Arranged as a path model, the constructs and indicators are given in Figure 5.

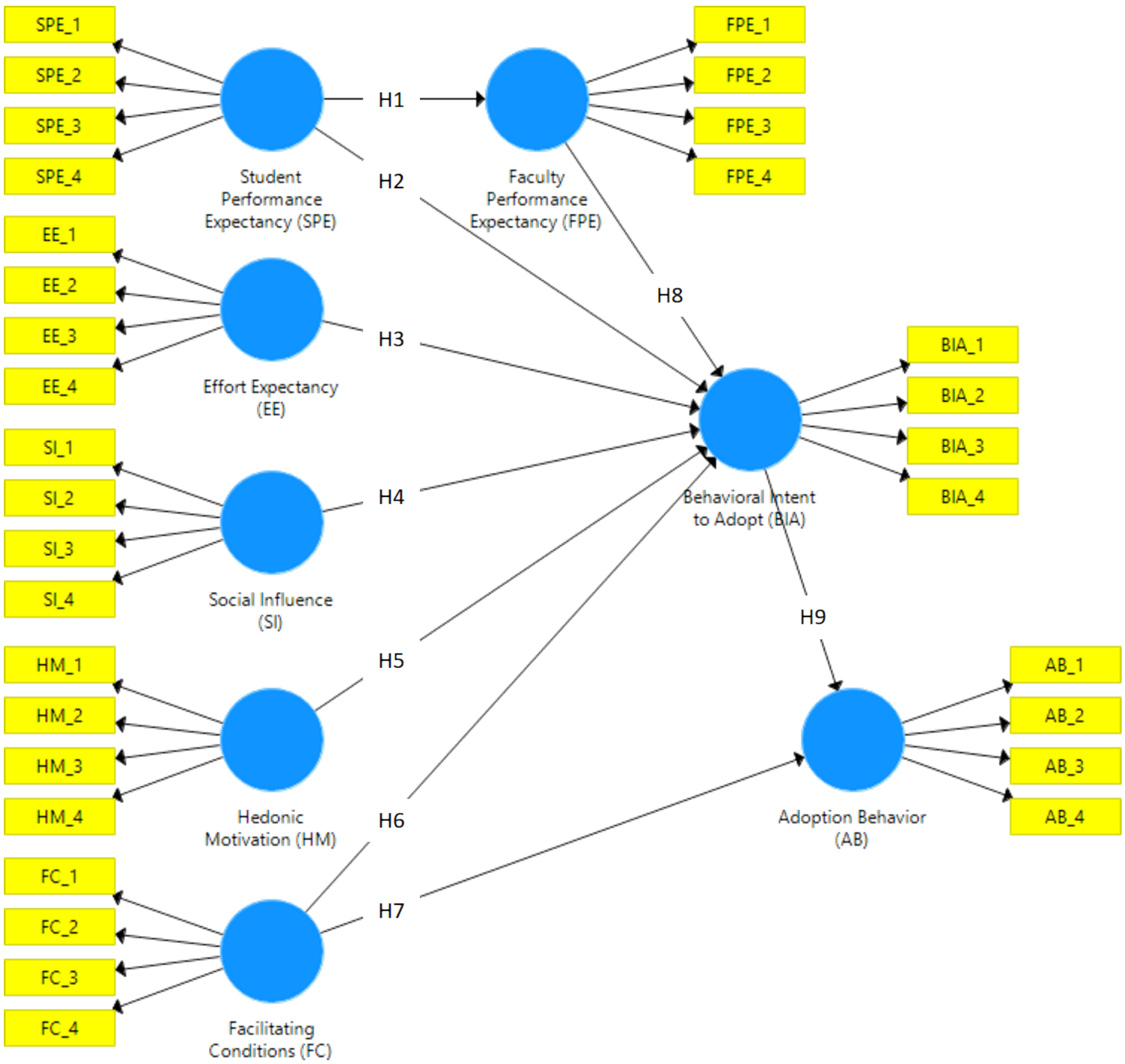

Figure 5: Proposed path model and hypotheses based on constructs in Table 3.

Figure 5 shows seven hypotheses which are captured in Table 4. An additional hypothesis related to the mediating effects of Faculty Performance Expectancy is also indicated.

Table 4: Hypotheses tested in Figure 5

Hypothesis	Explanation
H1	SPE → FPE: Student Performance Expectancy is positively related to Faculty Performance Expectancy.
H2	SPE → BIA: Student Performance Expectancy is positively related to Behavioral Intention to Adopt.
H3	EE → BIA: Effort Expectancy is positively related to Behavioral Intention to Adopt.
H4	SI → BIA: Social Influence is positively related to Behavioral Intention to Adopt.
H5	HM → BIA: Hedonic Motivation is positively related to Behavioral Intention to Adopt.
H6	FC → BIA: Facilitating Conditions is positively related to Behavioral Intention to Adopt.
H7	FC → AB: Facilitating Conditions is positively related to Adoption Behavior.
H8	FPE → BIA: Faculty Performance Expectancy is positively related to Behavioral Intention to Adopt.
H9	BIA → AB: Behavioral Intention to Adopt is positively related to Adoption Behavior.
H10	The effect of FC on AB is mediated by BIA.
H11	The effect of SPE on BIA is mediated by FPE.

Participants

The unit of analysis in the research was a survey response from a college faculty member, staff member, or academic administrator with responsibility over a cybersecurity-related major, minor, certificate, or course. The the survey was delivered anonymously. Data from the instrument was collected as well as demographic and mediating information (sex, age, experience level, voluntariness of adoption, faculty role, highest degree attained, etc) were also gathered. Information about currently considered standards (NSA, ACM, ABET, or industry certifications) was captured, as well.

Participants were contacted through numerous cybersecurity mailing lists catering to 2- and 4-year college faculty (e.g. 3CS, The National CyberWatch Center, CSSIA, CCW, BATEC). Consent was gained through the first page of the survey instrument.

There are two methods for determining the requisite number of participants. The first is the PLS "rule of 10" and the second is to use a calculation based on the work of Cohen.

The first is the PLS-SEM "rule of 10" that can be used to determine significance and power. This rule states that the number of samples is determined by the larger of

1. 10 times the largest number of formative indicators used to measure a single construct, or
2. 10 times the largest number of structural paths directed at a particular construct in the structural model (J. F. Hair, Hult, Ringle, & Sarstedt, 2017, p. 24).

Since all indicators were reflective, the first option is excluded. Using the second option, the construct with the largest number of structural paths was that of behavioral intention to adopt, with 6 incoming paths (see Figure 5). According to this rule, a minimum of 60 observations were required.

The second approach is to follow calculations based on Cohen's guidelines (1988). Cohen suggests setting appropriate α (probability of a Type I false positive) and β (probability of a Type II false negative) levels combined with the number of latent variables to produce the requisite number of observations required. While $\alpha = 0.05$ is fairly conventional in information systems and social science research, regarding β and power, Cohen states

> It is proposed here as a convention that when the investigator has no other basis for setting the desired power value, the value 0.80 be used. This means that β is set at 0.20. This arbitrary but reasonable value is offered for several reasons. The chief among them takes into consideration the implicit convention for α of 0.05. The β of 0.20 is chosen with the idea that the

general relative seriousness of these two kinds of errors is of the order of 0.20/0.05, i.e., that Type I errors are of the order of four times as serious as Type II errors (1988).

The relationship between α and β probabilities for this study are shown in Figure 6.

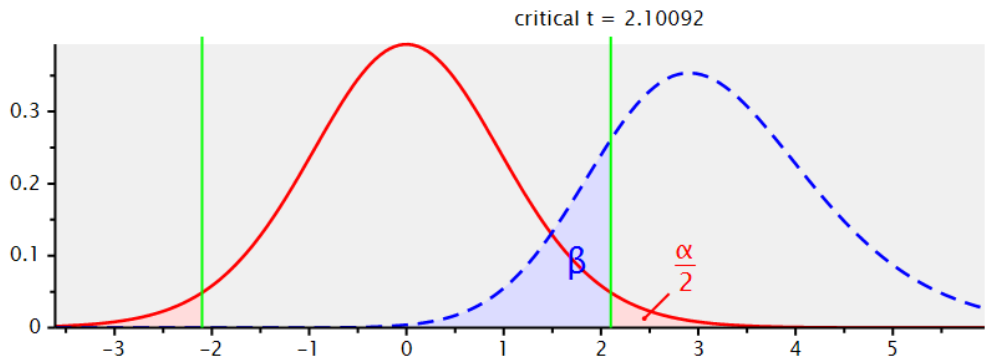

Figure 6: Relationship between α and β levels.

Using G*Power – a commonly used statistical power analysis tool developed by the Department of General and Work Psychology at Heinrich Heine Universität in Düsseldorf, Germany – the number of requisite samples can be calculated based on the anticipated f^2 effect size, α error probability, power ($1 - \beta$ probability) and number of predictors. Using a t-test for linear multiple regression, fixed model, single regression coefficient algorithm with inputs of a moderate effect size of $f^2 = 0.15$, a two-tailed $\alpha = 0.05$, a power=0.80 ($\beta = 0.20$), and 7 reflectively-based predictors, the minimum needed total sample size was 55. Since this method is more statistically sound than a rule-of-thumb, 55 samples were used as the required minimum.

Figure 7 shows the power levels attained at a given sample size for various effect sizes. Larger effects can be detected at smaller sample sizes whereas smaller effects require higher sample sizes.

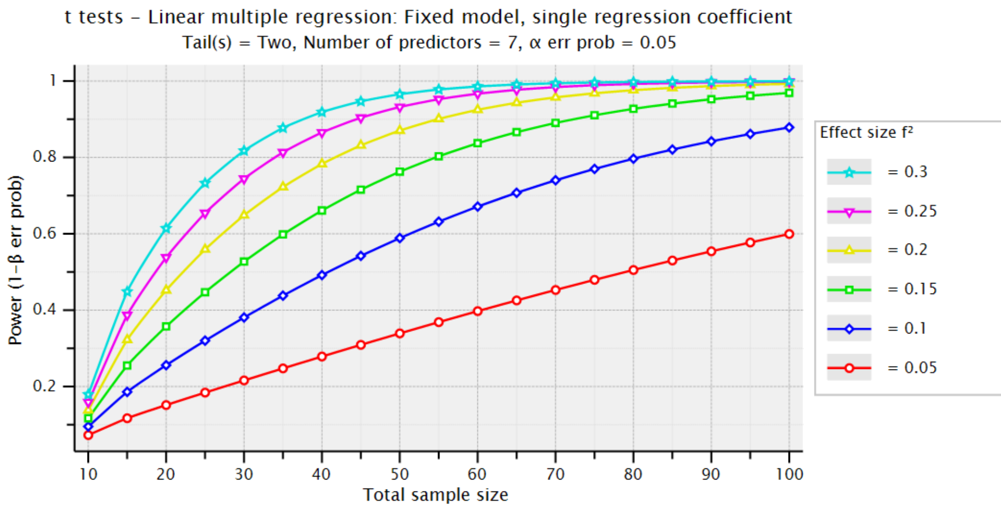

Figure 7: Sample size versus power for given effect sizes.

Measures

A new instrument was used to measure the latent variables in the model. All questions were based on published sources from Venkatesh et al. (2003, 2012) and Thomas et al. (2013), although they have been contextualized from technology acceptance to curriculum adoption. For example, the indicator for performance expectancy was changed from "I would find the system useful in my job," to "My students would find the curriculum useful in their future jobs," for student performance expectancy and to "I would find the curriculum useful in my job," for faculty performance expectancy.

The instrument gathered additional demographic information from participants, inclusive of sex, age, experience level, and voluntariness of the curricular adoption consistent with the same mediators given in Venkatesh et al. (2003). Responses were on a seven-point Likert scale anchored by "strongly agree" and "strongly disagree" and is consistent with Venkatesh et al. (2012). The complete instrument is given in "Appendix A: Survey Instrument" on page 92.

Data Analysis

Data analysis proceeded according to standard PLS-SEM techniques as documented in J. F. Hair, Black, Babin, and Anderson (2010) and J. F. Hair et al. (2017). The six step process is:

1. Define individual constructs
2. Develop overall measurement model
3. Design a study to produce empirical results
4. Assess the measurement model validity
5. Specify the structural model
6. Assess structural model validity

The first three Steps 1-3 are specified in this chapter. A description of how to accomplish the last three is given here with results in the next chapter.

According to Gefen and Straub (2005), the first step in assessing the measurement model is to determine factorial validity through convergent and discriminant validity measures. Convergent validity is established “when each of the measurement items loads with a significant t-value on its latent construct.” PLS-SEM software produces these results through the “bootstrap” procedure that shows both the loading and the t-value for each indicator.

Discriminant validity is established through two factors:

1. Latent variable correlation with the associated indicators should be highly loaded (at least 0.60) while those same indicators should be at least an order of magnitude smaller for other variables. (Gefen & Straub, 2005).

2. The square root of average variance extracted (AVE) for each construct should be “much larger than any correlation among any pair of latent constructs,” (Gefen & Straub, 2005). In addition, the square root of AVE should be at least 0.50.

Again, PLS-SEM software will produce those results in tabular form.

Reliability of the measurement model can be determine by composite reliability as developed by Werts, Linn, and Joreskog (1974). Average variance extracted, composite reliability and Chronbach's alpha are also used.

Hypotheses from Table 4 were assessed by the path coefficient from PLS-SEM and their associated t-statistic. Mediation effects can be determined by removing links from the model and rerunning the bootstrap procedure to determine if an unmediated variable is significant. Once that is established, the mediating links can be re-inserted and the new path coefficients and t-statistics determined through a second bootstrap. Moderating effects of demographic indicators (age, experience, etc.) can be determined by adding a cross-product of indicator values between a latent variable's indicators and the moderator indicators.

Parsimonious Models and Stepwise Regression

Should some of the hypotheses shown in Table 4 be unsupported, a reduction in model complexity through path or construct elimination can be used to produce a more parsimonious model. As is expected in any research study that is deductive (e.g. starting from theory and progressing to hypothesis, observation, and confirmation), some hypotheses will be supported and some will not. If the full model has preductive power and relevance, could a model with fewer paths or variables may be constructed that has similar predictive power and relevance.

The literature review of technology acceptance models starting on page 7 shows that over time, the models became more complex to account for more variance in the dependent variable of acceptance. The research in this study started from one of the more complex models – UTAUT2 – and then added an additional construct. As an application of theory in a new context, it is therefore reasonable to seek a more parsimonious model from which to begin the next phase of research into curriculum adoption. This is analogous to finding the equivalent of the simplicity of TAM, but for curriculum. This is an exploratory or inductive approach that fits naturally after the deductive approach.

It is important to note that Venkatesh et al. (2003) used a similar approach to produce the original UTAUT model. Venkatesh et al. used an extensive questionnaire with 32 constructs drawn from 8 different theories. Predictivly relevant constructs and indicators were then grouped according to construct and based on original theory. The remaining constructs that provided little or no predictive relevance were removed from the model. All constructs were analyzed using PLS.

Henseler et al. (2014), defends the use of PLS-SEM for exploratory analysis, stating that it is legitimate to "start the exploratory analysis with a likely overparameterized or even saturated model and [drop] non-significant paths." This process of dropping non-significant paths (and therefore constructs connected only by those paths) is akin to stepwise linear regression.

Stepwise regression techniques have been described by many authors starting with Efroymson in 1960. In essence, stepwise regression is an automated technique of identifying significant constructs and paths based on inserting or removing paths and constructs and determining which of these has the highest predictive power through the F-test or t-test. It is a heuristically based process since the all-possible-subsets problem requires exponential computing time based on input size. The process can move forward (adding paths) or backward (removing paths) as needed. Variants like hierarchical regression, in which the researcher inserts constructs and paths in a predefined order based on theory (Lewis, 2007), are also commonplace. As a heuristic, however, the process has been subject to any number of criticisms (Thompson, 1995, 2001; Mundry & Nunn, 2009) involving the degrees of freedom and replicability of the study, and the possibility of Type I errors. However, all of these criticisms are based on procedures that are based on covariance approaches that try to minimize differences, not on partial least squares which attempts to maximize explained variance.

Therefore parsimonious model construction will follow this approach. Starting with the least significant and smallest path coefficients, paths and constructs were removed from the original model. Comparisons of adjusted R^2 values after each removal will be performed to ensure that the final model is nearly as predictive as the full model.

CHAPTER 4

RESULTS

Analysis[1] was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) software – SmartPLS. 55 observations were analyzed following the process in J. F. Hair et al. (2017), the first step of which is to evaluate the reflective measurement model. The measurement model evaluation assesses the relationships between the indicators and the constructs, or latent variables. The second step is to evaluate the structural, or path model, which assesses the relationships between the constructs.

Measurement Model Evaluation

To assess the relationships between the indicators and the latent variables, the PLS algorithm is used to yield a number of results relevant to establishing convergent validity; construct reliability, validity and internal consistency; and discriminant validity. These concepts and their associated measures (indicator loadings, AVE, Crobach's Alpha, heterotrait-monotrait rations, etc) are all discussed below.

Convergent Validity

Convergent validity is "the extent to which a measure correlates positively with alternative measures of the same construct," (J. F. Hair et al., 2017) and is established by the indicators loading significantly on the associated construct and a high average variance extracted (AVE) by the indicators for each construct. Any indicator loading higher than 0.7 should be kept and any indicator loading less than 0.4 should be removed from the model. The initial loadings are given in 5.

[1]Many of the following results have been previously published by Whittaker and Noteboom (2019).

Table 5: Initial loadings of indicators. Highest loading construct is in bold.

	AB	BIA	EE	FC	FPE	HM	SI	SPE
AB_1	0.408	0.072	0.152	0.137	**0.431**	0.181	0.112	0.167
AB_2	**0.567**	0.136	0.233	0.248	0.356	0.138	0.307	0.096
AB_3	**0.871**	0.614	0.209	0.486	0.370	0.282	0.567	0.311
AB_4	**0.913**	0.596	0.149	0.407	0.552	0.333	0.478	0.451
BIA_1	0.550	**0.824**	0.258	0.363	0.525	0.341	0.447	0.426
BIA_2	0.386	**0.666**	0.154	0.072	0.262	-0.033	0.134	0.141
BIA_3	0.564	**0.904**	0.128	0.215	0.331	0.125	0.389	0.410
BIA_4	0.493	**0.838**	0.147	0.277	0.343	0.284	0.364	0.446
EE_1	0.106	0.189	**0.803**	0.294	0.052	0.134	0.146	-0.044
EE_2	0.010	0.050	0.386	**0.417**	0.201	0.248	-0.025	0.014
EE_3	0.284	0.159	**0.776**	0.297	0.432	0.357	0.199	0.216
EE_4	0.214	0.011	0.481	**0.573**	0.239	0.383	0.173	-0.020
FC_1	0.213	0.013	0.489	**0.686**	0.111	0.421	0.289	0.025
FC_2	0.322	0.234	0.263	**0.671**	0.285	0.265	0.357	0.060
FC_3	0.107	0.056	0.269	0.323	0.402	**0.515**	0.095	0.407
FC_4	0.476	0.311	0.300	**0.855**	0.190	0.370	0.533	0.132
FPE_1	0.617	0.482	0.306	0.416	**0.920**	0.460	0.433	0.612
FPE_2	0.464	0.441	0.094	0.151	**0.871**	0.495	0.213	0.678
FPE_3	0.402	0.372	0.369	0.272	**0.874**	0.584	0.258	0.632
FPE_4	0.277	0.155	0.310	0.224	**0.653**	0.419	0.310	0.351
HM_1	0.095	0.009	0.213	0.366	0.385	**0.827**	0.177	0.351
HM_2	0.138	0.106	0.400	0.524	0.461	**0.854**	0.259	0.411
HM_3	0.197	0.125	0.287	0.374	0.345	**0.854**	0.134	0.371
HM_4	0.418	0.309	0.273	0.461	0.633	**0.954**	0.343	0.621
SI_1	0.446	0.325	-0.064	0.263	0.278	0.090	**0.880**	0.211
SI_2	0.447	0.446	-0.011	0.336	0.252	0.104	**0.882**	0.267
SI_3	0.459	0.281	0.496	**0.702**	0.268	0.503	0.672	0.155
SI_4	0.426	0.170	0.453	**0.563**	0.345	0.424	0.497	0.204
SPE_1	0.389	0.520	0.067	0.163	0.676	0.516	0.262	**0.931**
SPE_2	0.304	0.336	0.028	0.105	0.675	0.542	0.190	**0.942**
SPE_3	0.484	0.479	0.090	0.170	0.582	0.480	0.333	**0.913**
SPE_4	0.314	0.361	0.144	0.179	0.676	0.585	0.253	**0.935**

Since EE_2, and FC_3 loaded at less than 0.4, these indicators were removed from the analysis. A quick examination of the heterotrait-monotrait (HTMT) ratios (described further below) indicated a discriminant validity problem between FC and EE as well as FC and SI (ratios over 0.9). If an indicator loads higher on a different construct than intended, that indicator should also either be be removed from the analysis or the indicator could be moved to the higher loading construct if the theory supports it (J. F. Hair et al., 2017, p. 120). This will help to establish convergent and discriminant validity. As a result, three additional indicators were removed from the analysis: AB_1, EE_4, and SI_4.

However, SI_3 was retained and moved to the FC construct. The indicator question was: "The leadership of the college has been helpful in changing the curriculum." While this question involves social influence, it turns out to be more of a facilitating condition. The theory would support moving this indicator. When the analysis was rerun with the SI_3 indicator on FC, the loading on FC increased substantially with relatively minor crossloadings on other constructs. Also, the AVE for both SI and FC constructs increases and the HTMT discriminant validity between SI and FC are resolved.

After removing the previous 5 indicators, and re-tasking the SI_3 indicator, the model was re-analyzed and loadings were once again examined. Any indicator loading between 0.4 and 0.7 was individually removed from the model and to determine if the average variance extracted (AVE) increased as a result of the removal. The three indicators examined were: AB_2, FC_2, FPE_4, and BIA_2. Independently removing each of those indicators increased the AVE for each of their associated constructs.

The final table of indicator loadings is given in 6. Note that each indicator loads significantly on its associated construct and more than 0.2 higher than the next highest crossloading in each case. Further, each of the individual indicator loadings are above 0.708 (the square of which is 0.5, meaning that the construct accounts for more than half of variance in the indicators (J. F. Hair et al., 2017, p. 115)). As a result, indicator reliability is established. See Figure 8.

Table 6: Final loadings of indicators. Highest loading construct is in bold. Note, SI_3 is now loading on FC, not SI.

	AB	BIA	EE	FC	FPE	HM	SI	SPE
AB_3	**0.921**	0.613	0.232	0.514	0.371	0.271	0.452	0.311
AB_4	**0.904**	0.597	0.172	0.396	0.571	0.312	0.389	0.451
BIA_1	0.571	**0.835**	0.253	0.282	0.522	0.330	0.449	0.426
BIA_3	0.619	**0.888**	0.146	0.269	0.366	0.108	0.349	0.410
BIA_4	0.536	**0.888**	0.143	0.305	0.359	0.270	0.295	0.446
EE_1	0.123	0.159	**0.778**	0.332	0.038	0.133	-0.032	-0.044
EE_3	0.229	0.176	**0.823**	0.344	0.408	0.355	0.024	0.217
FC_1	0.193	0.040	0.434	**0.742**	0.111	0.428	-0.061	0.025
FC_4	0.504	0.343	0.266	**0.913**	0.172	0.365	0.285	0.132
SI_3	0.472	0.320	0.478	**0.924**	0.252	0.499	0.313	0.155
FPE_1	0.583	0.485	0.304	0.374	**0.914**	0.447	0.301	0.612
FPE_2	0.445	0.437	0.122	0.040	**0.884**	0.482	0.212	0.678
FPE_3	0.340	0.366	0.365	0.185	**0.894**	0.573	0.171	0.632
HM_1	0.086	0.040	0.179	0.344	0.357	**0.850**	0.013	0.351
HM_2	0.129	0.137	0.361	0.479	0.452	**0.870**	0.041	0.411
HM_3	0.209	0.167	0.261	0.366	0.344	**0.869**	-0.053	0.371
HM_4	0.411	0.347	0.271	0.460	0.617	**0.940**	0.170	0.621
SI_1	0.437	0.336	-0.020	0.260	0.259	0.081	**0.964**	0.211
SI_2	0.460	0.465	0.009	0.281	0.241	0.093	**0.982**	0.267
SPE_1	0.419	0.555	0.071	0.121	0.675	0.503	0.229	**0.930**
SPE_2	0.318	0.358	0.060	0.061	0.696	0.530	0.187	**0.942**
SPE_3	0.493	0.515	0.118	0.171	0.594	0.466	0.310	**0.913**
SPE_4	0.307	0.385	0.184	0.177	0.692	0.572	0.204	**0.935**

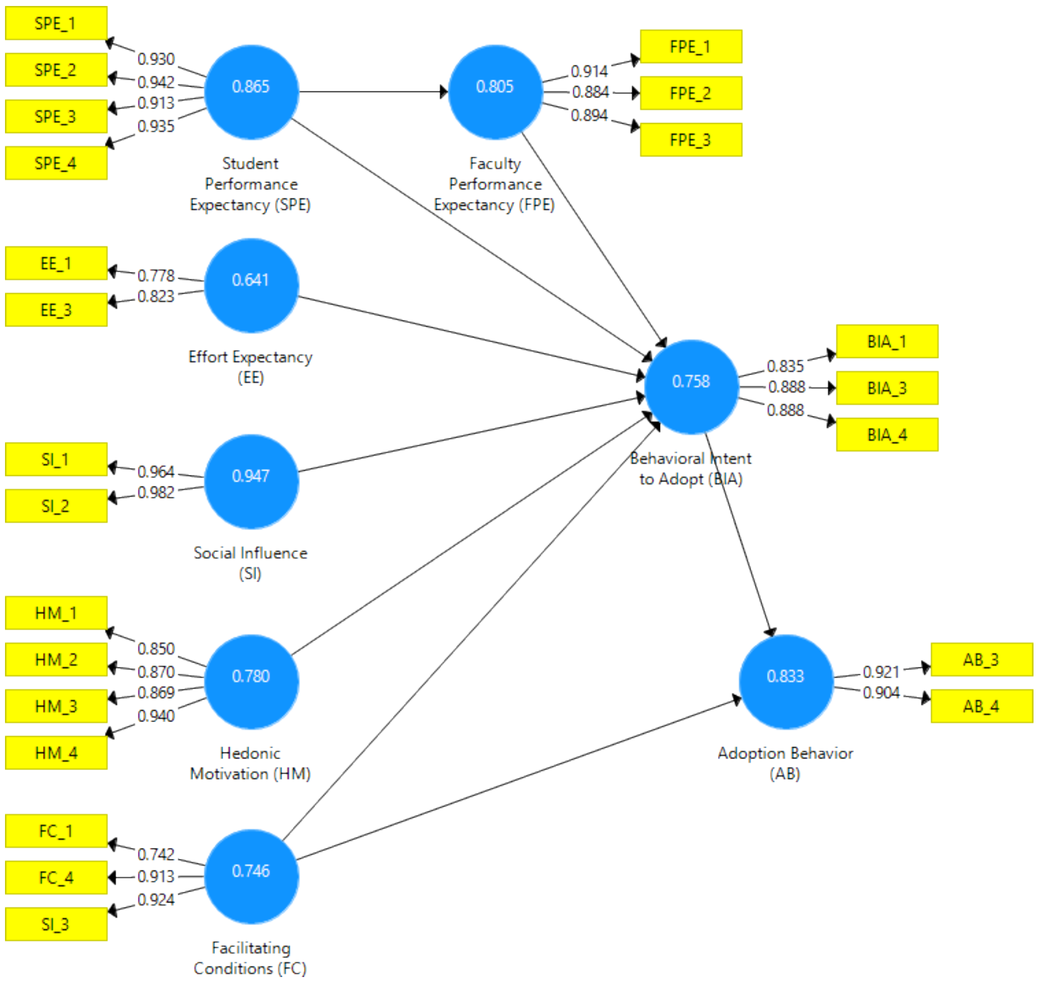

Figure 8: Measurement model; indicator outer loadings and construct AVE.

Construct reliability, validity, and consistency

Construct reliability, validity, and internal consistency is established through a number of means, including Cronbach's Alpha, composite reliability, and average variance extracted (AVE). Cronbach's Alpha tends to underestimate reliability (J. F. Hair et al., 2017, p. 111), whereas composite reliability tends to overestimate it (J. F. Hair et al., 2017, p. 112), therefore both are reported in Table 7 with the AVE.

Table 7: Construct reliability and validity.

	Cronbach's Alpha	Composite Reliability	AVE
AB	0.800	0.909	0.833
BIA	0.840	0.904	0.758
EE	0.442	0.781	0.641
FC	0.845	0.897	0.746
FPE	0.879	0.925	0.805
HM	0.924	0.934	0.780
SI	0.945	0.973	0.947
SPE	0.948	0.962	0.865

Only the EE construct has a low Cronbach's alpha (less than 0.7), however, composite reliability and AVE are all within acceptable ranges.

Discriminant Validity

Discriminant validity has traditionally been established by checking crossloadings of indicators on other constructs and by the Fornell-Larker criterion. The first measure is met in Table 6 by noting that each indicator loads highly (more than 0.708) on its associated construct and has no crossloadings within 0.2 of another construct. The second measure of the Fornell-Larker criterion has fallen out of favor since it has trouble distinguishing between constructs "when indicator loadings of the constructs under consideration differ only slightly," (J. F. Hair et al., 2017, p. 118).

However, the current practice in PLS-SEM favors the heterotrait-monotrait ratio (HTMT) approach. HTMT is "the ratio of the between-trait correlations to the within-trait correlations," (J. F. Hair et al., 2017, p. 118). A threshold value of 0.9 is typically used; any ratio above 0.9 indicates lack of discriminant validity between constructs. Table 8 shows that none of the HTMT ratios are above 0.9, meaning that the constructs are distinct from one another.

Table 8: HTMT discriminant validity; all values < 0.9

	AB	BIA	EE	FC	FPE	HM	SI	SPE
AB	-	-	-	-	-	-	-	-
BIA	0.806	-	-	-	-	-	-	-
EE	0.367	0.341	-	-	-	-	-	-
FC	0.539	0.325	0.737	-	-	-	-	-
FPE	0.612	0.554	0.519	0.250	-	-	-	-
HM	0.269	0.244	0.455	0.544	0.546	-	-	-
SI	0.528	0.458	0.053	0.280	0.280	0.082	-	-
SPE	0.479	0.547	0.258	0.144	0.782	0.520	0.260	-

Finally, the bootstrap procedure is employed with a large number (5000) of samples to determine if the bias-corrected HTMT ratios fall within a 95% two-tailed confidence interval. From Table 9, it can be seen that all the original HTMT values fall between 2.5% and 97.5% indicating good discriminant validity.

Table 9: HTMT bias-corrected confidence intervals.

	Original Sample	Lower bound (2.50%)	Upper bound (97.50%)
BIA → AB	0.806	0.577	0.962
EE → AB	0.367	0.036	0.608
EE → BIA	0.341	0.056	0.617
FC → AB	0.539	0.318	0.741
FC → BIA	0.325	0.103	0.556
FC → EE	0.737	0.199	1.167
FPE → AB	0.612	0.331	0.837
FPE → BIA	0.554	0.220	0.808
FPE → EE	0.519	0.101	1.025
FPE → FC	0.250	0.088	0.473
HM → AB	0.269	0.104	0.489
HM → BIA	0.244	0.097	0.426
HM → EE	0.455	0.083	0.774
HM → FC	0.544	0.280	0.782
HM → FPE	0.546	0.244	0.767
SI → AB	0.528	0.274	0.716
SI → BIA	0.458	0.197	0.698
SI → EE	0.053	0.011	0.062
SI → FC	0.280	0.094	0.507
SI → FPE	0.280	0.131	0.470
SI → HM	0.082	0.030	0.099
SPE → AB	0.479	0.230	0.694
SPE → BIA	0.547	0.179	0.840
SPE → EE	0.258	0.051	0.488
SPE → FC	0.144	0.050	0.329
SPE → FPE	0.782	0.315	0.989
SPE → HM	0.520	0.189	0.742
SPE → SI	0.260	0.102	0.456

Structural model evaluation

The structural model is evaluated in six steps according to J. F. Hair et al. (2017, p. 191) as follows:

1. Assess the structural model for collinearity
2. Assess the significance and relevance of the structural model relationships
3. Assess the coefficient of determination (R^2) level
4. Assess the effect size of R^2 (f^2 level)
5. Assess the predictive relevance (Q^2) level
6. Assess the effect size of Q^2 (q^2 level)

Each of these concepts and their related statistics are discussed below.

Assessing the Model Fit

In covariance-based structural equation modeling, there would be a step to assess "goodness-of-fit" of the model which contrasts the covariance matrix of the model against the covariance matrix of the samples and yielding a χ^2 statistic. However, partial least squares is based on maximizing *prediction* by goal-seeking to "maximize the explained variance instead of minimizing the differences between covariance matrices," (J. F. Hair et al., 2017, p. 192). Thus path coefficients, R^2 values, f^2 effect size, Q^2 predictive relevance, and q^2 effect size are considered the best way of evaluating the structural model.

However, many reviewers wish to see a goodness-of-fit section that corresponds to what would be seen in CB-SEM methods. There are a few measures of GoF that have begun to appear in the literature. The most relevant are the standardized root mean square residual (SRMR) and the "exact fit" test.

SRMR is the "root mean square discrepancy between the observed correlations and the model-implied correlations," where zero implies a perfect fit (J. F. Hair et al., 2017, p. 193). In CB-SEM, a value less than 0.08 is considered a good fit. However, this again does not consider that the goals of CB-SEM (minimizing covariance matrix differences) and PLS-SEM (maximize explained variance) are different. Therefore this threshold is too low. Instead, the sample differences between saturated and estimated models are produced. Instead of a threshold value for goodness, instead a cutoff is used at either the 95$^{\text{th}}$ percentile or 99$^{\text{th}}$ percentile – meaning that only 5% or 1% of saturated or estimated model differences from the samples are out of range. If the original sample is less than those percentiles, it indicates a good fit. SRMR for the model of Figure 8 is given below in Table 10. Since the original sample is smaller than the more rigorous 95$^{\text{th}}$ percentile cutoff, this is deemed to be a good fit.

Table 10: SRMR fit estimates.

	Original Sample	Sample Mean	95$^{\text{th}}$ percentile	99$^{\text{th}}$ percentile
Saturated Model	0.100	0.069	0.109	0.180
Estimated Model	0.110	0.083	0.125	0.185

A second model fit estimate is the exact fit test. Based on χ^2 processes, the test uses bootstrapping "to derive p valuesof the discrepancy between the observed correlations and the model implied correlations," in the form of Euclidean and geodesic residual distances (J. F. Hair et al., 2017, p. 194). It uses the same percentile cutoff technique that SRMR does. Exact fit for the model of Figure 8 is given below in Table 11. Since the original sample is smaller than the more rigorous 95$^{\text{th}}$ percentile cutoff, this is deemed to be a good fit.

Table 11: Exact fit estimates.

	Original Sample	Sample Mean	95th percentile	99th percentile
Saturated Model	2.770	1.449	3.253	8.930
Estimated Model	3.343	2.053	4.343	9.414

Assessing Collinearity

To test for collinearity, PLS-SEM employs a variance inflation factor (VIF) value, which is the reciprocal of the tolerance value. VIF is a measure of the collinearity between endogenous and exogenous constructs; values less than 5 (that is, tolerance less than 0.2) indicate little if any collinearity and therefore measure different real-world constructs. In formative models, VIF is calculated not only for the constructs, but also for each of the indicators on the constructs. However, in reflective models – such as this one – indicators are expected to be interchangeable and therefore outer VIF values are not included. The table of inner VIF values for the constructs of the model in Figure 8 is given below in Table 12.

Table 12: Inner VIF values between endogenous and exogenous constructs.

	AB	BIA	EE	FC	FPE	HM	SI	SPE
AB	-	-	-	-	-	-	-	-
BIA	1.120	-	-	-	-	-	-	-
EE	-	1.350	-	-	-	-	-	-
FC	1.120	1.712	-	-	-	-	-	-
FPE	-	2.406	-	-	-	-	-	-
HM	-	2.123	-	-	-	-	-	-
SI	-	1.253	-	-	-	-	-	-
SPE	-	2.387	-	-	1.000	-	-	-

Since all values in Table 12 are less than 5, the model is considered not to have collinearity issues.

Assessing the Structural Model's Significance

The structural model is evaluated via the path coefficients and significance (p-values) for each of those paths. Coefficients are determined by the PLS algorithm while significance is determined by samples via the bootstrapping procedure. The path coefficients, t-statistics, p-values, and confidence intervals are depicted graphically in Figure 9 and in tabular form in Table 13.

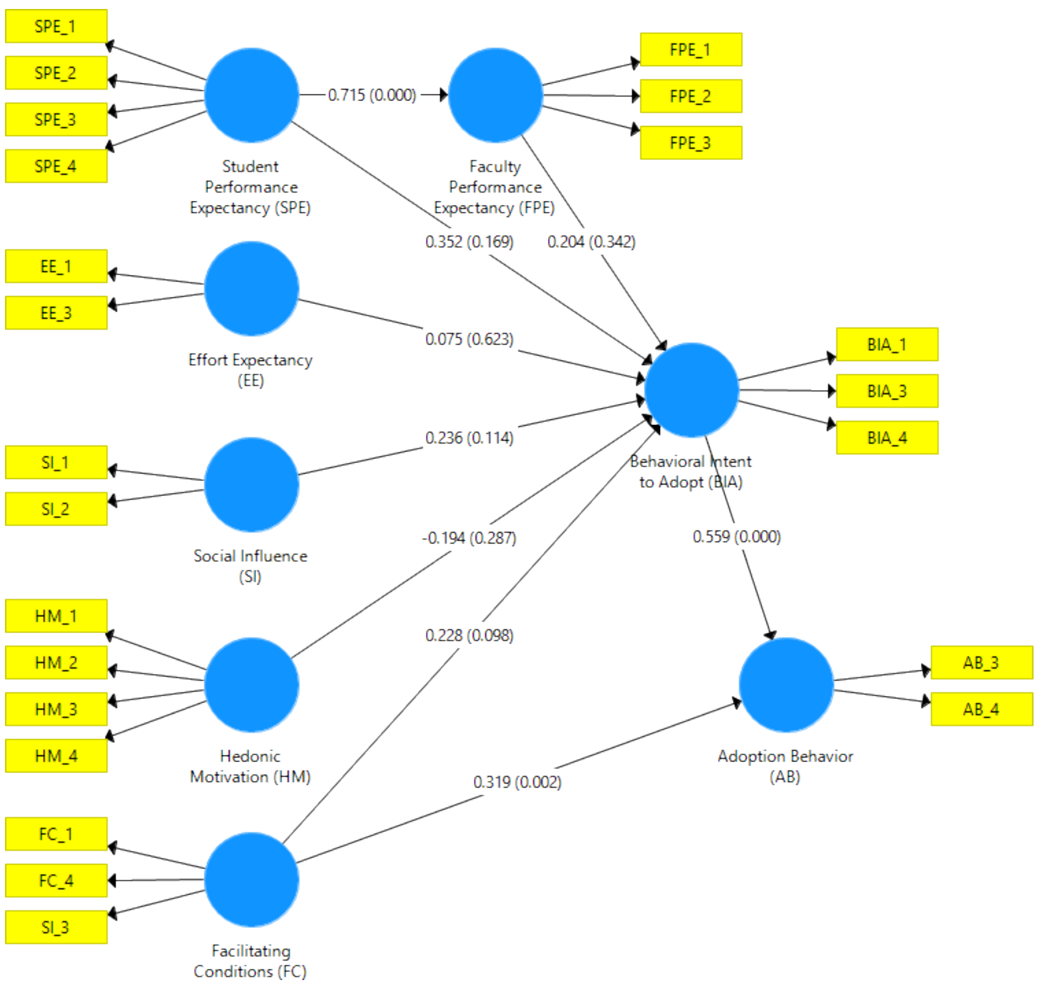

Figure 9: Model path coefficients and significance

Table 13: Path coefficients and significance of the model in Figure 9

	Path Coefficients	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
BIA → AB	0.559	6.036	0.000*	[0.346, 0.723]
EE → BIA	0.075	0.491	0.623	[-0.232, 0.357]
FC → AB	0.319	3.160	0.002*	[0.105, 0.504]
FC → BIA	0.228	1.653	0.098	[-0.017, 0.518]
FPE → BIA	0.204	0.951	0.342	[-0.306, 0.534]
HM → BIA	-0.194	1.065	0.287	[-0.549, 0.159]
SI → BIA	0.236	1.582	0.114	[-0.062, 0.523]
SPE → BIA	0.352	1.375	0.169	[-0.153, 0.884]
SPE → FPE	0.715	4.347	0.000*	[0.250, 0.914]

In addition to direct effects (path coefficients), the bootstrapping procedure generates the total effects through intermediate constructs. Therefore it is possible, for example to determine the effect of SPE on AB through the intervening BIA construct. Table 14 shows the effect sizes, t-statistics, p-values, and confidence intervals for the total effects of the model of Figure 9. Note that if there is only a single direct path between constructs, the data in Table 14 is the same as reported in Table 13.

Table 14: Total effects and significance of the model in Figure 9.

	Effect size	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
BIA → AB	0.559	6.036	0.000*	[0.346, 0.723]
EE → AB	0.042	0.473	0.636	[-0.129, 0.216]
EE → BIA	0.075	0.491	0.623	[-0.232, 0.357]
FC → AB	0.446	4.105	0.000*	[0.249, 0.678]
FC → BIA	0.228	1.653	0.098	[-0.017, 0.518]
FPE → AB	0.114	0.922	0.357	[-0.191, 0.305]
FPE → BIA	0.204	0.951	0.342	[-0.306, 0.534]
HM → AB	-0.108	1.02	0.308	[-0.318, 0.091]
HM → BIA	-0.194	1.065	0.287	[-0.549, 0.159]
SI → AB	0.132	1.339	0.181	[-0.031, 0.351]
SI → BIA	0.236	1.582	0.114	[-0.062, 0.523]
SPE → AB	0.279	2.075	0.038*	[0.015, 0.519]
SPE → BIA	0.498	2.069	0.039*	[0.022, 0.894]
SPE → FPE	0.715	4.347	0.000*	[0.250, 0.914]

The effect sizes for BIA → AB, FC → AB, SPE → BIA, SPE → FPE are large and significant. SPE → AB (indirect) is moderate and significant. FC → BIA and SI → BIA are moderate, but not significant at the $p < 0.05$ level. A more parsimonious model (described later) may have better significance for these latter relationships.

Assessing the Coefficient of Determination (R^2)

The coefficient of determination (R^2) measures the predictive power of a model for the endogenous variables. For example, an $R^2 = 0.35$ for an endogenous variable means that roughly 35% of the variance in the construct is explained by the model – this is why the goodness-of-fit measures for PLS-SEM include R^2 instead the χ^2 measure typical for CB-SEM. Because more complex models can typically explain more variance, there is an adjusted R^2 value that considers the number of endogenous predictor variables. Both adjusted and unadjusted R^2 values will be reported here.

There is little agreement about the interpretation of R^2 values in PLS-SEM. For some fields, $R^2 = 0.20$ is considered substantial, while in others, a 0.75 cutoff is used (J. F. Hair et al., 2017; J. Hair, Hollingsworth, Randolph, & Chong, 2017). For this research, the categories recommended by Urbach and Ahlemann (2010) will be employed: values around 0.670 as substantial, 0.333 as moderate, and 0.190 and lower as weak. Table 15 provides the R^2 and adjusted R^2 for the three endogenous variables of the model in Figure 9.

Table 15: R^2 values.

	R^2	R^2 Adjusted
AB	0.531	0.512
BIA	0.408	0.334
FPE	0.511	0.502

In both the unadjusted and adjusted values, the R^2 values AB and FPE are in the substantial range while BIA is in the moderate range. 51% of adoption behavior can be explained by the model of Figure 9 and it is concluded that this model has between moderate and substantial predictive power.

Assessing the R^2 Effect Size (f^2)

The effect size (f^2) is a estimation of the contribution of a particular exogenous construct on its associated endogenous constructs. This is calculated by calculating the R^2 when the exogenous construct is included and again when it is removed from the model. The percentage difference between the two R^2 values is the effect size of the exogenous variable on the endogenous variable. Values of 0.02, 0.15, and 0.35 represent small, medium and large effects respectively (J. F. Hair et al., 2017). Table 16 shows the effect sizes for the model of Figure 9.

Table 16: Effect sizes (f^2).

	AB	BIA	EE	FC	FPE	HM	SI	SPE
	AB	BIA	EE	FC	FPE	HM	SI	SPE
AB	-	-	-	-	-	-	-	-
BIA	0.594	-	-	-	-	-	-	-
EE	-	0.007	-	-	-	-	-	-
FC	0.193	0.051	-	-	-	-	-	-
FPE	-	0.029	-	-	-	-	-	-
HM	-	0.030	-	-	-	-	-	-
SI	-	0.075	-	-	-	-	-	-
SPE	-	0.088	-	-	1.044	-	-	-

From these data, it can be seen that BIA has a very large effect on AB, FC has a medium effect on AB, and SPE has an extreme effect on FPE. The constructs FC, FPE, HM, SI, and SPE all have small effects on BIA, and EE has no effect on BIA.

Assessing the Predictive Relevance (Q^2)

The predictive relevance, or Q^2 value, is "an indicator of the model's out-of-sample predictive power or predictive relevance," (J. F. Hair et al., 2017). Since only the endogenous variables are predicted, a Q^2 values greater than zero indicates predictive relevance for that endogenous variable.

Q^2 is calculated by a "blindfolding" procedure by systematically eliminating every n^{th} indicator data point (where n is the "omission distance") by column. The ratio of the sum of the squares of the errors – where missing data is replaced by averages – and the sum of the squares of the real observations is used to form the Q^2 value. The omission distance must not be a factor of the number of total observations or else entire rows (observations) will be eliminated.

Table 17: Predictive relevance (Q^2).

	SSO	SSE	$Q^2 = 1 - \frac{\text{SSE}}{\text{SSO}}$
AB	110.000	66.068	0.399
BIA	165.000	123.972	0.249
FPE	165.000	102.474	0.379

Since the Q^2 values for each of the endogenous constructs are significantly different from zero, the model has high predictive relevance.

Assessing the Q^2 Effect Size (q^2)

Just as f^2 determined the effect size of each exogenous construct on each endogenous construct's R^2 coefficient of determination value, so does q^2 determine the effect size of each exogenous construct on each endogenous construct's Q^2 predictive relevance value. The calculation for q^2 is analogous to that of f^2: the Q^2 initial values are calculated (see Table 17) and then each exogenous construct is individually removed and the new Q^2 for each endogenous construct is calculated. The ratio of the differences between the two Q^2 values versus the original is the effect size. Again, as with f^2, q^2 values of 0.02, 0.15, and 0.35 represent small, medium and large effects respectively.

The software package used for analysis, SmartPLS, does not automatically generate the q^2 level. Instead, each exogenous construct must be manually removed and blindfolding rerun. These data are captured in Table 18,

Table 18: Q^2 effect sizes (q^2).

	AB	BIA	EE	FC	FPE	HM	SI	SPE
AB	-	-	-	-	-	-	-	-
BIA	0.077	-	-	-	-	-	-	-
EE	-	-0.001	-	-	-	-	-	-
FC	0.090	0.029	-	-	-	-	-	-
FPE	-	0.003	-	-	-	-	-	-
HM	-	0.012	-	-	-	-	-	-
SI	-	0.035	-	-	-	-	-	-
SPE	-	0.045	-	-	0.264	-	-	-

From these data, it can be seen that BIA and FC have a medium-small predictive relevance effect on AB. Further, FC, SI, and SPE have a small predictive relevance effect on BIA. Finally, SPE has a medium large predictive relevance effect on FPE. However, EE, FPE, and HM have no significant predictive relevance on BIA.

Hypothesis Results

Based on the data in Tables 13 and 14, the hypotheses from Table 4 can be evaluated. If the p-value of the path coefficient was significant from Table 13, then the hypotheses were supported directly. If the total effect of a construct was significant in Table 14, then the hypothesis was partially supported even though the direct path may not be significant. The results of the evaluation of the hypotheses are given below in Table 19.

Table 19: Hypothesis testing results.

Hypothesis	Explanation	Supported?
H1	SPE → FPE	Yes
H2	SPE → BIA	Partial
H3	EE → BIA	No
H4	SI → BIA	No
H5	HM → BIA	No
H6	FC → BIA	No
H7	FC → AB	Yes
H8	FPE → BIA	No
H9	BIA → AB	Yes
H10	FC → AB is mediated by BIA.	No
H11	SPE → BIA is mediated by FPE.	No

By way of explanation, all supported hypotheses have a significant ($p < 0.05$) path coefficient. Partially supported hypotheses have an insignificant path coefficient, but a significant ($p < 0.05$) total effect. Unsupported hypotheses have insignificant direct and total effects.

Moderating Effects

The original UTAUT model also considered the moderating effects of demographic and other characteristics of both participants and the information system being adopted (Venkatesh et al., 2003). Figure 4 shows moderators of gender, age, experience, and voluntariness of use. To those were also add the scope of the project, the education level of the faculty member, and the type of school (2-year vs. 4-year) to the list of moderators.

The moderators of gender, age, experience, and voluntariness were examined based on the model of Figure 4. The remaining moderators were tested for effects on intention to adopt as well as actual adoption behavior.

This phase of analysis was similarly carried out using PLS-SEM techniques in SmartPLS. If a categorical variable is increasing (e.g. has "more"at higher category levels) then that categorical variable can be used directly as an indicator on its own construct. Age, experience, and education level fit well here. However, if a categorical variable isn't increasing (e.g. there isn't"more" gender or voluntariness) then a dummy variable is created with 0/1 values. In either case, the dummy or categorical variable's construct is causally connected to the latent variables in question and a second construct representing a product-of-indicators is also causally connected. The path coefficient of this second construct represents the magnitude of the moderating effect and the *p*-value of that coefficient is the significance of the moderating effect.

Citing Henseler and Chin (2010), J. F. Hair et al. (2017) provides guidelines for the approach to moderator testing. The three options include

- Product indicator: in this case, the interaction term's indicators are the pairwise product of each latent variable indicator with the moderator indicator value. The interaction variable is then used in a standard way in PLS and bootstrapping to determine the magnitude and significance of its effect on the latent variable (J. F. Hair et al., 2017, p. 254) (Henseler & Chin, 2010).
- Two-stage: The two stage approach takes into account the difference between formative and reflective indicators. If the moderator or latent variable uses formative indicators, this is the only approach to use. Stage 1 main effects are estimated using PLS. In stage 2, the latent variable scores are used with a product-based interaction term as reflective indicators and the same analysis is rerun (Henseler & Chin, 2010). The two-stage approach also has greater statistical power and is good for determining the significance of the effect.
- Orthogonalizing approach: This technique is built on top of the product indicator approach but attempts to eliminate collinearity in the PLS path model when using standardized indicators. Further, it has the benefit of distinguishing the main

effect of two variables as distinct from the moderating effect. Thus the orthogonalizing approach is good for determining the magnitude of the effect (J. F. Hair et al., 2017, p. 256).

As the goal of this research is to determine the factors affecting curriculum adoption, maximizing predictive power via the orthogonalizing approach is most warranted. Therefore following tables report the moderating effects of demographic indicators using orthogonalization. Each moderator effect was tested independently of all other moderator effects.

Age

Figure 10 shows the distribution of respondents' age.

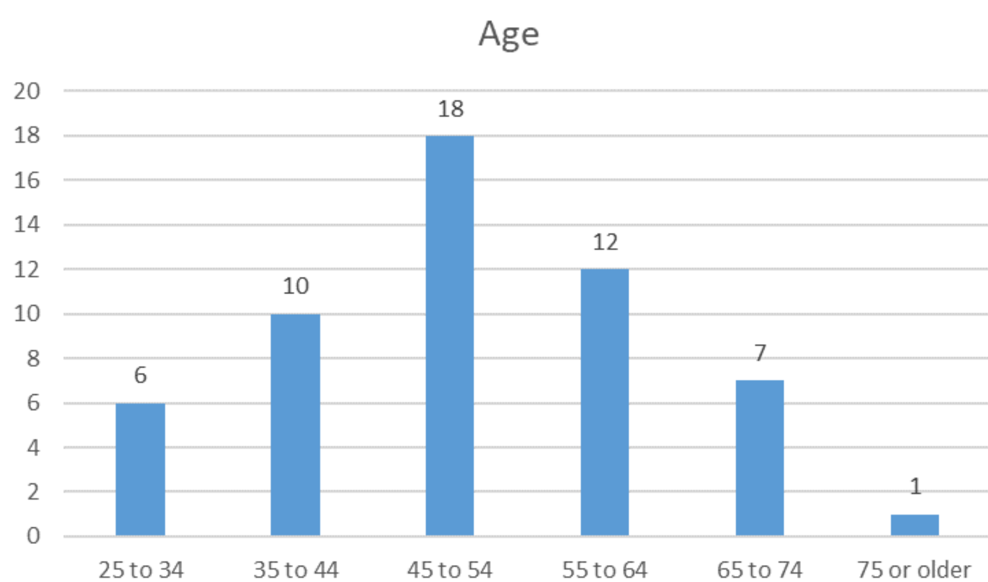

Figure 10: Moderation: age distribution

In Table 20, there is a statistically significant positive moderating influence of age on faculty performance expectation (FPE) and on hedonic motivation (HM). Thus older faculty members expect that their performance will increase as a result of curriculum adoption and that they will have fun adopting new curriculum at greater rates than younger faculty.

Table 20: Moderating effects and significance of age in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE → BIA	0.199	1.018	0.309	[-0.265, 0.531]
FC → AB	0.019	0.120	0.904	[-0.458, 0.255]
FC → BIA	0.253	1.510	0.131	[-0.214, 0.488]
FPE → BIA	0.307	1.975	0.049^*	[-0.201, 0.534]
HM → BIA	0.362	2.031	0.042^*	[0.052, 0.694]
SI → BIA	0.011	0.069	0.945	[-0.316, 0.284]
SPE → BIA	0.317	1.105	0.270	[-0.364, 0.713]

Education level

The data analyzed contained very few participants with associates degrees and bachelors degrees. As a result, although education level could be considered to be a more continuous variable, it was reduced to a dummy variable representing masters and doctoral degrees in order for the analysis to have meaning. Figure 11 shows the distribution of participants' education level.

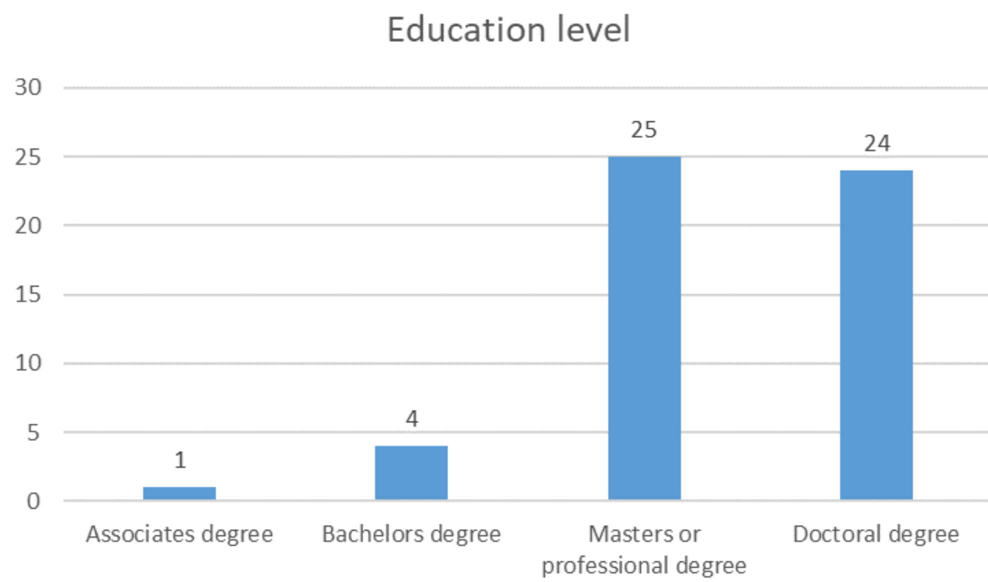

Figure 11: Moderation: education level distribution

The analysis in Table 21 demonstrates that there is no statistically significant moderating influence of holding a doctorate rather than a masters. Hedonic motivation would have been significant at the $\alpha = 0.10$ level, however, and its magnitude is substantial. This relationship bears further examination.

Table 21: Moderating effects and significance of education level (doctorate) in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE $\rightarrow$ BIA	-0.073	0.292	0.770	[-0.429, 0.432]
FC $\rightarrow$ AB	0.077	0.465	0.642	[-0.253, 0.305]
FC $\rightarrow$ BIA	0.148	0.761	0.447	[-0.350, 0.450]
FPE $\rightarrow$ BIA	0.145	0.535	0.593	[-0.304, 0.503]
HM $\rightarrow$ BIA	0.352	1.743	0.082	[0.006, 0.775]
SI $\rightarrow$ BIA	0.146	0.983	0.326	[-0.175, 0.416]
SPE $\rightarrow$ BIA	0.218	0.922	0.357	[-0.319, 0.648]

Table 22 captures the moderating effects of respondents holding a masters degree. As with those holding a doctoral degree (Table 21), there was no statistically significant effect.

Table 22: Moderating effects and significance of education level (masters) in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE → BIA	0.058	0.264	0.792	[-0.429, 0.426]
FC → AB	-0.111	0.677	0.498	[-0.370, 0.168]
FC → BIA	0.107	0.475	0.635	[-0.233, 0.615]
FPE → BIA	0.219	0.903	0.367	[-0.316, 0.529]
HM → BIA	0.023	0.098	0.922	[-0.416, 0.417]
SI → BIA	-0.008	0.045	0.964	[-0.316, 0.338]
SPE → BIA	0.241	0.904	0.366	[-0.251, 0.534]

Experience

Figure 12 shows the distribution of respondents' years of experience in higher education.

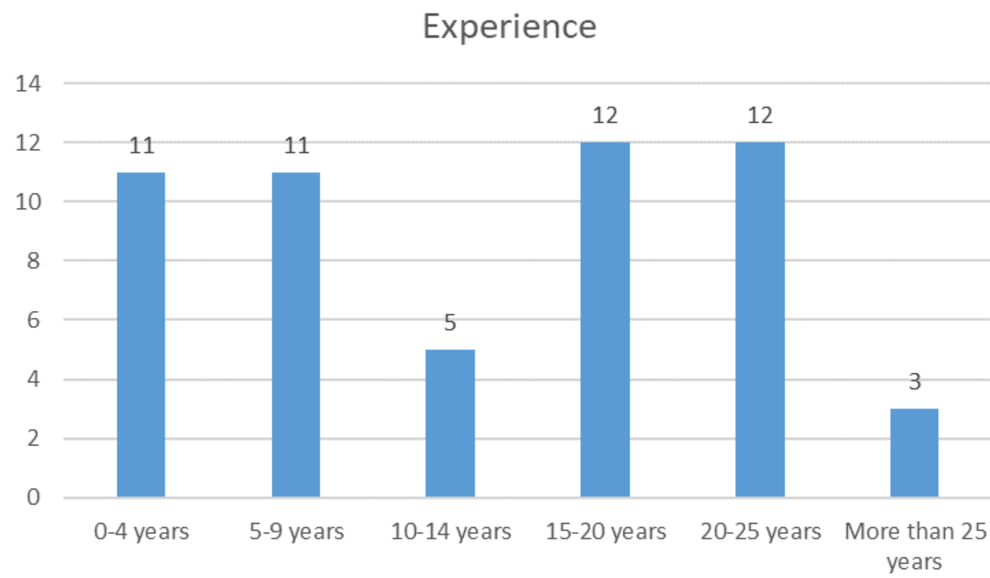

Figure 12: Moderation: experience distribution

Table 23 displays the moderating effects of the number of years of experience in higher education that a respondent has. There was no statistically significant relationship evident for any of the paths.

Table 23: Moderating effects and significance of experience in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE $\rightarrow$ BIA	0.202	1.068	0.286	[-0.220, 0.476]
FC $\rightarrow$ AB	-0.093	0.595	0.552	[-0.335, 0.229]
FC $\rightarrow$ BIA	-0.144	0.660	0.510	[-0.644, 0.179]
FPE $\rightarrow$ BIA	0.211	0.778	0.437	[-0.609, 0.518]
HM $\rightarrow$ BIA	0.133	0.710	0.478	[-0.329, 0.459]
SI $\rightarrow$ BIA	0.035	0.266	0.790	[-0.258, 0.258]
SPE $\rightarrow$ BIA	0.346	0.886	0.376	[-0.538, 0.919]

Gender

Figure 13 shows the distribution of respondents' gender.

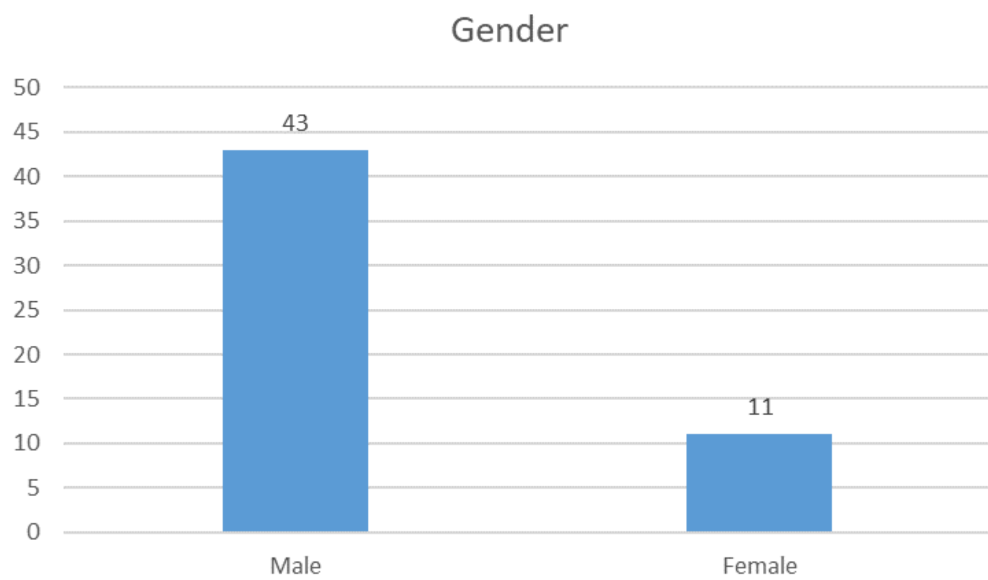

Figure 13: Moderation: gender distribution

Table 24 displays the effects of gender on the various constructs. However, there was only sufficient data for those who identified as male. Only 20% of respondents were female and there was insufficient data for meaningful results for women. Nonetheless, men had no statistically significant impacts on the paths.

Table 24: Moderating effects and significance of gender (male) in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE → BIA	-0.378	1.396	0.163	[-0.962, 0.136]
FC → AB	-0.111	0.390	0.697	[-0.641, 0.446]
FC → BIA	-0.211	0.787	0.431	[-1.086, 0.223]
FPE → BIA	0.261	0.379	0.705	[-1.083, 0.949]
HM → BIA	0.073	0.366	0.714	[-0.284, 0.391]
SI → BIA	-0.141	0.693	0.489	[-0.437, 0.288]
SPE → BIA	0.203	0.125	0.901	[-2.048, 2.212]

School level

Figure 14 shows the distribution of respondents' school level.

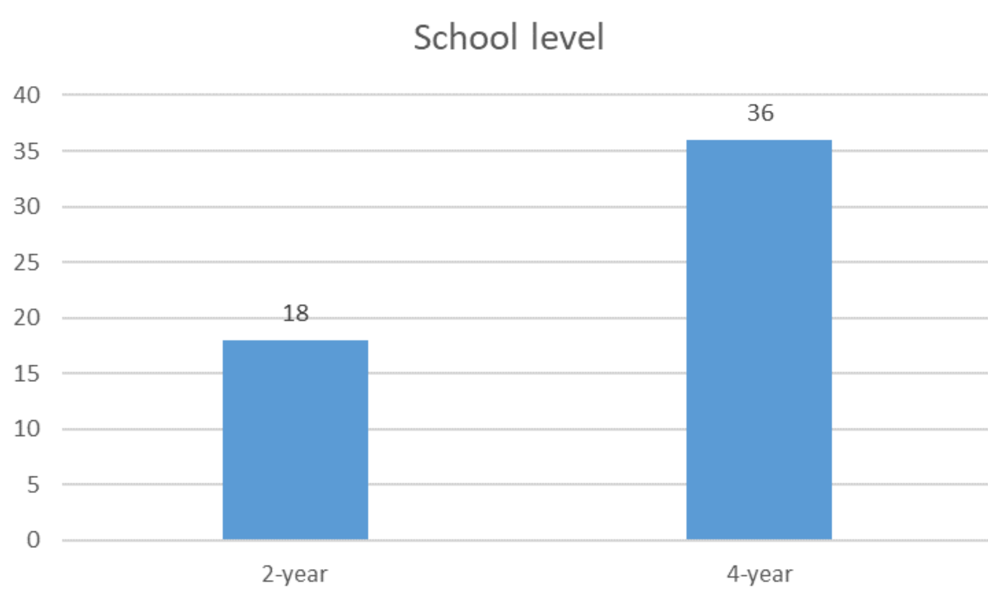

Figure 14: Moderation: school level distribution

Tables 25 and 26 identify the effects of the undergraduate level—associates or bachelors—on each construct. None of the paths were significant in Table 25 at the associates level, however, the path coefficients were almost always negative. By contrast Table 26 for bachelors level schools tells a different story. The paths HM $\rightarrow$ BIA and SPE $\rightarrow$ BIA were both large and statistically significant. Roughly interpreted, being at a 4-year institution meant that having fun with curriculum was more significant and expecting student performance increases was more significant. Further, in contrast to the 2-year data, nearly all path coefficients were positive at 4-year institutions. Thus, there is a meaningful difference between the way curriculum is adopted at the 2-year and 4-year levels.

Table 25: Moderating effects and significance of school level (2-year) in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE $\rightarrow$ BIA	0.029	0.159	0.874	[-0.366, 0.341]
FC $\rightarrow$ AB	-0.018	0.164	0.870	[-0.191, 0.237]
FC $\rightarrow$ BIA	-0.235	0.913	0.361	[-0.553, -0.002]
FPE $\rightarrow$ BIA	-0.049	0.112	0.911	[-0.379, 0.431]
HM $\rightarrow$ BIA	-0.145	0.832	0.405	[-0.427, 0.297]
SI $\rightarrow$ BIA	-0.119	0.781	0.435	[-0.342, 0.258]
SPE $\rightarrow$ BIA	-0.271	0.895	0.371	[-1.101, 0.066]

Table 26: Moderating effects and significance of school level (4-year) in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE → BIA	-0.119	0.647	0.518	[-0.484, 0.199]
FC → AB	0.053	0.423	0.672	[-0.208, 0.247]
FC → BIA	0.172	0.682	0.495	[-0.260, 0.558]
FPE → BIA	0.192	0.960	0.337	[-0.380, 0.428]
HM → BIA	0.341	2.062	0.039*	[0.063, 0.619]
SI → BIA	0.128	0.878	0.380	[-0.263, 0.331]
SPE → BIA	0.331	1.981	0.048*	[0.033, 0.703]

Scope of change

Figure 15 shows the distribution of of the scope of the curriculum change.

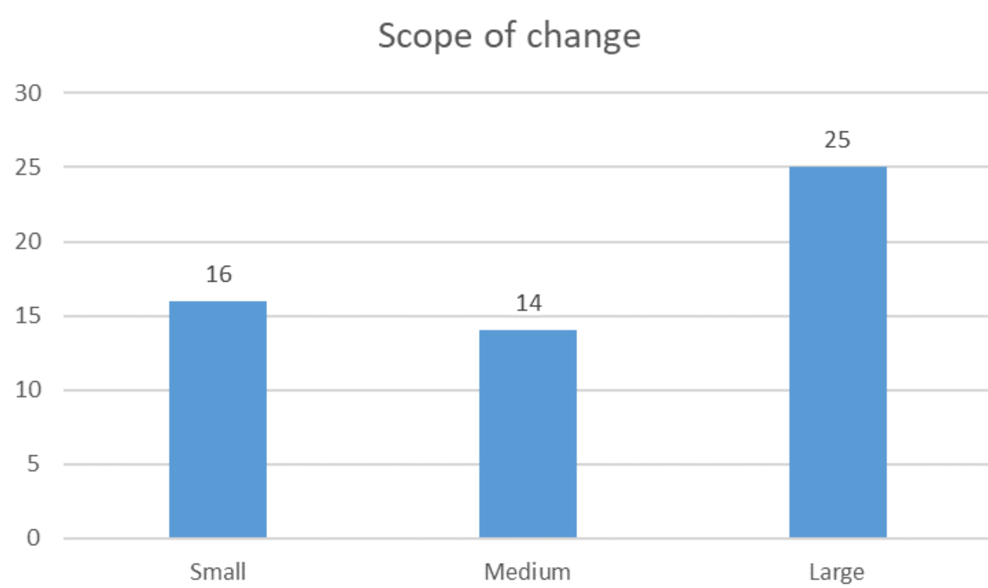

Figure 15: Moderation: scope distribution

Table 27 captures the impact of the scope of curriculum changes (small, medium, or large). The negative path coefficients mean that larger projects negatively influence adoption. To that end there were three statistically significant and large magnitude paths: FC $\rightarrow$ AB, FPE $\rightarrow$ BIA, and SI $\rightarrow$ BIA. Again, roughly interpreted, institutional support influences adoption at a higher magnitude when then changes are smaller, faculty expect their performance to improve more when the changes are smaller, and the influence of socially significant people is greater when the changes are smaller. Large changes had universally negative impacts.

Table 27: Moderating effects and significance of scope in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE $\rightarrow$ BIA	-0.253	1.647	0.100	[-0.563, 0.040]
FC $\rightarrow$ AB	-0.310	2.201	0.028*	[-0.612, -0.067]
FC $\rightarrow$ BIA	-0.130	0.902	0.367	[-0.369, 0.241]
FPE $\rightarrow$ BIA	-0.322	1.972	0.049*	[-0.658, -0.011]
HM $\rightarrow$ BIA	-0.256	1.567	0.117	[-0.659, -0.01]
SI $\rightarrow$ BIA	-0.267	2.065	0.039*	[-0.523, -0.027]
SPE $\rightarrow$ BIA	-0.288	1.463	0.144	[-0.595, 0.231]

Voluntariness

Figure 16 shows the distribution of the voluntariness of the change.

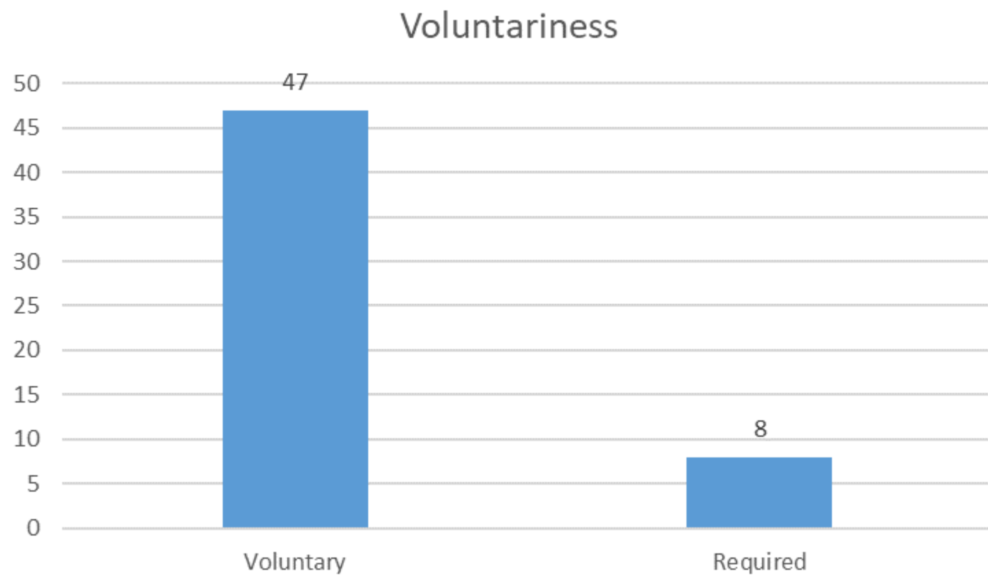

Figure 16: Moderation: voluntariness distribution

Finally, Table 28 captures the influence of voluntariness on the measurement model. As with many of the other moderators, there was no statistically significant impact of making a change voluntarily versus being required to make a change.

Table 28: Moderating effects and significance of voluntariness in the model of Figure 9.

	Path coefficient	t-statistic	p-value ($p < 0.05^*$)	95% Confidence Intervals
EE → BIA	-0.297	1.718	0.086	[-0.606, 0.021]
FC → AB	0.186	0.353	0.724	[-0.009, 0.485]
FC → BIA	-0.074	0.135	0.893	[-0.894, 0.267]
FPE → BIA	-0.156	0.120	0.905	[-0.348, 2.403]
HM → BIA	-0.035	0.162	0.872	[-0.278, 0.419]
SI → BIA	0.413	0.016	0.987	[-0.524, 1.501]
SPE → BIA	-0.118	0.127	0.899	[-1.14, 0.196]

Parsimonious Model Construction

Since the complete model had high predictive power and relevance (see Tables 15 and 17) the question arises as to whether or not a model with fewer paths or variables may be constructed that has similar predictive power and relevance. Following the process outlined in Chapter 3 a parsimonious model was constructed through stepwise regression.

According to the process in Henseler et al. (2014), a backward elimination strategy was initiated. Starting from the full measurement model of Figure 8, the least significant paths were eliminated and the adjusted R^2 calculated for the endogenous variables of BIA and AB. The path removal process proceeded as follows:

1. EE $\rightarrow$ BIA had both the largest p-value and the smallest absolute value path coefficient and was removed from the model, prompting the removal of the EE construct. Adjusted R^2 for BIA improved.

2. HM $\rightarrow$ BIA had the next largest p-value and the next smallest absolute value path coefficient after the first removal. Removing that path and the HM construct lowered the adjusted R^2 for BIA.

3. FPE $\rightarrow$ BIA had the next largest p-value and the next smallest absolute value path coefficient after the previous removal. Removing the FPE construct and its paths improved the adjusted R^2 for BIA, but lowered it for AB. However, the path SI $\rightarrow$ BIA became significant with $p = 0.045$. This raises the specter of a possible Type I error, so particular care should be taken in a subsequent study to identify its true significance.

4. FC $\rightarrow$ BIA was now the only insignificant path with $p = 0.091$. Removing that path made all remaining paths more significant, but lowered the adjusted R^2 for BIA and AB slightly.

Table 29 shows the changes in adjusted R^2 for each path removal from the model. Although the final adjusted R^2 for AB is slightly lower at the end of the stepwise backward elimination, the resulting model has all paths significant and is substantially more parsimonious than the original model at a tiny cost to predictive power.

Table 29: Adjusted R^2 values by path removal.

Path removed	R^2 AB	R^2 BIA
None (original model)	0.512	0.334
EE $\rightarrow$ BIA	0.512	0.343
HM $\rightarrow$ BIA	0.512	0.339
FPE $\rightarrow$ BIA	0.511	0.344
FC $\rightarrow$ BIA	0.510	0.320

The model of Figure 17 is the final parsimonious model.

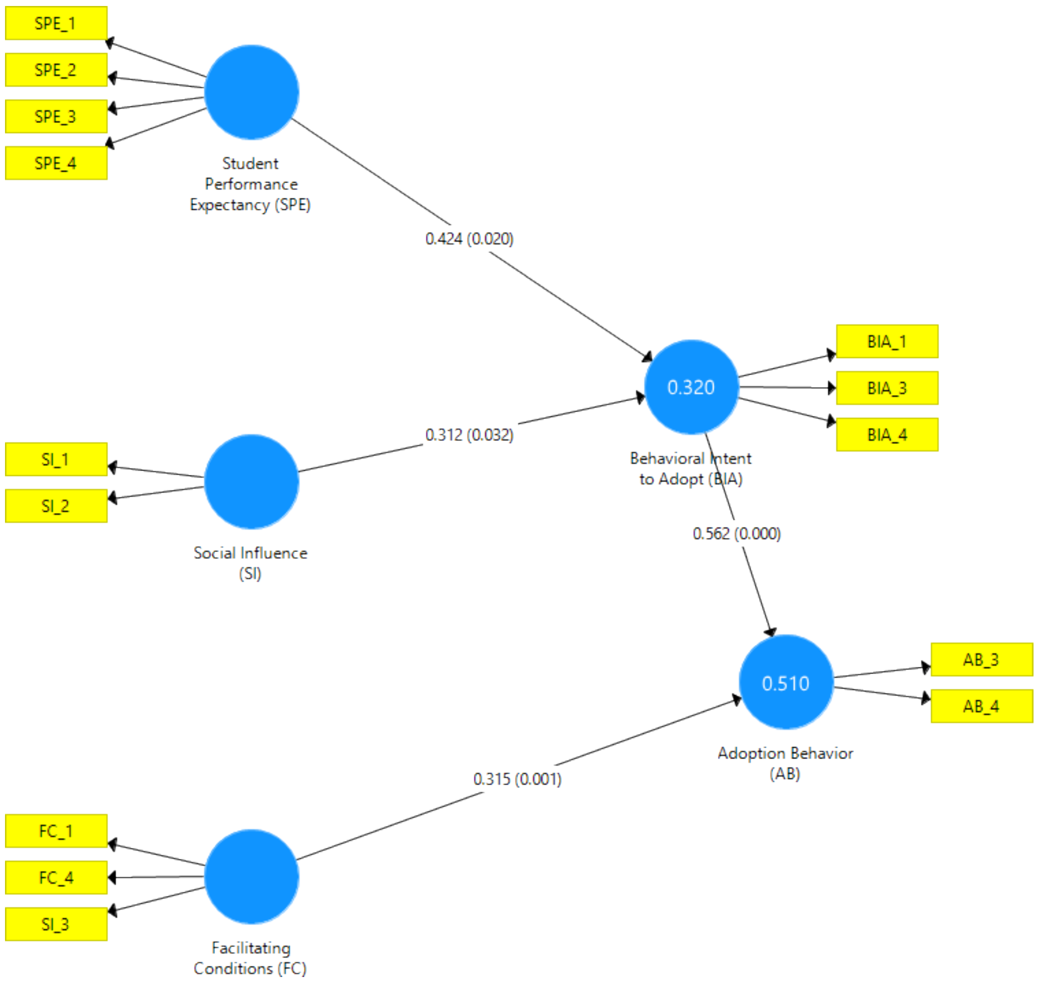

Figure 17: Parsimonious model; Adjusted R^2 is given on the endogenous constructs and paths show coefficients and p-values.

CHAPTER 5

DISCUSSION

Based on the results in Chapter 4, the model of Figure 8 is a good fit; it has good convergent validity, construct reliability and validity, and discriminant validity as demonstrated by the numerous fitness and validity measures. Further, the model has moderate to substantial predictive power concerning actual adoption behavior and accounts for more than 50% of variance in the dependent variable. Effect sizes of each of the constructs were moderate to large and the model had high predictive relevance. Thus, the inferences drawn below are based on extensive prior theory, good methodological design, and sound statistical analysis. The sections below will discuss each of the hypotheses of Table 19 situated in the relevant literature and referencing both the full structural model of Figure 9 and the parsimonious model of Figure 17.

Hypothesis Insights

Hypothesis H1 (SPE $\rightarrow$ FPE) was directly supported in the structural model ($p = 0.000$) and had a very large path coefficient. The path from student performance expectancy (third party) to faculty performance expectancy (first party) is not found in technology acceptance models. However, the case from Allen (2016), Lowry et al. (2015), Freeman and McVea (2001), and Byrne and Flood (2005) makes it clear that there was a reasonable expectation that faculty should be considering the outcomes for students. Further, the large path coefficient (0.715) indicates a very strong connection between expectations of student performance and expectation of faculty performance. The direction of the connection from SPE to FPE is supported by both the magnitude and the significance when the mediating connection is removed – that is, the SPE to BIA connection was slightly larger and slightly more significant than the FPE to BIA connection. Thus the intrinsic and altruistic student performance expectancy construct is a slightly better predictor of intention and actual behavior than the extrinsic faculty performance expectancy construct.

This significant relationship between constructs means that faculty do consider that their personal goals for performance are, in fact, closely tied to the future performance of their students. Student preparation for future courses and jobs influences their own expectations – after all the next person to encounter a well prepared student may be themselves in a subsequent course.

Hypothesis H2 (SPE $\rightarrow$ BIA) was partially supported in the measurement model but fully supported in the parsimonious model. In other words, the direct path in the measurement model wasn't significant but the total effects of SPE on BIA – including mediation through FPE – was moderate and significant. Further, in the parsimonious model, this path coefficient was large and significant. Situated in the literature, especially Lowry et al. (2015), intrinsic motivations of influence, altruism, approval, reputation, leadership, and knowledge sharing can substantially contribute to the understanding of actual system use. As mentioned previously, SPE and FPE were highly correlated, but SPE was a better predictor of BIA and AB than FPE indicating that the altruistic motivation on behalf of students was more powerful than the motivation for self via extrinsic reward.

The implications of this hypothesis being supported in its total effects and fully in the parsimonious model are very significant. It is not just that student performance affects their performance (extrinsically via H1), but that student performance is a factor driving overall intention. Since the path from FPE to BIA (hypothesis H8) was not significant in the full model (directly or indirectly) nor in the parsimonious model, it cannot be that FPE is a direct substitution for SPE. Instead, faculty consider future student performance expectancy *more important* than their own performance expectancy. This cannot be underestimated – faculty considerations of student performance contributes more to changes in curriculum than their expectations of own performance does. And it means that in the "curriculum as technology" analogy, a performance expectation construct still exists in the acceptance model, but the perspective is that of a third party and its motivation is altruistic.

Hypothesis H3 (EE $\rightarrow$ BIA) was not supported in either the measurement model or the parsimonious model. This represents a departure from the technology acceptance models – effort expectancy in UTAUT (Venkatesh et al., 2003) and perceived ease of use in TAM (Davis, 1989). In UTAUT, effort expectancy was significant in only one of three collected data sets and had a moderate (0.20) path coefficient. In TAM Davis, Bagozzi, and Warshaw (1989) found that early in his study, perceived ease of use was a significant (but secondary) construct compared to perceived usefulness. However, "at the end of 14 weeks, intention was directly affected by usefulness alone, with ease of use affecting intention only indirectly via usefulness," (Davis et al., 1989). This is aligned with the findings in this study since participants were asked to reflect on a past curriculum change. It would therefore be expected – under TAM – that ease of use (or effort expectancy in UTAUT) would not be a factor at the time of asking. What this means is that (at least in the long run) efforts to make curriculum adoption easier ultimately do not contribute to the decision to change in the first place. Instead, the decision is made based on other criteria and then, perhaps, a choice among alternatives would be influenced by effort expectancy.

Hypothesis H4 (SI $\rightarrow$ BIA) was not supported in the measurement model but was supported in the parsimonious model. The initial p-value in Table 13 was small (yet not significant) and the path coefficient moderate. However, its total effects in the parsimonious model were very significant. As mentioned previously, this could be an indicator of a Type 1 error (incorrectly rejecting a null hypothesis). However, the support of existing theory in favor of this construct provides reassurance that it is not, in fact, a Type 1 error. Existing psychological and technology acceptance theories concerning subjective norms and subjective culture (Venkatesh et al., 2003; Fishbein & Ajzen, 1975; Davis, 1989) provide solid evidence in favor of its inclusion. Further, it is also consistent with teacher motivation theories (Börü, 2018) and stakeholder theory (Jones & Wicks, 1999).

There is a very reasonable explanation as to why the hypothesis wasn't significant in the measurement model: the measurement model was based on UTAUT2 and had an additional path from facilitating conditions to behavioral intention that was not present in the original UTAUT model. Venkatesh et al. (2012) discusses this addition as distinct in consumer technology adoption:

> In UTAUT, facilitating conditions is hypothesized to influence technology use directly based on the idea that in an organizational environment, facilitating conditions can serve as the proxy for actual behavioral control and influence behavior directly (Ajzen 1991). This is because many aspects of facilitating conditions, such as training and support provided, will be freely available within an organization and fairly invariant across users. In contrast, the facilitation in the environment that is available to each consumer can vary significantly across application vendors, technology generations, mobile devices, and so on. In this context, facilitating conditions will act more like perceived behavioral control in the theory of planned behavior (TPB) and influence both intention and behavior (Ajzen 1991).

With this distinction in mind, the path FC $\rightarrow$ BIA was removed and boostrapping indicated that social influence became significant. Therefore this result is consistent with existing theory on organizational technology acceptance and may mean that curriculum adoption is more analogous to technology adoption in that context than in the consumer context – this is further supported when examining hypothesis H5 below. Considering that this path is supported in the parsimonious model and is supported in the absence of FC $\rightarrow$ BIA, it indicates that peer interactions and administrative influence does influence the decision of faculty members to adopt new curriculum advances.

Hypothesis H5 (HM $\rightarrow$ BIA) was neither supported in the measurement model nor the parsimonious model. This construct of "fun" was imported from UTAUT2 – a consumer focused technology adoption model – as something that might reasonably influence curriculum adoption. It turns out that it does not, in fact, do so. Curriculum adoption is not analogous to consumer adoption of technology but rather is analogous more to the workplace adoption of technology as has been repeatedly studied in MIS literature. Venkatesh et al. (2012) states the relevance of this construct only for consumer technologies: "hedonic motivation is a critical determinant of behavioral intention and was found to be a more important driver than performance expectancy is *in non-organizational contexts*." In organizational contexts, it wasn't significant. Therefore, this result is consistent with existing theory on organizational technology acceptance. What this means practically is that faculty don't really consider how difficult or easy it will be to make a curriculum change as a driver for intention. Instead, other factors (such as student performance expectancy and social influence) take precedence.

Hypothesis H6 (FC $\rightarrow$ BIA) was not supported in the measurement model or in the parsimonious model. As mentioned in the discussion of hypothesis H4 above, this path is part of the UTAUT2 model aimed at consumer acceptance of technology, but not present in the original UTAUT model aimed at organizational acceptance of technology. The results obtained are consistent with organizational contexts. Thus, the facilitating conditions construct only influences actual behavior and not intention and is consistent with UTAUT Venkatesh et al. and the Theory of Planned Behavior (Ajzen, 1991).

Hypothesis H7 (FC $\rightarrow$ AB) was supported in both the measurement model and in the parsimonious model and is consistent with the UTAUT model upon which this hypothesis is based. This lends more credence that the "curriculum as technology" analogy holds true. The implications of this hypothesis are that faculty need actual institutional support beyond intention to adopt. They need specific people, such as instructional designers, educational technologists, and even systems administrators to be able to bring real world security curriculum into the classroom. Further, the institution needs to provide the necessary resources such as hardware/software for instruction, professional training and development, and course teaching release. Overall, faculty must know that the leadership of the organization is backing their efforts to make changes.

Hypothesis H8 (FPE $\rightarrow$ BIA) was not supported in the measurement model or in the parsimonious model. However, the relationship with student performance expectancy is such that the parsimonious model could be built with either FPE $\rightarrow$ BIA or SPE $\rightarrow$ BIA and still be significant. The model that includes FPE and excludes SPE has a similar adjusted R^2 for adoption behavior and a slightly smaller adjusted R^2 for behavioral intention (0.308 versus 0.320). Thus, SPE contributes more to intention, but FPE and SPE both yield the same adoption behavior. If the indicators for SPE and FPE are combined on a single composite student/faculty performance expectancy, then the adjusted R^2 for intention rises to 0.344 but adoption behavior remains the same. It could be that the SPE and FPE constructs measure very similar concepts even though the indicators are not outside of accepted bounds for crossloadings. Given the choice between the two, SPE (as mentioned in the explanation for hypothesis H1 above) as an intrinsic motivator is a slightly better predictor of intention and actual behavior than the extrinsic faculty performance expectancy construct.

Existing technology acceptance model literature clearly supports the inclusion of first-party performance expectancy (e.g. in TAM as perceived usefulness and UTAUT as performance expectancy). However, this research does not rule out first-party performance expectancy since a slightly worse parsimonious model can be built to include it. Regardless *some* form of performance expectancy is necessary in a curriculum adoption model. And to that end, the use of SPE or FPE is still an open question. The implications are that those wishing to influence faculty toward curriculum adoption can make the case for performance expectation for students which leads to performance expectation for faculty via hypothesis H1.

Hypothesis H9 (BIA $\rightarrow$ AB) was supported in both the measurement model and the parsimonious model and is consistent with all available literature on technology adoption models. Davis et al. (1989) states that "people's [technology] use can be predicted reasonably well from their intentions," and this result agrees; intention is the most substantial single contributor to adoption behavior with the largest effect size (0.559) and t-statistic (6.036). Further, the R^2 and adjusted R^2 for BIA compares favorably to that of TAM (0.408 versus 0.51). The implication for this path is that the formation of intention is crucial for actual behavior and is supported throughout the literature from TRA, TPB, TAM, and UTAUT all containing this construct. For those wishing to influence faculty adoption of curriculum, the focus should be on the formation of intent and its precursors (in this case, performance expectancy and social influence).

Hypothesis H10 (FC $\rightarrow$ AB is mediated by BIA) was not supported in either the measurement model or the parsimonious model. Since the path from FC $\rightarrow$ BIA wasn't significant, neither was the mediation effect. As mentioned in the discussion of hypothesis H4 and H6 above, the path from FC to BIA only exists in UTAUT2 aimed at consumer acceptance – organizational contexts have training and support across all users and therefore is said to not affect intention but only actual adoption. Therefore, the results obtained are consistent with UTAUT and organizational contexts.

Hypothesis H11 (SPE $\rightarrow$ BIA is mediated by FPE) was not supported in either the measurement model or the parsimonious model. As mentioned in the discussion of hypothesis H8, the inclusion of both the FPE and SPE constructs rendered both insignificant. Exclusion of one of them made the other significant. However, SPE was the better predictor of BIA and AB than FPE was. Since the inclusion of both constructs in the model rendered both insignificant, mediation of an insignificant effect is itself insignificant. Therefore, SPE alone is sufficient for the model and no mediation effects are present.

Moderation results

UTAUT has the most extensive collection of moderation interactions tested with significant gender related interactions with performance expectancy on intention, gender and age interactions with effort expectancy on intention, and gender age and voluntariness interactions with social influence on intention. Further, age interacted with facilitating conditions on usage behavior. Most of these interactions involve gender – and in this study there was insufficient data points to apply to women. Further, the number of responses in UTAUT (Venkatesh et al., 2003) allows multiple interactions to have sufficient statistical power. But this is not the case with this study. There are only sufficient responses for single interaction effects. Thus, the UTAUT moderation results cannot be reasonably compared to those in this study.

Instead, the following table summarizes the significant moderation effects found in this study and is followed by some possible explanations and implications.

Table 30: Significant moderating effects.

Path	Moderator	Path coefficient	t-statistic	p-value
FPE $\rightarrow$ BIA	Age	0.307	1.975	0.049
HM $\rightarrow$ BIA	Age	0.362	2.031	0.042
HM $\rightarrow$ BIA	4-year	0.341	2.062	0.039
SPE $\rightarrow$ BIA	4-year	0.331	1.981	0.048
FC $\rightarrow$ AB	Scope	-0.310	2.201	0.028
FPE $\rightarrow$ BIA	Scope	-0.322	1.972	0.049
SI $\rightarrow$ BIA	Scope	-0.267	2.065	0.039

The age moderator indicates that older faculty members expect that their performance will increase as a result of curriculum adoption and that they will have fun adopting new curriculum at greater rates than younger faculty. This could be a function of tenure processes (although it did not manifest with the experience moderator) or it could be that older faculty have changed jobs from industry to teaching and therefore they are in a life circumstance where they are working for altruistic and hedonic reasons rather than intrinsic ones.

The 4-year institution moderator indicates that being at a 4-year institution (as opposed to a community college) meant that having fun with curriculum was more significant and expecting student performance increases was more significant. There was no correlation between age and institution type. Further, in contrast to the 2-year data, nearly all path coefficients were positive at 4-year institutions. Thus, there is a meaningful difference between the way curriculum is adopted at the 2-year and 4-year levels.

The scope moderator indicates that institutional support influences adoption at a higher magnitude when then changes are smaller, faculty expect their performance to improve more when the changes are smaller, and the influence of socially significant people is greater when the changes are smaller. Large changes had universally negative impacts.

Based on these moderators younger faculty and community college faculty will be more difficult to influence to adopt cybersecurity curriculum. Further, larger changes will represent a significant challenge for curriculum adoption. As a result, those wishing to promote change should focus efforts on making the case for student performance at 4-year institutions. Further, more grants for smaller projects is better than fewer grants for larger projects.

Curriculum as Technology

There is solid evidence that the application of technology acceptance models to curriculum adoption is a valid approach to studying the motivations of faculty. From a theoretical standpoint, UTAUT is a better base model than UTAUT2 for organizational technology acceptance. The overlap between the results of the UTAUT model

(Venkatesh et al., 2003) and the model presented here (especially the parsimonious model) is substantial.

First, both models have some kind of performance expectancy. For UTAUT this was a first party performance expectancy and in this model it is a third party performance expectancy for students. Although either SPE or FPE could be used in the parsimonious model and be significant, SPE was a better predictor. Second, both models have a facilitating conditions construct that contributes directly to adoption behavior. Third, the lack of an effort expectancy construct in the parsimonious model is consistent with Davis et al.'s explanation that after-the-fact questions about use behavior makes effort expectancy insignificant. Finally, the parsimonious model has a significant social influence component construct. Fourth, the R^2 values for both intention and behavior compare favorably to those of other models – especially that of behavior. Intention wasn't as large for this study as it was for either TAM or UTAUT, but the use construct was at least as good as UTAUT and better than TAM. See Table 31.

Table 31: Comparison of R^2 values.

	Measurement		Parsimonious		TAM		UTAUT	
	R^2	R^2 adj	R^2	R^2 adj	R^2	R^2 adj	R^2	R^2 adj
Intention	0.408	0.334	0.396	0.320	0.51	N/A	0.76	0.69
Behavior	0.531	0.512	0.528	0.512	0.23	N/A	0.53	0.47

This can be seen even more clearly in Figure 18, which contrasts UTAUT with the parsimonious model.

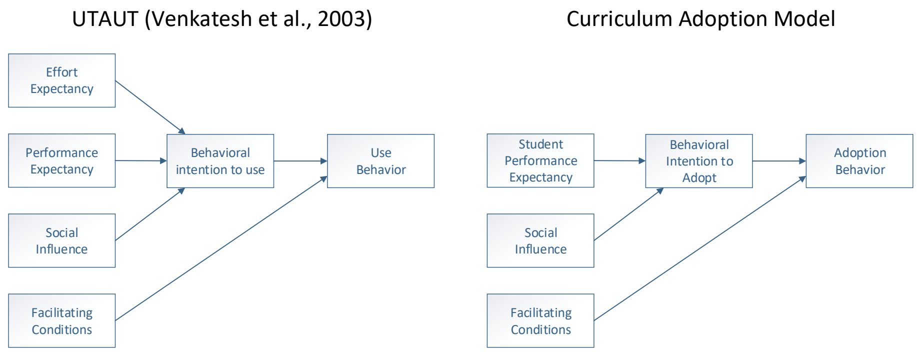

Figure 18: UTAUT model vs. Curriculum Adoption Model. The missing effort expectancy is consistent with post-adoption data per Davis et al. (1989).

Summary

What does motivate faculty to adopt new curriculum?

First, the largest effect size of an exogenous construct is that of facilitating conditions. In particular, when a specific person or group was available to assist with curricular challenges and when the organization provided the support infrastructure needed to make a curriculum change, the probability of making a change increased. Organizational leadership also played a significant role; when senior administration is supportive to faculty efforts, it is more likely for those efforts to be successful. Thus, it is recommended that administrators wishing to see substantive curricular improvement invest in the right resources (hardware, software, subscriptions, etc.) and people (instructional designers, educational technologists) in order to advance their security programs.

The second largest effect size is that of student performance expectancy – the faculty member's estimate of the future performance of students based on the change being made. In contrast to the current pop-culture narrative that colleges and universities are years behind in what they teach and that their disinterest in change is hurting students, the respondents in this survey are deeply motivated by how their students will do in their future workplace. Finding jobs and being effective in those jobs was as important as meeting educational outcomes and preparation for subsequent academic work.

Although faculty performance expectancy through extrinsic reward wasn't a significant predictor of intention or actual behavior, faculty did see that their success was tied to student success. The causal link between student performance expectancy and faculty performance expectancy through the SPE $\rightarrow$ FPE path had the largest effect size and predictive relevance between exogenous and endogenous constructs. Faculty want to be effective and they want to keep current in the field. They saw student success as a precursor to their own success.

Social influence was not significant at the $\alpha = 0.05$ level in the measurement model, but it was in the parsimonious model. With only two indicators loading on that construct, a different instrument may be better able to determine its influence.

Equally satisfying were those paths that were not significant: it didn't matter to faculty that the change was a lot of work (effort expectancy) or if they had fun doing it (hedonic motivation) or if there were extrinsic rewards (faculty performance expectancy). In essence, if it would help students and they got the support of the institution, faculty are very likely to try to improve their courses and curriculum.

The moderating effects were similarly interesting to examine. Although not many moderators were significant, the ones that were prove to be illuminating:

- **Age:** Older faculty were much more likely to be extrinsically motivated – that is being useful in their job, keeping current in the field, and increasing classroom effectiveness. Older faculty likewise were motivated by the fun and excitement of adopting new curriculum. They were least likely to be influenced by others. It may be that older faculty have greater job security than younger faculty and are, therefore, more likely to be interested in their teaching effectiveness and the joy of learning new things.
- **School level:** Faculty at 4-year institutions were more likely to adopt new curriculum if it was fun and exciting or if they saw positive effects on their students.

Further, every path coefficient except for effort expectancy was *positive*. By contrast, for 2-year faculty every path coefficient was *negative* except for effort expectancy. This substantially highlights the divide between 2- and 4-year institutions. It is well known that teaching loads at community colleges are very high – sometimes as many as 5 courses per semester. By contrast, teaching loads at 4-year institutions tend to be lighter and faculty frequently have access to teaching assistants. Although many 4-year faculty have research obligations that 2-year faculty do not, it could be that 4-year faculty are more willing to experiment with their curriculum due to decreased loads.

- **Scope:** Universally, the path coefficients for the effects scope were negative, meaning that larger changes were less likely to be made. Phrased differently, there was better institutional support for smaller changes; smaller changes were linked to better faculty performance; and smaller changes are influenced more by significant others (e.g. colleagues).

The remaining moderators had no statistically significant effect.

Recommendations based on these results are straightforward. Those wishing to influence curriculum adoption should consider these steps to motivate change:

- Provide support for faculty to adopt new curriculum. This could look different to many institutions: release time to develop new courses, instructional designers and learning technologists to assist with course design, training and professional development, or even reduced class sizes.
- Demonstrate that better curriculum has significant impacts on student outcomes. Table 14 shows that while student performance expectancy had an insignificant path coefficient to intention, the total effects of SPE on actual adoption was significant. This indicates that faculty do see student performance as a motivator.
- More effort is required to influence younger faculty and faculty at two-year colleges. Younger faculty fresh out of doctoral programs may see good curriculum

as less important than continuing publications out of their dissertation research. Given the choice of publications toward tenure or good teaching, publications will win unless emphasis is placed on good teaching and curriculum. As for two year faculty, teaching loads may be of concern. Reduced teaching loads may help influence a better pace of change in community colleges.

- Encourage smaller, evolutionary changes to curriculum rather than large scale reinvention. Large scope universally negatively affected adoption and significantly affected facilitating conditions, faculty performance expectancy, and social influence. In other words, large changes tended to be less supported by others, less valuable to faculty, and have less institutional support.

CHAPTER 6

LIMITATIONS, CONCLUSION, AND FUTURE WORK

Assumptions, Delimitations, Limitations

Assumptions, delimitations, and limitations are important to report for any research study so that those seeking to review or replicate the research understand the intentions and constraints of the researcher. Acknowledging these items improves the credibility of the research (Ellis & Levy, 2009).

Assumptions

Assumptions are the background of any research and constitute what the researcher has taken for granted. Without stating assumptions, there is ample opportunity for misunderstanding. "All assumptions that have a material bearing on the problem should be openly and unreservedly set forth. If others know the assumptions a researcher is making, they are better prepared to evaluate the conclusions that result from such assumptions," (Leedy & Ormrod, 2015, p. 62).

The research design provided specific definitions for ideas like "curriculum" as any designed set of educational experiences. The instrument in this study (see Appendix A: Survey Instrument on page 92) defined these similarly to prevent misunderstandings for the participants. All constructs were explicitly defined and consistently operationalized, as well, to avoid assumptions.

One assumption in the instrument is that all participants have influence over and made changes to cybersecurity curriculum. A question on the survey explicitly confirms this assumption, however. Another assumption would be that the participants recall a particular change (out of likely many changes) and answer the survey honestly and accurately. When the experiences and environment of the participant affect the responses given, self-reporting bias is a possibility.

Limitations

A limitation is "the systematic bias that the researcher did not or could not control and which could inappropriately affect the results," (Price & Murnan, 2004). Limitations take on the form of internal and external threats to validity. Internal validity is "the approximate truth of inferences regarding cause-effect or causal relationships," (Trochim & Donnelly, 2008, p. 158) between constructs. In other words, are there alternative explanations for the observations that are not based on the program or treatment? External validity is "the degree to which the conclusions in [a] study would hold for other persons in other places and at other times," (Trochim & Donnelly, 2008, p. 57) In other words, to what extent are the conclusions of the study able to be generalized geographically, socially, and temporally?

Threats to internal validity have been minimized in this study by extensive use of existing theory and research for the path model and instrument. Prior published works were extensively referenced and have established validity and reliability. Further, much of the outset of this chapter was devoted to establishing internal validity through any number of statistical measures. However, a technology acceptance model like UTAUT2 has not been specifically applied to the domain of curriculum adoption, so this is a possible limitation. Another threat to internal validity is that actual adoption behavior was a foregone conclusion since one of the first questions on the instrument asks for participants to "think of a recent change that you have made in your cybersecurity curriculum." The reflective construct of adoption behavior measures the extent to which the actual adoption corresponded to their intention.

Threats to external validity manifest in reduced generalizability. As such, the context of this study (e.g. the population, time, geography, etc.) is the most significant threat the external validity. The population chosen was a “member of faculty, staff, or administration who teaches, designs, or oversees cybersecurity curriculum (courses, certificates, minors, majors) at the associate or baccalaureate level.” This population was reached through mailing lists of interest to those teaching cybersecurity. Participants were self-selecting and it is possible that those who opted-in to those mailing lists (and to this study) are also those who have an interest in effective changes to cybersecurity curriculum. Thus, the largest threat to generalizability is self-selection bias. Self-selection bias is

> when survey respondents are allowed to decide entirely for themselves whether or not they want to participate in a survey. To the extent that respondents' propensity for participating in the study is correlated with the substantive topic the researchers are trying to study, there will be self-selection bias in the resulting data. In most instances, self-selection will lead to biased data, as the respondents who choose to participate will not well represent the entire target population (Lavrakas, 2008, p. 808).

However, the research goal was to identify factors leading to curriculum change and those interested in change are the most likely population. The diversity of mailing lists may help diffuse the results, however, and make them more generalizable.

Delimitations

Finally, a delimitation is “a systematic bias intentionally introduced into the study design or instrument by the researcher,” (Price & Murnan, 2004). The researcher has control over the delimitations and they are frequently related to the population from which the data is drawn. In this case, the population was limited to faculty, staff, and administrators with responsibility over cybersecurity curriculum in 2- and 4-year undergraduate programs. Further, the participants must have made a recent change to the curriculum over which they preside. The use of mailing lists through the Community College Cyber Summit (3CS), The National CyberWatch Center, Center for Systems Security and Information Assurance (CSSIA), and the ACM special interest group for computer science education (SIGCSE) represents a convenience sample.

Conclusion

Increased demand in the cybersecurity workforce requires a significant response from colleges and universities in order to meet that demand. The federal government has emphasized both cybersecurity education at the 2- and 4-year levels as a way to meet that demand, yet there is wide variance in curriculum. This study purposed to discover what factors influence the adoption of new curriculum in undergraduate cybersecurity programs through the adaptation and application of UTAUT to curriculum adoption. The results can be used by higher education administrators, standards bodies, accreditors, and the federal government to direct resources into colleges in order to maximize benefit.

This research contains three significant contributions to the field of information systems and cybersecurity education. The first is the result itself – faculty are motivated by student performance expectancy and facilitating conditions. It is also possible that social influence plays a role, but a subsequent study would be required to confirm this. Efforts by standards bodies, accreditors, university leaders, and the federal government to drive curriculum change should focus on making the case about improved student outcomes and funding to drive change.

The second contribution is that this research represents a first step toward a curriculum adoption (or acceptance) model that parallels that of technology acceptance. The "curriculum as technology" approach is valid in that the model of Figure 8 can account for 51% of actual adoption behavior through the given constructs. Likewise, the model of Figure 17 accounts for the same variance but with fewer constructs. The results obtained parallel those of UTAUT and TAM both theoretically (from the literature) and experimentally.

The third contribution is that the model contains a unique and significant construct for third-party performance expectancy in student performance. This new theoretical construct accounted for nearly half of the variance in intention to adopt and more than a quarter of the variance in actual adoption behavior. Although searched for diligently, this type of construct has not appeared in any prior technology acceptance model. By triangulating on this construct from the intrinsic motivations found in the multimotive information systems continuance model and role of students via stakeholder theory (as well as common sense), the foundation is laid for future exploration of this factor.

The results of this study are applicable directly to undergraduate cybersecurity education since the data were drawn from that population. However, the results may also be generalizable to overall undergraduate STEM education, or perhaps to undergraduate education in general. None of the indicators specifically addressed cybersecurity – although that was the context of the survey – and subsequent studies can be conducted in related areas to confirm this generalization.

Future work on this model will explore the “curriculum as technology” contribution by validating the proposed model of Figure 17 through another independent experiment. Other future contributions will further explore the third party performance expectancy as an intrinsic motivator. Other intrinsic motivational theories such as achievement goal theory (Kaplan, 2014; Richardson, Watt, & Karabenick, 2014), expectancy-value theory (Kaplan, 2014; De Jesus & Lens, 2005; Richardson et al., 2014), and self-determination theory (Kaplan, 2014; Richardson et al., 2014; Börü, 2018; Roth, 2014) could also be explored. Finally, a qualitative study based on responses to open-ended questions can be mined for further insights into instructor motivations for curriculum adoption behavior. That qualitative data was gathered as part of this research but has yet to be analyzed.

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APPENDIX A

SURVEY INSTRUMENT

The following pages contain the survey instrument used for the study. Note that the instrument contains qualitative questions that are not examined in this study. The data for those questions will be for future work.

Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Informed Consent

December, 2018

Dear participant:

I am conducting a research project entitled "Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs" as part of my dissertation at Dakota State University.

The purpose of the study is to determine what factors influence the adoption of new curriculum in 2- and 4-year undergraduate programs based on decision models. The study is significant in that understanding curriculum adoption precursors will help government, industry, and academic standards bodies to advance cybersecurity education in a constantly changing environment.

As a member of faculty, staff, or administration with influence over cybersecurity curriculum, you are invited to participate in the study by completing the online survey. We realize that your time is valuable and have attempted to keep the requested information as brief and concise as possible. It will take you approximately 20 minutes of your time. Your participation in this project is voluntary. You may withdraw from the study at any time without consequence.

There are no known risks to you for participating in this study. The study's outcomes could be important in advancing cybersecurity education in institutions like yours.

Your responses are strictly confidential. Quantitative data will be analyzed statistically and presented in aggregate, with no linkage to your name, title, or any other identifying item. Qualitative data will be analyzed thematically and presented in aggregate. When presented in quoted form, qualitative data will be anonymized by removing any identifying characteristics or proper nouns.

Your consent is implied by the return of the completed questionnaire. Please keep this letter for your information. If you have any questions, now or later, you may contact us at the number below. Thank you very much for your time and assistance.

If you have any questions regarding your rights as a research participant in this study, you may contact The Dakota State University Institutional Review Board at 605-256-5038 or at irb@dsu.edu.

Sincerely,

Todd Whittaker
245 E. Schrock Rd, Westerville, OH 43081
tawhittaker@pluto.dsu.edu
614-266-3779

* Do you consent to take the survey?

- Yes
- No

Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Qualification

This survey is designed for faculty, staff, and administrators at 2- and 4-year colleges and universities who are involved in teaching, designing, or overseeing cybersecurity curriculum (e.g. a course, certificate, minor, or major that is focused on cyber or information security topics).

* Are you a member of faculty, staff, or administration who teaches, designs, or oversees cybersecurity curriculum (courses, certificates, minors, majors) at the associate or baccalaureate level?

- Yes
- No

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Change and Scope

Please think of a recent change that you have made in your cybersecurity curriculum (course, certificate, minor, major, etc). This could be small -- such as creating new assignments in a single course, or large -- such as replacing several courses in a program, or changing program outcomes.

* In a few sentences, please describe the change you made.

* What was the scope of this change?

- Large (affects a entire major, minor, or certificate)
- Medium (affects more than one course)
- Small (affects one course or part of one course)

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* Would you best characterize this change as voluntary (i.e. something you wanted or initiated) or was it required by external factors or constituencies?

- Voluntary
- Required

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Student performance expectation

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
My students will find the curriculum change useful in their future jobs.							
The changed curriculum will enable my students to achieve the learning outcomes better.							
The changed curriculum will increase my students' effectiveness in their future jobs.							
The changed curriculum will better prepare my students for their subsequent education (e.g. future courses or next-level degrees).							

4

What benefits did you expect your students to get out of the curriculum change?

Were your expectations for students realized?

- Yes
- No
- Partly

What helped or prevented the realization of your expectations for students?

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Faculty performance expectation

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Changing the curriculum was useful to me in my job.							
Changing the curriculum encouraged me to keep current in the field.							
Changing the curriculum increased my effectiveness in the classroom.							
Changing the curriculum increased my chances of getting tenure, promotion, or a raise.							

What benefits did you personally expect to get out of the curriculum change?

Were your expectations for yourself realized?

- Yes
- No
- Partly

What helped or prevented the realization of your expectations for yourself?

Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Effort expectancy

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Finding materials to support the curriculum change was easy for me.	○	○	○	○	○	○	○
Learning what was needed to make the curriculum change was easy for me.	○	○	○	○	○	○	○
Teaching the changed curriculum was easy for me.	○	○	○	○	○	○	○
Overall, I found the changed curriculum easy to adopt.	○	○	○	○	○	○	○

What made this change more difficult?

What could have made it easier?

Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Social Influence

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
People who influence me thought that I should make the change to the curriculum.	○	○	○	○	○	○	○
People who are important thought that I should make the change to the curriculum.	○	○	○	○	○	○	○
The leadership of the organization has been helpful with the change to the curriculum.	○	○	○	○	○	○	○
In general, the organization supported the change to the curriculum.	○	○	○	○	○	○	○

Who did you consider as stakeholders in this change?

How did those stakeholders influence your decisions?

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Facilitating conditions

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I had the resources necessary to make the curriculum change.	○	○	○	○	○	○	○
I had the knowledge necessary to make the curriculum change.	○	○	○	○	○	○	○
The change fit well within the existing curricular structure.	○	○	○	○	○	○	○
A specific person (or group) was available to assist me with curricular challenges.	○	○	○	○	○	○	○

How were you supported (or not) by your institution in your efforts to change the curriculum?

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Hedonic motivation

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Making the curriculum change was fun.	◯	◯	◯	◯	◯	◯	◯
Making the curriculum change was enjoyable.	◯	◯	◯	◯	◯	◯	◯
Making the curriculum change was entertaining.	◯	◯	◯	◯	◯	◯	◯
Making the curriculum change was exciting.	◯	◯	◯	◯	◯	◯	◯

What did you like best about making this change?

What did you dislike about making this change?

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Behavioral intention

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I thought significantly about the curriculum change prior to implementing it.	◯	◯	◯	◯	◯	◯	◯
I formulated a plan to make the curriculum change.	◯	◯	◯	◯	◯	◯	◯
I consulted with others about the curriculum change.	◯	◯	◯	◯	◯	◯	◯
I communicated my intent to others about making the curriculum change.	◯	◯	◯	◯	◯	◯	◯

How did you prepare to implement the change?

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Behavior

* Considering the curriculum change you previously described ("{{ Q3 }}")
Please rate your agreement with the following statements.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I implemented the curriculum change according to my thoughts about it.	◯	◯	◯	◯	◯	◯	◯
I implemented the curriculum change according to my plan.	◯	◯	◯	◯	◯	◯	◯
I implemented the curriculum change according to the input from others.	◯	◯	◯	◯	◯	◯	◯
I implemented the curriculum change according to my communicated intent.	◯	◯	◯	◯	◯	◯	◯

Would you make a similar decision to change the curriculum in the future?

◯ Yes

◯ No

Why or why not?

DSU DAKOTA STATE

Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Curriculum standards

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* How are the following curricular guides, standards, or certifications being used in your cybersecurity offerings?

	Targeted directly in courses or programs	Influenced curriculum decisions	Investigated earnestly	Familiar with	Not heard of it
National Security Agency Center of Academic Excellence in Cybersecurity (NSA CAE)	◯	◯	◯	◯	◯
ACM Joint Task Force for Cybersecurity Curricular Guidelines (CSEC 2017)	◯	◯	◯	◯	◯
Accrediting Body for Engineering and Technology (ABET) Cybersecurity Accreditation	◯	◯	◯	◯	◯
National Initiative for Cybersecurity Education (NICE) Workforce Framework	◯	◯	◯	◯	◯
ISC2 Certifications (CISSP, SSCP)	◯	◯	◯	◯	◯
SANS Institute Certifications (GIAC exams)	◯	◯	◯	◯	◯
EC-Council Certifications (CEH, CHFI, etc.)	◯	◯	◯	◯	◯
CompTIA Certifications (Network+, Security+, etc.)	◯	◯	◯	◯	◯
Cisco Certifications (CCNA Security)	◯	◯	◯	◯	◯
Microsoft Certifications (MCSA, MCSE, etc.)	◯	◯	◯	◯	◯

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	Targeted directly in courses or programs	Influenced curriculum decisions	Investigated earnestly	Familiar with	Not heard of it
Linux Certifications (RHCA, LPI, Linux+)	○	○	○	○	○

Other (please specify)

* Does your institution hold the NSA CAE designation?

- ○ Yes
- ○ No, but actively applying
- ○ No, but considering
- ○ No, and not interested

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Demographics

* What is your gender?

- ○ Female
- ○ Male

* What is your age?

- ○ 18 to 24
- ○ 25 to 34
- ○ 35 to 44
- ○ 45 to 54
- ○ 55 to 64
- ○ 65 to 74
- ○ 75 or older

* What is the highest level of education you have completed?

- ○ High school diploma
- ○ Associates degree
- ○ Bachelors degree
- ○ Masters or professional degree
- ○ Doctoral degree

* How many years have you worked in higher education

- ○ 0-4 years
- ○ 5-9 years
- ○ 10-14 years
- ○ 15-20 years
- ○ 20-25 years
- ○ More than 25 years

* Which best describes your role in higher education?

- ○ Staff
- ○ Contingent (adjunct) faculty
- ○ Full time faculty
- ○ Administrator

Other (please specify)

* Which best describes your undergraduate institutional level? A 2-year (associates level) or 4-year (bachelors level) college or university?

- 2-year (associates level)
- 4-year (bachelors level)

DSU DAKOTA STATE Factors Influencing Curriculum in 2- and 4-year Undergraduate Cybersecurity Programs

Done

Thank you for your time!

If you know of another member of faculty, staff, or administration who teaches, designs, or oversees undergraduate cybersecurity curriculum, please consider sharing this survey with them. Merely copy and paste the following into a text or email message:

I just completed a research survey entitled "Factors influencing curriculum in 2- and 4-year undergraduate cybersecurity programs" and thought you might be interested in taking the survey as well. Here is the link: https://www.surveymonkey.com/r/9B5SF8V.