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**ENGINEERING, TEACHING, AND TECHNOLOGY:
A NATIONWIDE ASSESSMENT OF INSTRUCTIONAL INTERNET USE BY
ENGINEERING FACULTY**

by

Alexander Lehman

**A dissertation submitted in partial fulfillment
of the requirements for the degree of**

Doctor of Philosophy

August, 2014

Dissertation Committee

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ABSTRACT

There has been an explosion of internet use among college students over the last decade for at least two important reasons: the proliferation of available resources and the arrival of a digital native generation to university campuses. Not surprisingly, engineering students are entering undergraduate programs possessing a much different skill set than previous generations, which has led to a decline in the popularity of traditional engineering pedagogy. Numerous conceptual models have been developed in the field of instructional technology, as researchers have attempted to classify and effectively integrate new technology practices into 21st century educational contexts. One of the most prominent models is Technology, Pedagogy and Content Knowledge (TPACK), which separates instructors' knowledge into the three listed categories and describes their instructional strategies based on the presence and level of integration of the three knowledge categories. A newer, engineering-specific model separates engineering faculty into three archetypes based on their instructional internet use: internet adopters, internet users, and internet resisters.

This study quantitatively assesses the instructional internet use by a sample of 1126 tenured and tenure-track engineering faculty in the United States. Factor analysis revealed three significant factors: use of internet resources for content delivery, guiding students' internet research, and faculty beliefs on the usefulness of internet resources. The distribution of these factors was used to attempt to identify each of the three archetypes, and to discretely measure the presence and level of integration of the technology component of the TPACK model. While exceptional cases could be identified as internet adopters or resisters, the results do not support the existence of three unique archetypes.

Similarly, the presence and degree of technology integration does not fit any categorical model, but rather a broad spectrum of internet technology usage and beliefs. Finally, regression analyses show that demographic and institutional variables are only minimally predictive of faculty beliefs and practices regarding instructional internet use.

This study contributes to the understanding of instructional internet use in undergraduate engineering education, and provides insight into the applicability of two instructional technology models. Findings from the study may also inform institutional policy and practice regarding professional development initiatives.

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Chapter One

Introduction

Over the past decade, there has been enormous growth in academic internet usage by college students (Alley et al, 2011). Online course management tools have facilitated communication between faculty and students, as well as between students as they work on homework or group projects. Search engines and databases have transformed how students do research, and online videos and discussions facilitate students making connections between classroom learning and real-world applications. Students are also turning to the internet for additional instruction, as online lectures are becoming increasingly popular as they continue to improve in quality. Unfortunately, the growth in student internet use has also helped facilitate plagiarism, as professionally-written papers are available for purchase, and many sites that are ostensibly intended to be learning resources are little more than textbook solution manuals posted online for students to copy.

In most cases, these emerging resources have been especially valuable to both students and faculty in the field of engineering; information, communication, and internet technologies can be used in engineering instruction in a number of ways to improve student engagement and learning (Alley et al, 2011). Case studies in undergraduate engineering courses have shown that e-learning allowed faculty to increase students' intellectual experimentation, provide greater authenticity, and enable more diverse access to course content (Chang & Richardson, 2011). Use of web-based models and dynamic representations, the sharing of information with other locations (including real-time images and remote laboratory experiments), access to industry experts in the topic being

studied, and online lectures and problems are all means by which faculty and students can engage the content on a deeper level (Hennessy et al, 2007; McCrory, 2008).

Similarly, the negative aspects of internet growth have had a dramatic impact on engineering education. Engineering students (even more so than students in other fields) are often driven by a problem/solution mindset which encourages students to tackle challenges as efficiently as possible (Bates, 2009), which can lead to shortcuts that provide problem solutions but do not promote student learning. Students are now entering undergraduate engineering programs with expertise in using these resources, and faculty have had to adjust to this drastic change in their students' prior knowledge (Felder & Brent, 2004a, 2004b).

Professional Development

Most higher education faculty lack recent pedagogical training, and there is a general lack of structured support for junior faculty in many colleges and universities (Brutkiewicz, 2010). Too often, this leads to faculty learning from the "school of hard knocks", and essentially reinventing the wheel for every course they teach. The result of this system is a tendency for faculty to fall back on the instructional model they experienced with their own teachers, and they teach as they were taught (McQuiggan, 2012). Faculty often assume that their students will be successful in learning content through these traditional models as well, but fail to realize that those who go on to become faculty were not typical students. Unsurprisingly, many of these strategies are not nearly as effective when working with the 21st century learners that make up a large percentage of current student populations. A survey of one competitive engineering program reported that only 19% of upperclassmen engineering students thought that

faculty made effective use of internet resources to help students learn (Lehman & Kohl, 2013).

As instructors and researchers have worked towards the integration of technology in their classrooms, a recurring mistake has been to focus efforts on the technologies themselves. Technology-based initiatives nearly always focus on the technology and the ability to "use" it over learning objectives and student learning styles, and "emphasize the divide between how and where skills are learned (e.g., workshops) and where they are to be applied (e.g., classrooms)" (Mishra & Koehler, 2006). This disconnect is even more pronounced with regard to engineering faculty. Engineering professors generally do not need training on how to use technology; they need training on how to *teach* with technology.

Technology, Pedagogy, and Content Knowledge. The difficulties in fully integrating technology into pedagogy and content, as opposed to treating it as an independent set of skills to be mastered, led to Koehler & Mishra (2005) adding technology knowledge to Shulman's (1986) pedagogical content knowledge model. Koehler & Mishra call their new model Technology, Pedagogy, and Content Knowledge (TPACK), which they represented by a Venn diagram (Koehler & Mishra, 2009, p. 63):

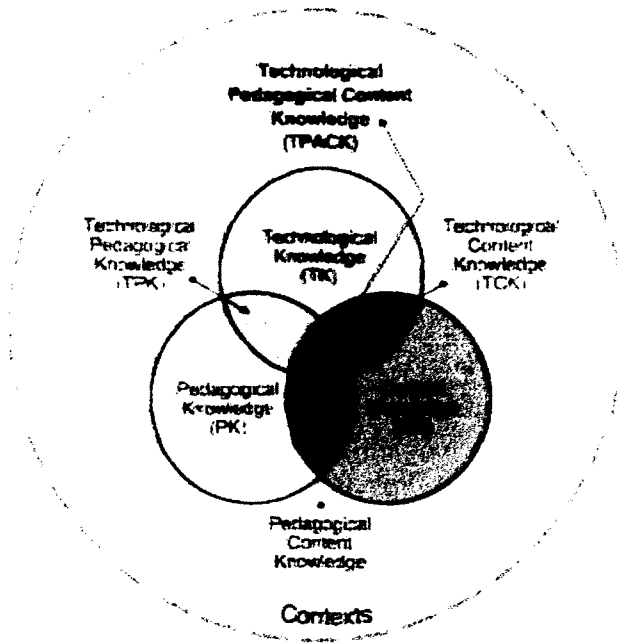


Figure 1: TPACK Venn Diagram

The circles represent the different types of knowledge relevant to teaching using technology: content knowledge, pedagogical knowledge, and technology knowledge. The areas where the circles overlap represent different competencies. Schulman's (1986) Pedagogical Content Knowledge is still present, representing an instructor's ability to effectively convey content to his or her students. Technological Content knowledge and Technological Pedagogical knowledge are new ideas in this model, representing knowledge of technological tools appropriate for a given content area, and knowledge of how to use technology tools to enhance instruction, respectively. Finally, the center segment is Technological, Pedagogical, and Content Knowledge, which represents the ability to leverage technology to enhance or transform how instructional goals are achieved within a given content area (Koehler & Mishra, 2009).

Faculty Archetypes

A previous study showed that engineering faculty within one particular program could be separated into three general categories based on their level of internet adoption in each of their courses: internet resisters, internet users, and internet adopters (Lehman

& Kohl, 2013). The three categories encompass both the faculty member's use of internet resources and his or her attitude towards student use of online content. It was also found that while professors would teach each individual course as a single archetype, most would teach different courses as different archetypes to best fit each course's structure, requirements, and content.

Internet Resisters. Faculty who resist internet use in a particular course tend to organize the course following the traditional lecture-example-homework model. Class time is typically spent on lecture, and homework and out of class resources are textbook-centered. When assigning projects that have a research component, little to no guidance is given regarding finding reliable, valid information on the internet. There is a heavy workload outside of class, and the professor typically does not offer help unless the student seeks them out in person. Within the context of the TPACK model, the technology component is not at all present in this instructional style, at least with respect to internet technology. Faculty may emphasize pedagogy and content to varying degrees, but try to keep internet use from disrupting a traditional instructional model.

Internet Users. Professors who fall into the internet user archetype have not restructured their teaching methodologies around online content, but use internet resources to facilitate learning activities they already employ. Lecture is still a significant portion of class time, but internet content is used to increase student engagement, show demonstrations, or replace costly or elaborate projects. They also show a willingness to adjust their homework assignments to discourage the use of online solution manuals, either by using design-based problems or by creating their own problem sets. When assigning projects that include an online research component, faculty of the internet user

archetype typically provide students with a list of useful resources they can find online. In this category of instruction, the technology piece of the TPACK model is present, but not integrated into the pedagogical and content pieces. The internet has not altered the traditional learning activities, but faculty make use of internet resources to enhance or facilitate traditional activities, and adjust their assessment strategies to accommodate student internet use.

Internet Adopters. Those faculty who fall into the internet adopter archetype are those who have used online content to transform their teaching, and internet use is an integral part of the learning process. There is frequently still a lecture component to the course, but it is often a multimedia presentation, or a series of online videos that can be viewed outside of class time. Faculty who fall into this category also often leverage internet resources to create a course based on student-defined research or design goals, and students are taught to find and evaluate the validity of internet content on their own. Other resources often include an online discussion forum or message board for students and faculty to communicate regarding course announcements, project brainstorming and feedback, and homework help. Textbooks may or may not be required, but in any case are used as a reference only. This instructional model represents the center of the TPACK venn diagram, where internet technology is fully integrated into the course and informs pedagogy and content delivery.

Problem Statement

To date, there has been no systematic, nationwide assessment of instructor practice regarding the use of online resources in engineering courses. Pedagogical studies in engineering education are overwhelmingly self-studies performed by

individuals or small groups of faculty members, so there is an overall lack of generalizable knowledge.

There is also a lack of consensus on pedagogical best practices for use of online resources, and even a disagreement on whether the internet is a positive influence on engineering education. The rapid growth of online resources for students and faculty has changed the way engineering courses must be run, yet change is happening in several directions at once. While some faculty are embracing new developments in online instruction and communication to better reach their students, others are discouraging student usage of the internet for completion of course requirements, as it reduces individual accountability and facilitates plagiarism. Despite all of these changes, few of the new pedagogical models have been studied and best practices have not yet been established.

Finally, faculty are adapting to new student needs through trial-and-error. Junior faculty often suffer from a lack of training and support, and experienced faculty may prioritize research and scholarship over pedagogy - in both cases instructors are left ill-equipped to meet the needs of their students. There is a lack of professional development that will help faculty understand how to best leverage technology in their teaching - integrating beneficial online resources and other technologies into their courses, while preventing students from being able to use the internet to circumvent requirements.

Purpose

This study will undertake three objectives:

1. To assess instructional use of the internet by engineering faculty nationwide, within the TPACK framework.

2. To provide a useful conceptual model to facilitate discussion of best practices for internet use in engineering education.
3. To identify faculty and institutional characteristics that may influence faculty members' instructional internet use, which can be used to develop targeted professional development programs.

Research Questions

The following questions will guide the study:

1. What is the current state of instructional internet use in undergraduate engineering classrooms nationwide, as measured by the presence and degree of integration of the technology component of the TPACK framework?
2. Do the three faculty archetypes (internet resister, internet user, and internet adopter) apply across the nationwide population? Is another model more appropriate?
3. What personal and institutional factors correlate with the extent of technology integration in professors' courses?

Chapter Two

Literature Review

Engineering faculty have begun to adapt to new instructional technologies and new student skill sets, but changes are not happening uniformly. While some faculty embrace the new resources, others attempt to discourage their use in order to preserve their existing pedagogical practices. As new ideas and resources for engineering education are introduced and studied, the growth of internet use outside of the classroom continues to progress without the same restraint. Because of this, the importance of online resources in college and university classrooms has lagged behind the importance of the internet in students' personal and professional lives. Perhaps most problematically, online technology use in engineering instruction has not kept up with the tremendous growth in online technology usage in engineering practice, often relegating undergraduate courses to the role of introducing concepts and modeling obsolete experimental methods (McCrory, 2008). This literature review is intended to provide a framework for understanding and assessing effective technology use in engineering classrooms, and to describe recent attempts to increase internet usage in engineering education. In order to achieve this, this review will undertake three objectives: a) to examine Technology, Pedagogy, and Content Knowledge (TPACK, formerly abbreviated as TPCK), one of the most popular and promising models for integrating technology into instructional practice, b) to provide a preliminary evaluation of the various methodologies for implementing and assessing TPACK in engineering classrooms, and c) to examine strengths and weaknesses of recent efforts to increase internet usage in engineering programs.

Pedagogical Content Knowledge

The first significant steps towards understanding the importance of combining pedagogy with content knowledge were made in Shulman's (1986) seminal piece on teacher preparation and certification. In his examination of teacher certification exams, Shulman noted that exam questions targeted either content knowledge or pedagogical knowledge (knowledge of teaching techniques), but never combined the two. He advocated preparing teachers with an understanding of the link between pedagogy and content, and of how pedagogy can depend on content (1986). This newer, more nuanced theory of instruction has come to be known as pedagogical content knowledge (PCK)

A number of researchers have built on Shulman's ideas, but the first significant attempts to include technology in the PCK model were in regard to information and communication technologies. Researchers noted that while information and communication technologies were becoming nearly universal, they were only very slowly being put into use in the educational setting (Watson, 2001). And while there was disagreement as to the cause of this delay, there was also a consensus among the majority of researchers that these new technologies needed to be connected to pedagogy in order to have a real effect on student learning (McCormick & Scrimshaw, 2001; Watson 2001). Teachers would need to outline their goals for a particular lesson or unit, and examine how technology could be used to modify their practice to more easily or more effectively reach those goals. Existing practice could also be extended or transformed through information and communication technology use (McCormick & Scrimshaw, 2001), especially through the use of new media in the arts (Watson, 2001).

Early applications of pedagogical content knowledge were closely tied to inquiry-

based learning and the constructivist view of knowledge, as well. Constructivist researchers quickly became advocates of pedagogical content knowledge, as the idea that effective pedagogical techniques depend on the content presented is grounded in constructivist theory. Within the realm of science and engineering instruction, the combination of pedagogical content knowledge and constructivist views of knowledge were important factors in the growth of inquiry-based learning activities, as students came to be "considered as thinkers rather than vessels to be filled with 'knowledge'" (Millar, 2005, p. 36). An excellent example of this is shown in Mishra and Girod's (2006) study of a high-school science project: students designed and built a complex, interactive display of life during the Mesozoic Era. This qualitative piece based on interviews with parents, students, administrators, and the classroom teacher showed that allowing the students to set goals, perform the research, and take ownership of the project improved motivation and learning, as well as instilling a level of pride in a class of low-achieving students who were not accustomed to success in the academic setting. This use of project design as inquiry into learning is often difficult to implement and causes difficulties in assessing student learning, but has been shown to create a greater depth of understanding and more effectively meet the needs of diverse learners (McComas, 2005; Millar, 2005).

The research on inquiry-based learning activities is clear in showing that:

The best laboratory experiences are stimulating and enjoyable and enhance content learning and the development of positive attitudes toward science. The rewards are great, but so too are the challenges. It takes time to develop the kinds of laboratories that will serve students most effectively. It requires experience on the part of teachers to engage students in supportive ways without interfering and it takes practice on the part of the students to grow accustomed to the responsibilities and opportunities that occur when verification-based, cookbook laboratories are replaced by authentic inquiry learning experiences (McComas, 2005, p. 29).

Technology, Pedagogy, and Content Knowledge

As practitioners and researchers have worked towards the integration of technology into Shulman's PCK model, a recurring mistake has been to focus efforts on the technologies themselves. The vast majority of technology initiatives have fallen into one of five categories (Harris, Mishra, & Koehler, 2009):

1. Software focused initiatives. Students are taught to solve problems using a particular software package.
2. Demonstrations of sample lessons, resources, and projects. These often occur during professional development opportunities or through commercial demonstrations, and always assume transferability from one classroom setting to others.
3. Technology-based educational reform efforts. These large-scale, large budget efforts involve new hardware and software, extensive professional development, and little lasting change due to teachers' comfort level with existing instructional strategies.
4. Structured professional development workshops or courses. Programs which aim to instill the same set of technology-based skills in all participants, regardless of grade level or subject taught.
5. Technology-focused teacher education courses. Most teacher education programs strive to ensure that all of their graduates have certain technology skills.

The problem with all five of these intervention types is that they are all techno-centric, emphasizing technology skills while largely disregarding their application to teaching and learning. An empirical study further showed the disconnect between technology-centered skills and student engagement and learning. Researchers conducted a series of observations and interviews in the classroom of a self-described technology-enthusiast science teacher. Despite the presence of technology in almost every classroom activity, the technical tools were being used primarily to expedite activities found in most non-technology based classrooms (data recording, word processing, etc). The teacher's inability to use the technology to transform or extend her practice prevented her students from learning any more than they would have from her non-technology-enthusiast

colleagues (Waight & Abd-El-Khalik, 2006).

Koehler & Mishra (2005b) attempted to address the complexities of teaching with technology by adding technology knowledge to Shulman's pedagogical content knowledge model. Koehler & Mishra called their new model Technological Pedagogical Content Knowledge (which they have since revised to Technology, Pedagogy, and Content Knowledge, or TPACK), which they represented by a Venn diagram (Koehler & Mishra, 2009, p. 63):

Each section of the diagram represents a different type of teacher knowledge. The three colored circles represent an instructor's knowledge of content, pedagogy, and technology, respectively. Shulman's (1986) Pedagogical Content Knowledge is still present, and represents knowledge of effective instructional strategies for

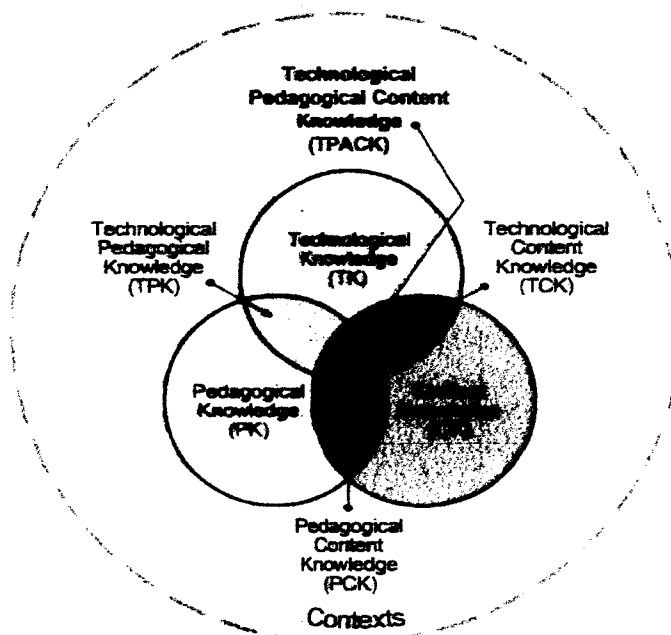


Figure 2: TPACK Venn Diagram

a particular content area. Technological Pedagogical Knowledge is an understanding of how to leverage technology to achieve instructional goals. Technological Content Knowledge is the knowledge of what technology resources are appropriate and effective for teaching specific content areas. And finally, Technological Pedagogical Content Knowledge is the understanding of how technology can be used to extend or transform pedagogy within a content area (Koehler & Mishra, 2005a, 2008, 2009). It is also worth noting that the entire Venn diagram is enclosed within a circle labeled Contexts,

reflecting the fact that all of the knowledge represented within the Venn diagram is dependent on the educational and social contexts in which a teacher works (Koehler & Mishra, 2009).

There are still multiple effective instructional strategies within the TPACK framework, however, as shown by Hennessy, Deane, & Ruthven's (2006) study of four teachers using a force and motion simulation software package in their physics classrooms. Two of the teachers used structured, worksheet-based activities where students proceeded through the activity step-by-step and had little freedom to explore the simulation. These two teachers missed an opportunity to allow the students to construct their own knowledge. The other two teachers, however, did demonstrate TPACK. The third teacher used the simulation as a demonstration, posing scenarios for the students to predict the results, and then running the simulation and guiding a discussion of the outcome. The fourth teacher allowed the students to "play" with the simulation software for a period of time, then required them to pose their own experimental questions to be answered. Ironically, this was the same strategy employed by the less effective teachers, except that students were responsible for creating their own experimental "worksheet", which both eliminated some of the teacher's preparatory work and greatly improved student engagement and depth of understanding (Hennessy, Deane & Ruthven, 2006).

This shows that placement of a course within the TPACK framework is also a function of the instructor involved, and what technologies and pedagogies fit his or her personality and teaching style. Because of this, there are many possibilities for effective instructional strategies depending on activity type, content, and available technology. These possibilities can be arranged into activity-type taxonomies, sorted by knowledge

building versus knowledge expression activities, as well as by activity type (written, oral, visual, concept-building, or product-oriented). The reason why lesson plan-based professional development is ineffective is because TPACK is dependent on matching these activities with the content presented, the technology available, and the instructor presenting the lesson (Harris, Mishra & Koehler, 2009). Case studies have also empirically shown that instructor beliefs about science and scientific knowledge are critical, in that curriculum activities that conflict with the classroom teacher's beliefs will often be misinterpreted, modified, or ignored (Wallace & Kang, 2004).

Several researchers have questioned the completeness of the TPACK model, however. Most notably, Angeli & Valenides (2009) have argued that TPACK is too broad and vague to apply to all technology types. They have presented the specific case of information and communication technologies (ICT), and how the TPACK model does not sufficiently constrain instructor practice with regard to information and communication technology to ensure effective teaching. They proposed an enhanced model for information and communication technologies, called ICT-TPACK. However, the flexibility of the TPACK model has been shown to be more of an asset than a weakness in research specifically examining information and communication technologies (McCormick & Scrimshaw, 2001), and in studies applying TPACK to information and communication technologies (Hennessy, Deaney & Ruthven, 2006; Trautmann & MaKinster, 2009; Graham et al, 2012).

Developing Technology, Pedagogy, and Content Knowledge in Practicing Faculty

The most popular means to increase the number of TPACK trained instructors is to introduce TPACK to pre-service teachers in their preparation programs. The

limitation, however, is that many pre-service teachers do not have the experience to successfully implement TPACK even if they understand it, which could lead to a reversion to simpler, yet less effective strategies. Researchers have conducted a number of studies on TPACK in pre-service teachers, both in terms of creating an understanding of TPACK through course development (Jang & Chen, 2010; Fransson & Holmberg, 2012; Larkin, Jamieson-Proctor, & Finger, 2012), and in terms of assessing their knowledge qualitatively (Graham, Borup, & Smith, 2012; Hechter, 2012; Mouza & Karchmer-Klein, 2013), or through a rigorous survey instrument (Schmidt et al, 2009). Results have shown that pre-service teachers are fully capable of gaining a practical understanding of TPACK, even if they are not capable of fully implementing it until they gain familiarity with pedagogical practice and establish their teaching style.

Additionally, a typical engineering faculty member does not go through a pedagogical training program, meaning there is little opportunity for introduction into TPACK before the instructor enters the classroom. Research has shown that pre-service teachers are more likely to be accepting of the TPACK model than established faculty, presumably because of the time and effort required for practicing instructors to change their instructional techniques and revise their lesson plans (Hug & Reese, 2006). So even professors who become trained in TPACK may not make use of new technology if their instructional practice is well established.

Learning by design. The most effective way for professors to implement TPACK also largely solves the problem associated with the time required to establish new practices, and that is through a learning by design model. Instead of faculty taking a technology tool and attempting to find places to integrate it into their lessons, they should

examine what skills and concept mastery they would like their students to achieve, and determine what technology tools and activities will help them achieve that goal. In this model, professors are only introducing technologies they are already familiar with. Ideally, faculty will continue to develop their technology skills and increase the number of technology resources available for their use, but choosing a technology to fit a specific learning outcome becomes much more powerful than trying to build a learning outcome around a technology. When using a technology tool that supports the learning objective and is embraced by the instructor, students become more engaged in the lesson, and are able to gain a deeper understanding of the content than they would without the technology resource. "In brief, learning by design appears to be an effective instructional technique to develop deeper understandings of the complex web of relationships between content, pedagogy and technology and the contexts in which they function" (Koehler & Mishra, 2005b, p. 131).

Learning by design also emphasizes *how* an instructor learns and implements technology skills, as opposed to *what* technology skills he or she should learn. Instead of being required to demonstrate a certain set of skills to complete a certification program or professional development workshop, professors decide for themselves which technologies and which activities will most benefit their practice, and their students. So instead of hypothetical exercises or discussions, faculty become engaged in authentic design tasks; tasks that will have an immediate positive effect in their classroom (Angeli & Valenides, 2009; Koehler & Mishra, 2005a). The overall approach of solving problems rather than teaching skills makes the implementation of TPACK both more practical and more effective.

Training instructors in the implementation of TPACK through learning by design has also been shown to be effective. Pre- and post-testing demonstrated that both university faculty and K-12 teachers showed increased understanding of TPACK through a lengthy (university semester-long) design task centered around online course development (Koehler, Mishra & Yahya, 2007; Koehler & Mishra 2005b). Another study showed that continuous assessment throughout the design process kept students focused on their development of TPACK, and increased both their gain in understanding and the quality of their design product (Angeli & Valenides, 2009).

Assessing Technology, Pedagogy, and Content Knowledge

There are two instruments endorsed by tpack.org for assessing TPACK: the previously mentioned survey constructed by Schmidt et al (2009), and Archambault and Crippen's (2009) shorter survey assessing TPACK specific to online learning. Chai et al (2011) summarized the two instruments:

Building on the TPACK framework, Schmidt et al. (2009) constructed the Survey of pre-service Teachers' Knowledge of Teaching and Technology which consisted of 58 items that measures all the seven constructs of TPACK with respect to the content areas of Mathematics, Social Studies, Science, and Literacy. ... The items were subjected to expert reviews and pilot-tested with 124 primary pre-service teachers. Schmidt and her colleagues reported high Cronbach alphas for each of the seven TPACK constructs (.80 and above). It is debatable that the instrument can be considered as validated because Schmidt et al. performed factor analysis for each factor independently and reported the factor loadings for the items within that factor.

Archambault and Crippen (2009) validated a 24-item survey to assess K-12 teachers' TPACK specifically for online teaching with over 500 practicing teachers. The findings yielded only three factors. CK, PK and PCK items loaded as one factor labeled as pedagogical content knowledge, the merged items of TPK, TCK, and TPCK was referred to as technological-curricular content knowledge. The only clear factor was the TK.

More qualitatively, Niess (2012) performed a three-year case study of in-service

middle school mathematics teachers, and specifically their practices regarding spreadsheets as learning tools. She was able to identify descriptors aligned with the four central components of TPACK that highlighted differences in teachers' knowledge levels, but was more focused on the growth and development of TPACK than precisely measuring it.

There have been attempts to assess teachers' understanding and use of TPACK internationally, as well. Yurdakul et al (2012) recently developed TPACK-deep, a survey instrument based on 72 indicators related to components of TPACK. The indicators were separated into 4 factors: design, exertion, ethics, and proficiency. Results from the pilot study were promising in terms of the instrument's ability to measure TPACK, but the pilot study involved only K-12 teachers in Turkey, and the survey instrument has not been made available. Similarly, Lee and Tsai (2010) conceptualized TPACK-W, an adaptation of TPACK specific to web-based technology, and administered a survey to 558 Taiwanese K-12 teachers. Although the survey proved to be extremely reliable, factor analysis showed it was unable to distinguish between pedagogical knowledge and pedagogical content knowledge, and survey elements were developed assuming a level of technical expertise well below that of most engineering faculty members. In a more promising study, Rienties, Brouwer, and Lygo-Baker (2013) found success using a pre- and post-test model to measure the development of TPACK skills among 81 higher education faculty in the Netherlands who participated in an online professional development program. But perhaps the most successful attempt to precisely measure TPACK in higher education faculty was made by Shih and Chuang (2013), who developed a 49-item survey that was administered to the *students* of faculty teaching in technology-supported learning

environments. This gave the researchers more observations to work with, and allowed them to accurately assess students' perceptions of each faculty member's knowledge and practice.

TPACK and Web-Based Technologies

Information, communication, and internet technologies can be used in engineering instruction in a number of ways to improve student engagement and learning (Alley et al, 2011). A series of case studies in undergraduate engineering courses led faculty to report that "e-learning allowed them to increase students' intellectual experimentation, to provide deepened authenticity and to improve accessibility to their learning materials" (Chang & Richardson, 2011). Use of web-based models and dynamic representations, the sharing of information with other locations (including real-time images and remote laboratory experiments), access to industry experts in the topic being studied, and online lectures and problems are all means by which faculty and students can engage the content on a deeper level (McCrory, 2008; Hennessy et al, 2007).

Computer models and simulations. Simulations are becoming an increasingly popular means to perform science and engineering experiments. In the biological sciences, simulations allow dissections without the cost or moral issues that come with real specimens. In the physical sciences, a simulation can allow processes to occur at a rate faster or slower than real time, allow for adjustments to be made to fundamental variables, and allow measurements that may not be accessible in a real experiment (McCrory, 2008).

In the context of undergraduate engineering courses, computer-based e-labs - simulated lab experiments - have been shown to lead to a higher completion rate and a

lower error rate than in-person labs, and student surveys report a positive impact on student learning (Morton & Uhomoibhi, 2011). However, it could be argued that the improved completion and error rates are due to the simulation idealizing the experiment, and removing some of the real-world interaction and learning that occurs in a traditional laboratory. Nickerson et al. (2007) developed a model for assessing the effectiveness of simulations and remote experiments in engineering courses, and found that while simulations are valuable in that they save money and space, they do not provide the same learning that occurs in a hands-on experiment. Their results regarding remote experiments were more promising; those will be discussed in a later section.

There is one undisputedly effective use of simulations, however: having the students create the simulation themselves. This takes students out of their role as observers, and makes them active participants in the activity (Dani & Koenig, 2008; Hennessy, Deaney & Ruthven, 2006). The risk with simulations in this role is their accuracy in representing reality. A simulation that is too simple may be too idealized to model the real response of a system; while a simulation that is too complex may break down and yield an inaccurate response if its inputs are not formatted correctly. Student-created simulations are also frequently long-term projects that involve a significant amount of troubleshooting and faculty guidance, which means they are often impractical within the time constraints of a typical undergraduate course.

Remote laboratories. A more recent development in computer-based lab experiences is the emergence of remote laboratories. Instead of the computer simulating the experiment, a webcam, microphone, and digital control setup allow students to perform and observe a live experiment from a remote location. Remote experiments

mitigate some of the cost and space requirements of in-person laboratories, as Universities are able to pool resources and share facilities (Guo, Kettler, & Al-Dahhan, 2006), as well as eliminating many possible safety concerns. While an off-site experimental apparatus can create logistical issues with setup and troubleshooting, a study performed among classes at two different North Carolina State campuses - one who performed the experiment in person, and one who performed it remotely - showed that there was no discernable difference in project grade or survey feedback between the two groups (Jernigan, Fahmy, & Buckner, 2009). Similarly, the assessment model created by Nickerson et al. (2007) also showed that remote experiments worked just as well as in-person experiments for discovering and reinforcing course concepts in the laboratory. A more in-depth analysis is provided by Lindsay and Wankat (2012), who break down 13 desired laboratory outcomes into fungible and non-fungible categories. Fungible outcomes - outcomes that are not affected by a transition to remote laboratory - include instrumentation, models, data analysis, learning from failure, creativity, communication, ethics, and teamwork. Experimentation is deemed largely fungible, but students are constrained by the control system in terms of their freedom to experiment with the laboratory apparatus. Four outcomes are not fungible, however, and are lost when an experiment is done remotely: design, psychomotor development, safety, and sensory awareness. The loss of the design outcome is not often a major concern; most experiments do not include a design element, and those that do cannot be pre-fabricated by faculty regardless. Students' inability to interact with the experiment in a tactile sense, and their dependence on camera and microphone placement, limits both psychomotor development and sensory awareness. Remote labs also eliminate safety concerns, which

may be considered a benefit despite the loss of a learning opportunity. Lindsay and Wankat have not performed any empirical studies to support their breakdown of learning outcomes, but earlier studies show that remote laboratories can be an effective means of using internet technology to facilitate experiments that would be otherwise unavailable to students.

Online problem sets. Problem sets generated or stored online are another common internet resource used in engineering courses. Some of the advantages of online problem sets are obvious: a nearly infinite number of problems can be generated or stored, students can access them anywhere at any time, and assignments can be scored automatically in real time. Several studies have attempted to determine how online problem sets compare to traditional homework in terms of student learning. Self-reported results are positive, as students feel that they are learning more and achieve target skills more easily (Kadiam, Mohammed, & Nguyen, 2010; Mendez & Gonzalez, 2010), though assessments in each case have failed to show a statistically significant increase in student performance. Taraban and Anderson (2005) monitored student usage of their online thermodynamics problem sets both in terms of time spent and problems completed, and found a positive correlation between online homework completion and exam scores, but no quantitative comparison was made to the gains provided by traditional homework assignments. Chung, Shel, and Kaiser (2006) used online problem sets in several discussion sections of an electrical engineering course, and found that "compared to typical discussion sessions, a large majority of respondents reported being more engaged, learning more, and interacting more with the instructor" (p. 4). No measurement of how students in those sections performed compared to their peers was made, however. The

effectiveness of online problem sets appears to be comparable to traditional homework assignments, but more empirical study is needed before it will be safe to say there are no drawbacks that offset some of the advantages of the digital medium.

Other applications. A variety of other, more novel applications of web-based technology have been studied to a limited degree. Games are more often used in the K-12 educational setting, but Ebner and Holzinger (2005) developed an online game for teaching structural concrete applications that achieved the same level of student learning as traditional instruction, yielding positive feedback both in terms of enjoyment and educational content. Webcams are being used in some construction engineering programs to facilitate online project tours and project supervision, enabling students to visualize construction methods and processes without time-consuming site visits (Jaselskis et al., 2011). Online lectures are very common in hybrid or distance-learning courses, but providing video lectures to support in-class instruction has been shown to be beneficial as well. While not all students make use of the additional resource, some of them do so to great benefit. And contrary to intuition, providing online recordings of each lecture does not measurably affect attendance for the in-person lecture (Konsky, Ivins, & Gribble, 2009).

Online group projects have been used in some engineering courses when in-person collaborative work is logistically problematic. Roberts and McInnerney's (2007) analysis of online collaborative learning yielded seven problems that frequently occur: student antipathy, group selection, lack of group-work skills, free-riders, inequalities in student abilities, withdrawal of group members, and assessing individuals within the group. However, it could easily be argued that those same seven problems emerge

regularly during in-person collaborative work, as well. Whitman and Malzahn (2005) compared the results of a design project where half the teams worked together in person and the other half collaborated online. While the performances on the final project were similar, those students working in the online groups were less satisfied with the experience. They reported that the frequency and quality of communication was lower, leading to a lack of role clarity.

Negative impact of unstructured internet use. It is particularly important, however, that the instructor be very familiar with any information, communication, or internet technology before encouraging student use, as this type of technology is easily misused. Engineering students in particular are often driven by a problem/solution mindset which encourages students to "tackle real-world challenges in the most efficient way possible" (Bates, 2009, p. A36), which can lead to shortcuts that provide problem solutions but do not promote student learning. Internet-facilitated cheating is a difficulty that many engineering professors are only beginning to appreciate. Engineering students are often encouraged (or required) to work in teams or groups to complete assignments, and for many students the line between collaboration and plagiarism has become blurred. Passow et al. (2006) found through a survey of 643 engineering students across 11 different institutions that students' history of cheating (copying) on homework assignments is a completely independent construct than cheating on an exam, and that cheating on out-of-class assignments is much more prevalent than on in-class assessments. Internet websites have emerged to specifically meet students' demand for homework solutions to published textbook problems, which has caused difficulties for professors who prefer to continue using the traditional lecture/example/homework

instructional model. A study of student and faculty use of Cramster - one of the largest "online study communities" which has solutions to homework problems from over 200 textbooks in math, science, and engineering - showed that while all 25 faculty surveyed were familiar with Cramster or other sites like it, only one encouraged her students to use it, and "nearly all others reported that they take some sort of action to deter students from using the Internet to obtain solutions, such as writing their own problems or not grading homework at all" (Grams, 2011, p. 225). 87% of student respondents, on the other hand, reported that they thought Cramster could help them earn a better grade. Students did, however, acknowledge that earning a better grade does not always equate to an increase in learning, as only 29% thought it would help them learn and understand course concepts.

Summary and Conclusion

This review shows the development of the Technology, Pedagogy, and Content Knowledge model, and its application to teaching in general and engineering education in particular. The TPACK model is promising in faculty members' hope to improve internet technology integration into undergraduate engineering classrooms. In particular, the learning by design strategy -- and its use of authentic design tasks to introduce instructors to the methods advocated by TPACK -- give professors a clear path towards further technology adoption.

There is still significant research to be done, however. New technologies are continuously emerging, and with them may come new pedagogies and new activity types to be developed and evaluated. The resistance to change from faculty members who have been effective enough without technology usage will always be an obstacle to overcome

as well. But as undergraduate education continues to become a technology-saturated field, the teaching of traditional lecture-based engineering courses will have to move in that direction as well, with the adoption of new technologies, new pedagogies, and as human knowledge grows, new content.

Chapter Three

Methodology

This study is a survey-based research project that will attempt to answer the following questions:

1. What is the current state of instructional internet use in undergraduate engineering classrooms nationwide, as measured by the presence and degree of integration of the technology component of the TPACK framework?
2. Do the three faculty archetypes (internet resister, internet user, and internet adopter) apply across the nationwide population? Is another model more appropriate?
3. What personal and institutional factors correlate with the extent of technology integration in professors' courses?

This chapter will discuss the four components of the execution of the study. The first section will describe the population of study participants and the procedure for survey distribution. The second section will provide a summary of the survey instrument, including the intended survey constructs. The third section will outline the analysis of the survey sample, and how it compares to the population as a whole. And finally, the fourth section will explain the procedure used for analyzing the collected data in order to best answer the research questions.

Population and Procedure

This study surveyed all tenured and tenure-track engineering faculty at non-profit institutions that award accredited engineering bachelor's degrees in the United States. Non-tenure track faculty were not included, as contact information is not always

available, and many part-time faculty split their time between departments or between institutions, making it difficult to pinpoint the effects of institutional variables. This may be a meaningful omission, as early career faculty are more likely to not yet be on tenure-track, and age may correlate with internet use to a measurable extent. However, the size of the population sampled should ensure adequate representation of early-career faculty in the final analysis.

For-profit institutions have been omitted for similar reasons. Tenure is not offered at most for-profit colleges and universities, so many of the characteristics that apply to non-tenure-track faculty at non-profit schools also apply to for-profit faculty. In addition, there are also only nine accredited, for-profit bachelor's degree programs in engineering in the U.S., so sample size limitations would prevent any significant conclusions from being drawn regarding for-profit versus non-profit institutions.

The list of U.S. colleges and universities that meet the required criteria was retrieved from the National Center for Education Statistics (NCES) database; there are currently 552 such institutions, although not all were included in the study for a variety of reasons outlined below.

For each institution, the following data were retrieved from the NCES database and associated with that institution's faculty:

1. Public or private institution
2. Campus setting (urban, suburban, or rural)
3. Total student population (university-wide)
4. Undergraduate student population (university-wide)
5. Percent of students that are undergraduates
6. Undergraduate admission rate (university-wide)

Each institution's website was visited, and a list of tenure-track engineering faculty and their contact email addresses was compiled. Of the 552 institutions examined, it was

decided that 145 did not meet the criteria for the study for the reasons shown in Table 1:

Table 1

Excluded Colleges and Universities

<u>Reason for Exclusion</u>	<u>Number of Institutions</u>
Degrees offered are not in traditional engineering disciplines (e.g. Engineering Science, Informational Technology, Computer Science, Video Game Design)	64
Engineering degrees are conferred by a different, affiliated institution (3-2 programs)	60
Faculty directory and/or contact information is not publicly available	12
Website or directory in a language other than English	7
No faculty tenure	2

After exclusions, the study population consisted of 24,252 faculty members at 407 colleges and universities.

Survey Instrument

A survey was developed and distributed via email to all potential participants. Qualtrics software was used to distribute the survey, and also to compile all raw data provided by respondents. The survey collected demographic information from each participant, including:

- Year of Birth
- Ethnicity
- Gender
- Native English speaker (yes/no)
- Current professional title
- Total number of years teaching
- Number of years at the current institution
- Courses taught per year
- Engineering discipline they most identify with professionally

The survey then asked about engineering courses the professor taught during the 2013 calendar year. The initial question asked what levels (freshman, sophomore, junior, senior, or graduate) were taught during that year. Graduate level courses were excluded,

as this study was designed to analyze the internet usage in undergraduate engineering courses. Courses taught to freshmen were also excluded from the study, as most engineering curricula prioritize math and science foundation courses for the first year, and the few engineering courses aimed at freshmen are often designed to introduce students to the different engineering disciplines rather than deliver rigorous engineering content.

In order to be able to control for the anchoring effect (Kahneman, 2011), the remainder of the survey items were asked in two different orders. Half of the recipients received a survey where the questions regarding their instructional practice were asked before those about their instructional beliefs, and the other half were asked about their beliefs before their practices.

For each of the courses most recently taught to primarily sophomores, juniors, and seniors, faculty were asked about their internet-related instructional practices. First, they were asked to provide the engineering discipline associated with the course, the format of the course (lecture, lab, discussion, or “other”), and then respond to a series of Likert-scale items regarding their use of the internet in the course.

Participants were also asked to complete a similar series of Likert-scale items regarding what they would do if they had the freedom and resources to teach in any way they pleased. This allowed a distinction to be made between what professors believe they should be doing in their courses and what they actually do.

The Likert-scale questions in all sections were designed to assess the presence and level of integration of the technology component of the Technology, Pedagogy, and Content Knowledge (TPACK) framework, as well as to identify faculty members as

internet adopters, users, or resisters.

Survey constructs. Four constructs were used in the survey design process to attempt to assess the extent of instructional internet use by participating faculty:

- Communication with students
- Homework
- Content delivery
- Research & design projects

The construct addressing communication with students attempted to determine the extent to which faculty communicate with students through online channels, and what value they place on such communication. It was anticipated that some faculty would be willing to remain constantly accessible to students through means such as websites, social media, or even email, while others would prefer to interact with students via in-person meetings or phone conversations.

Similarly, the homework construct attempted to assess how the internet has affected each faculty member's approach to homework and other short-term assignments. Some faculty have either ignored the proliferation of homework-related internet resources, or have responded by assuming students have access to problem solutions and stopped counting homework assignments towards course grades. Others have modified traditional assignments to make use of online resources, or added components that require students to think beyond what is provided by solution guides. And a few have used online tools to create web-based homework assignments that can self-score, and even adjust to each student's ability level.

Professors' level of internet integration was also represented in the way in which they deliver course content, from traditional lecture to an inverted classroom or fully online model. Many faculty use online videos and simulations as demonstrations during

class to reinforce concepts and improve engagement, while others have turned to fully online content through video lectures or multimedia packages. Project-based courses have equivalent levels of online presence, as students can build a physical project, a computer aided drafting (CAD) or finite-element model, or they can use online multimedia tools to present their ideas in a unique way.

Finally, professors' comfort with internet-based instruction also manifests itself in their approach to research and design projects. Those that are uncomfortable with or resistant to online research provide little to no guidance for students researching on the internet, leaving them to search and evaluate resources on their own. Those that are more comfortable usually direct students towards reliable sources that will provide the information they need, while others emphasize the students' skill development and teach them to find and evaluate resources themselves.

The survey items were validated through a review process involving three practicing engineering faculty and a survey research expert. A pilot version of the study was then sent to 12 volunteer faculty members spread out among five engineering departments at three universities, with the objective of verifying the survey's clarity and functionality. As a result, two questions were re-phrased, and instructions were added to the demographics section. Finally, the survey was distributed via email to all eligible participants; a copy of this final version of the survey is included as Appendix A. The initial email included an introductory paragraph and a survey link; each survey link was unique, so institutional data could be associated without having to request it from participants. A reminder email, including both the survey link and a paragraph reiterating the importance of the survey, was sent out to approximately 5000 potential participants 2

weeks after the initial email. Due to Qualtrics' limits regarding the number of emails sent by a single user account, it was not possible to send a reminder email to all recipients.

The survey links remained active for five weeks after the initial solicitations, after which the data was aggregated and downloaded. Incomplete surveys were included when possible, but those that did not include a completed Likert-scale section for at least one course or the instructional beliefs sections were discarded. The final sample consisted of 1651 courses taught by 1126 faculty members.

Analysis

The analysis began with an assessment of the representativeness of the sample. As institutional variables were pulled from the NCES database while assembling the survey panel, those values were available for all members of the population. Independent sample t-tests were performed to verify that the university total populations, undergraduate populations, and acceptance rates that were present in the sample were not statistically significantly different than those of the population as a whole. Similarly, chi-squared tests verified the representativeness of the sample with regards to whether the institution was public or private, and whether it was situated in an urban, suburban, or rural setting.

Faculty members' gender, rank, and engineering discipline were not collected as part of the survey panel assembly, but that information was available for most institutions. Therefore, a random sample of 41 institutions (out of 407 eligible for the study) was drawn and each faculty members' gender, rank, and department were recorded. The gender, rank, and engineering discipline data collected from this random sample was then compared to the corresponding data for the study participants through a

series of chi-squared tests.

Age, ethnicity, and native language data was not available for those who did not participate in the study, so no measure of sample representativeness was possible for these three variables.

Factor analysis. A factor analysis was run on all courses ($n=1651$) consisting of all Likert-scale items regarding the faculty member's practices in that course and their beliefs regarding instructional internet use in general. This yielded a total of 39 survey items included in the analysis: 23 related to internet-related practices, and 16 based on the professor's beliefs. Kaiser-Meyer-Olkin's Measure of Sampling Adequacy was checked to verify the potential usefulness of a factor analysis, and then the analysis was performed, identifying all factors with an eigenvalue greater than 1. After a varimax rotation, items with factor loadings of greater than 0.4 were considered significant, and those factors that consisted of less than three significant items were eliminated. The factor analysis was then run again constrained to the new number of factors; this process continued iteratively until a factor analysis was found where each factor consisted of at least 3 items with a loading of greater than 0.4. In this case, this yielded a 4 factor solution.

Once a reduced factor analysis was found, items that did not load on any of the factors were removed. Kaiser-Meyer-Olkin's Measure of Sampling Adequacy was checked with the smaller number of items, and then the factor analysis was run a final time to determine ultimate factor loadings.

Each factor was then checked for reliability. Those factors with a Cronbach's alpha of at least 0.7 were considered reliable; those below 0.7 were disregarded through

the rest of the study. Three of the four factors were determined to be reliable: two measuring instructional practices, and one measuring instructional beliefs. Items that loaded on more than one factor were checked in both factors, then the decision on which factor to include them in was made based on the resulting alpha values and a qualitative assessment of which set of items it shared the greatest similarity with.

Distributions and regressions. Once the relevant factors were determined, an independent samples t-test was performed on each factor to determine whether anchoring had any effect on survey outcomes. Those participants that took the “non-anchored” version of the survey (where they answered the questions about their practices before those regarding their beliefs) were compared to those that took the “anchored” version of the survey to verify that anchoring effects were not significant across the entire sample.

A frequency histogram was then constructed for each of the three factors to provide a view of the distribution of internet usage among the faculty sample. In addition, the two factors relating to instructional practice were summed, and a frequency histogram was created for that construct. Finally, the factor relating to beliefs was scaled up to match the range of the sum of the factors relating to practice, and the difference between beliefs and practices for each course was plotted as a fifth frequency histogram.

Next, multi-linear regressions were run to determine which institutional and individual demographic variables had any predictive value for each of the three factors, and for the sum of the two instructional practice factors. Independent variables were tested at the 95% level for both statistical significance and for collinearity with each other. In addition, the beliefs factor was included as an independent variable in a separate set of multi-linear regressions to test if it had any predictive value towards a professor's

practice in a given course.

The beliefs factor as well as the sum of the practices factors both resembled normal distributions, so those factors were reduced to standard scores (z-scores) in an attempt to identify internet adopters and resisters. Initially, those courses where both beliefs and practices had z-scores above one were labelled as being taught by internet adopters, and those where both beliefs and practices had z-scores less than negative one were labelled as being taught by internet resisters. Binary logistic regressions were performed to attempt to predict internet adopters and resisters based on demographic data. Then, all courses that did not fit into the internet adopter or resister were excluded, and a binary logistic regression was run to determine if the two groups could be distinguished from one another based on the demographic data. Both of these processes were repeated for z-score cutoffs of 0.8 and 0.6.

Next, the beliefs factor was ignored, and those courses where the sum of the practices factors had a z-score greater than one were labelled as being taught by internet adopters, and those with a practices z-score of less than negative one were labelled as being taught by internet resisters. Another set of binary logistic regressions were run to attempt to identify internet adopters and resisters under this alternate definition. Again, this process was repeated for z-score cutoffs of 0.8 and 0.6.

Courses where the z-score for beliefs was more than one standard deviation greater than the z-score for practices were identified, and a binary logistic regression was run to attempt to distinguish those courses from among the entire sample. This was done in an attempt to identify those faculty whose practice lagged the most behind their beliefs, and might therefore be most receptive to professional development.

Finally, the assertion that faculty members can teach different courses as different archetypes was examined. Courses taught to sophomores, juniors, and seniors were separated and z-scores were calculated for the sum of the instructional practices factors for each grade level. Then, for each faculty member who taught more than one course, the range of z-scores for their courses was calculated. Those professors whose range of z-scores was at least 1.5 were identified as those who potentially taught as different archetypes in different courses, and a binary logistic regression was run to attempt to identify those professors from among all those that taught multiple courses.

Chapter Four

Analysis

This chapter will review the analytical methods used in addressing the research questions. There were four primary steps to the analysis: assessing response rate and sample representativeness, the factor analysis, examining frequency distributions, and regression analyses. Smaller concerns that were addressed during the study include the anchoring effect, which will be discussed immediately after the factor analysis, and examining faculty who responded regarding more than one course, which will be done at the end of this chapter.

Response Rate and Sample Representativeness

The survey instrument was sent to 24,252 recipients, and there were 1175 full or partial survey responses that included enough information to be included in the study. However, 36 email addresses were rejected, meaning that only 24,216 faculty members received a survey link, leading to an actual response rate of 4.85%. Of those 1175 responses, 33 self-selected out of the study as non-tenure-track faculty, and 16 were discarded because the respondent had not taught an engineering course since the beginning of 2013. This yields a final count of 1126 surveys included in the analysis. It would not be appropriate to re-calculate the response rate based on this final number, as some of the non-respondents would be selected out of the study for the same reasons some of the respondents were. In addition, because the survey asked about multiple courses for each faculty member the number of courses available for analysis is greater than the number of faculty respondents ($n = 1651$ when analyzing courses), but for the purposes of measuring sample representativeness it is the faculty members that are

important, not individual courses.

For variables associated with a professor's institution, values were recorded from the National Center for Educational Statistics (NCES) database during the assembly of the survey panel. This means that the values for these variables are available for the entire recipient population. For continuous institutional variables, independent-samples t-tests were performed to verify that the sample was not significantly different from the population (see Table 2):

Table 2

Sample Representativeness: Continuous Institutional Variables

<u>Variable</u>	<u>Sample Mean</u>	<u>Sample Std. Dev.</u>	<u>Population Mean</u>	<u>Population Std. Dev.</u>	<u>p-value</u>
Total Student Population	22566.93	14966.14	24426.1	14577.3	.124
Undergraduate Population	16763.25	11567.77	17968.9	11387.9	.730
Percentage Undergrad	0.75449	0.136592	0.7541	0.4231	.984
Acceptance Rate	58.62556	22.55677	56.4	23.4	.958

Similarly, categorical variables were checked using chi-squared tests (see Table 3):

Table 3

Sample Representativeness: Categorical Institutional Variables

<u>Category</u>	<u>Actual (Sample) Value</u>	<u>Expected (Population) Value</u>	<u>p-value</u>
Public Institution	786	810.7	.101
Private Institution	340	315.3	
Urban	778	803.4	.110
Suburban	214	209.2	
Rural	134	113.5	

For variables associated with individual professors, it was not possible to obtain values for the population in its entirety. However, some of the values were available in faculty directories and personal web pages. A random sample of 41 institutions (out of

407 total institutions included in the study) was taken and the gender, professional title, and departmental placement for each faculty member at those schools were recorded. If an institution did not provide all of that information, another was drawn in its place. This random sample was compared to the sample of participants in this study, and a chi-squared test was performed to quantify the significance of any differences (see Table 4). In this case, values from the random sample are treated as the “expected” value:

Table 4

Sample Representativeness: Categorical Personal Variables

<u>Category</u>	<u>Actual Value</u>	<u>Expected Value</u>	<u>p-value*</u>
Male	884	869.4	.291
Female	232	246.6	
Full Professor	519	511.6	.493
Associate Prof.	320	310.8	
Assistant Prof.	282	299.6	
Other Tenured Prof.	4	0	
Aerospace	36	47	.0005
Agricultural	14	8	
Architectural	3	0	
Biomedical	70	82	
Chemical	119	112	
Civil	166	171	
Computer	91	98	
Construction	10	14	
Electrical	170	151	
Geological	4	0	
Industrial	58	51	
Manufacturing	9	11	
Materials	66	51	
Mechanical	199	213	
Mining	3	12	
Nuclear	16	0	
Systems	13	16	
Other Engineering	51	67	
Multi-Disciplinary	21	23	
Non-Engineer	8	0	
*chi-squared test excludes categories with expected values of zero			

These tests show that there is no significant difference between the sample examined in this study and the national population of engineering faculty with regards to institutional variables. They also show that there is no significant difference between this study's sample and a random sample in terms of participants' gender and professional rank. The analysis does indicate a statistically significant difference between the random sample and the study sample in terms of the engineering disciplines represented. However, it is likely this difference is due to the sampling and data collection methods employed. In terms of data collection, faculty members in the random sample were associated with the discipline corresponding to the department they served in, whereas faculty members in the study sample could self-report whichever discipline they most identified with. For instance, someone with a background in architectural engineering teaching in a department of civil engineering would be categorized as an architectural engineer in the study sample and a civil engineer in the random sample. In addition, because entire institutions were selected in the random sample rather than individuals, the presence/absence of members of some of the more unusual engineering disciplines in the random sample is a function of which schools were drawn. For example, there were no geological engineers in the random sample because none of the 41 schools drawn had a department of geological engineering. However, had Colorado School of Mines been one of the schools drawn, there would have been more than 30 geological engineers in the random sample. In this way, the limitations of the sampling and data collection methods call into question the accuracy with which the random sample represents the population in terms of engineering disciplines. Therefore, in order to alleviate the small sample size problems in some of the more unusual disciplines, faculty members were aggregated into

groups of similar discipline. These aggregated groups allowed for a more meaningful analysis of sample similarities, and there no statistical difference between the survey sample and the random sample when measured in this way (see Table 5):

Table 5

Sample Representativeness: Aggregated Engineering Disciplines

<u>Category</u>	<u>Actual Value</u>	<u>Expected Value</u>	<u>p-value</u>
Aerospace, Mechanical, & Materials	301	311	.7538
Agricultural, Architectural, Civil, Construction, Geological, Mining, & Nuclear	216	205	
Biomedical & Chemical	189	194	
Electrical & Computer	261	249	
Industrial, Manufacturing, Systems, Multidisciplinary, & Other	160	168	

Finally, data regarding non-responding professors' age, ethnicity, and native language were not available. Age correlates strongly with professional rank within the survey sample (Pearson correlation coefficient of .706), so it can be argued that because the sample is representative in terms of rank, it is also highly likely to be representative in terms of age. So while there were limitations in terms of collecting demographic variables for the population, the sample is representative of the population in every way that could be accurately measured.

Factor Analysis

A factor analysis was performed that included all 39 instructional practices and beliefs-related questions. All 1651 courses were analyzed, with the goal of identifying constructs that could be used to accurately measure faculty members' instructional internet use.

Kaiser-Meyer-Olkin's Measure of Sampling Adequacy (KMO) was calculated for the entire sample to ensure the usefulness of the analysis, and with a value of 0.718, it

falls within the “good” range. The initial factor analysis allowed any number of factors; the only constraint was that each had to have an eigenvalue of greater than one. This led to 13 factors, but seven of them had less than three questions with factor loadings of greater than 0.4. The factor analysis was then re-calculated restricting the solution to six factors; one of them consisted of less than three questions with sufficient loading. A five-factor solution also included a factor with too few items, until a four factor model converged with all four factors as significant (see Table 6):

Table 6

Factor Loadings on all Survey Items

Item				
Number	Factor 1	Factor 2	Factor 3	Factor 4
Q341_13	.757			
Q341_12	.734			
Q341_11	.657			
Q341_4	.542			
Q38	.526			
Q36	.479			
Q341_3				
Q341_1				
Q313				
Q611_46				
Q341_5		.779		
Q341_6		.765		
Q341_7		.632		
Q341_8		.528		
Q341_9		.526		
Q35				
Q341_2				
Q310				
Q314				
Q611_44			.610	
Q611_43			.586	
Q611_41			.580	
Q611_45			.554	
Q611_42			.543	
Q611_37			.513	
Q611_38			.512	
Q611_49			.498	
Q611_50			.476	
Q611_39				
Q611_35				
Q312				
Q611_40				
Q39				.605
Q611_48				.603
Q611_47				.565
Q311				-.541
Q611_36				
Q37				
Q341_10				

In the four factor solution, there were 15 questions that did not load significantly on any of the four constructs. Those 15 items were dropped from the analysis. The new data set - consisting of the 24 remaining items - had a KMO of .734, indicating that a factor analysis is still appropriate. The four factor solution still has sufficient loading on each of the four constructs, and explains 44.1% of the variance. Final factor loadings can be seen in Table 7:

Table 7

Factor Loadings on Relevant Survey Items

Item Number	Factor 1	Factor 2	Factor 3	Factor 4
Q341_5	.821			
Q341_6	.813			
Q341_7	.644			
Q341_8	.621			
Q341_4	.571			
Q341_9	.554			
Q341_3				
Q341_13		.776		
Q341_12		.758		
Q341_11		.644		
Q611_44		.546	.485	
Q611_45		.536	.484	
Q36		.481		
Q38		.459		
Q611_41			.698	
Q611_42			.672	
Q611_43			.566	
Q611_38			.537	
Q611_37			.517	
Q611_50			.428	
Q611_48				.707
Q611_47				.603
Q39				.551
Q37				.450
Q611_36				.440
Q311				-.433
Q611_39				

Note that items 611-44 and 611-45 load significantly on both factors two and three. Despite the fact that the loading is slightly higher on factor two for both items, they were both included in factor three, as it made more sense to group those items with others that addressed faculty beliefs about instructional internet use.

Each of the four factors was then tested for reliability. Factor one consists of six items and yields a Cronbach's alpha of 0.785. Factor two includes five items and has a Cronbach's alpha of 0.735, and factor three has eight items and a Cronbach's alpha of 0.710. Each of these factors is reliable enough to be considered a measurement of an individual construct. Factor four, however, has a Cronbach's alpha of 0.490, which indicates it is not a reliable measurement and as a result will not be considered through the remainder of the analysis.

Because factor three is the only one to include any of the questions regarding instructional beliefs, a separate factor analysis was performed including only those eight items, in hopes of being able to split it into multiple belief-related factors. This factor analysis was based on data with a KMO of 0.650, which falls in the "mediocre" range. The decision on whether to continue with a factor analysis based on a sub-par sample was made irrelevant by the fact that seven of the eight items all loaded on the first factor of the new analysis. Because of this, factor three was left as a single factor.

Identifying the constructs. Factor one consists of the following items:

- How often did you do each of the following:
 - Send out links to online content related to course concepts?
 - Use online videos in class to demonstrate a course concept?
 - Use online videos in class to engage student interest?
 - Use multimedia (photographs, music, video, etc.) to deliver instruction?
 - Use digital simulations (live or recorded) in place of live demonstrations?
 - Assign recorded lectures for students to watch?

All of these items describe the frequency with which the professor uses online resources or multimedia to teach course content. This construct was therefore labeled “use of internet resources for content delivery”. Factor two also includes items related to instructional practice:

- How often did you do each of the following:
 - Discuss strategies for performing thorough internet research with your students?
 - Discuss strategies for assessing the validity of internet sources with your students?
 - Require students to perform internet-based research related to course concepts?
- How often did students send you links to online content related to course concepts?
- When students were required to perform research on the internet, how frequently did you provide links to suggested information sources?

All of these items refer to students doing their own research on the internet, so this construct has been labeled “guiding students’ internet research”. Finally, factor three is composed of the following Likert scale agree-disagree statements:

- Courses with an online presence (course webpage, learning management system page, etc.) make it simpler for students to meet course expectations.
- Sharing online content recommended by students is a valuable use of class time.
- Including multimedia content (photographs, music, video, etc.) in class time improves student learning in engineering courses.
- Including multimedia content (photographs, music, video, etc.) in class time improves student engagement in engineering courses.
- Researching an engineering topic on the internet is a valuable learning experience for students.
- Engineering faculty should teach students how to thoroughly search for information on the internet.
- Engineering faculty should teach students how to identify reliable sources on the internet.
- Online resources have changed how faculty should assess student learning.

While these items do span a variety of internet-related learning activities, they all address what the faculty member believes about internet-based instruction rather than what he or she actually does in the classroom. Therefore, this construct has been labeled “faculty

beliefs about the usefulness of internet resources”.

Anchoring Effect

As half of the surveys were distributed with the questions regarding instructional practices before those regarding instructional beliefs (the “non-anchored” version), and the other half asked about beliefs before practices (the “anchored” version), it is important to determine if the order of the questions affected responses to any measurable degree. An independent-samples t-test was performed on each of the three factors to determine if the participants that took the non-anchored survey provided different responses than those that took the anchored version. As seen in Table 8, the order of the questions had no statistically significant effect on responses:

Table 8

Measuring the Anchoring Effect

<u>Factor Number</u>	<u>Non-Anchored Mean</u>	<u>Non-Anchored Std. Dev.</u>	<u>Anchored Mean</u>	<u>Anchored Std. Dev.</u>	<u>p-value</u>
1	2.199	0.840	2.142	0.797	0.314
2	1.827	0.735	1.747	0.692	0.356
3	3.744	0.529	3.825	0.528	0.600

Frequency Distributions

The frequency distributions for each of the three factors were plotted, and are included as Figures 3, 4, and 5:

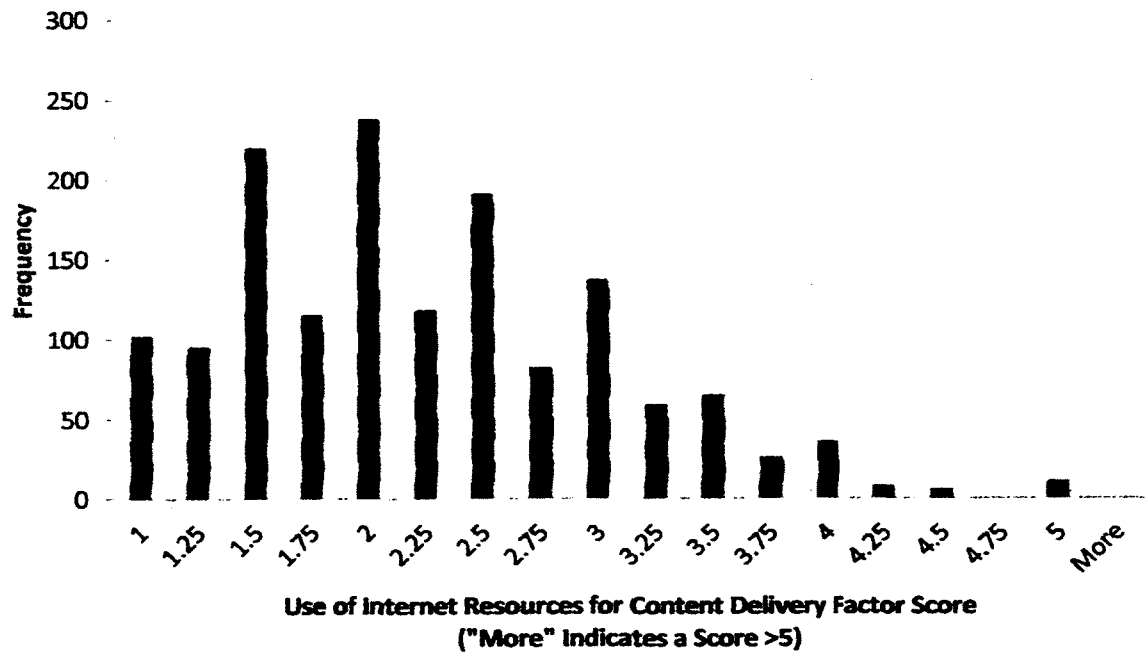


Figure 3: Use of Internet Resources for Content Delivery Frequency Histogram

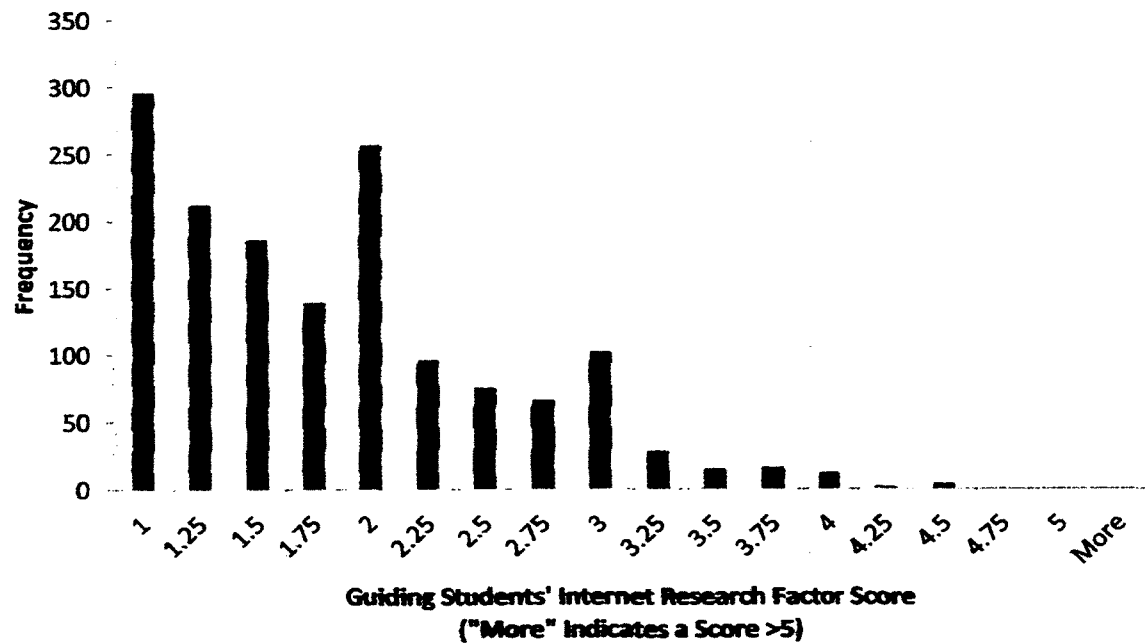


Figure 4: Guiding Students' Internet Research Frequency Histogram

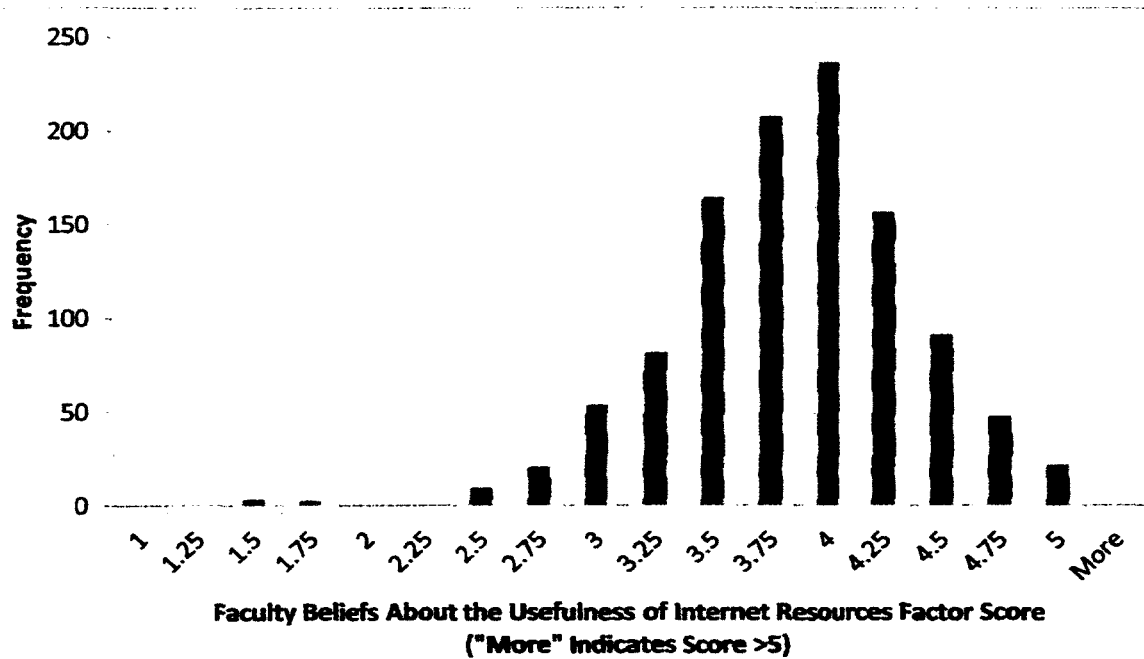


Figure 5: Faculty Beliefs About the Usefulness of Internet Resources Frequency Histogram

Clearly, there is no bi- or tri-modal shape to any of these distributions that would support the classification of internet usage archetypes, or the idea that the technology knowledge component of TPACK can be measured in a discrete rather than continuous manner. In order to better compare instructional beliefs to instructional practices, the two constructs relating to practice were summed and the resulting frequency histogram is shown in Figure 6:

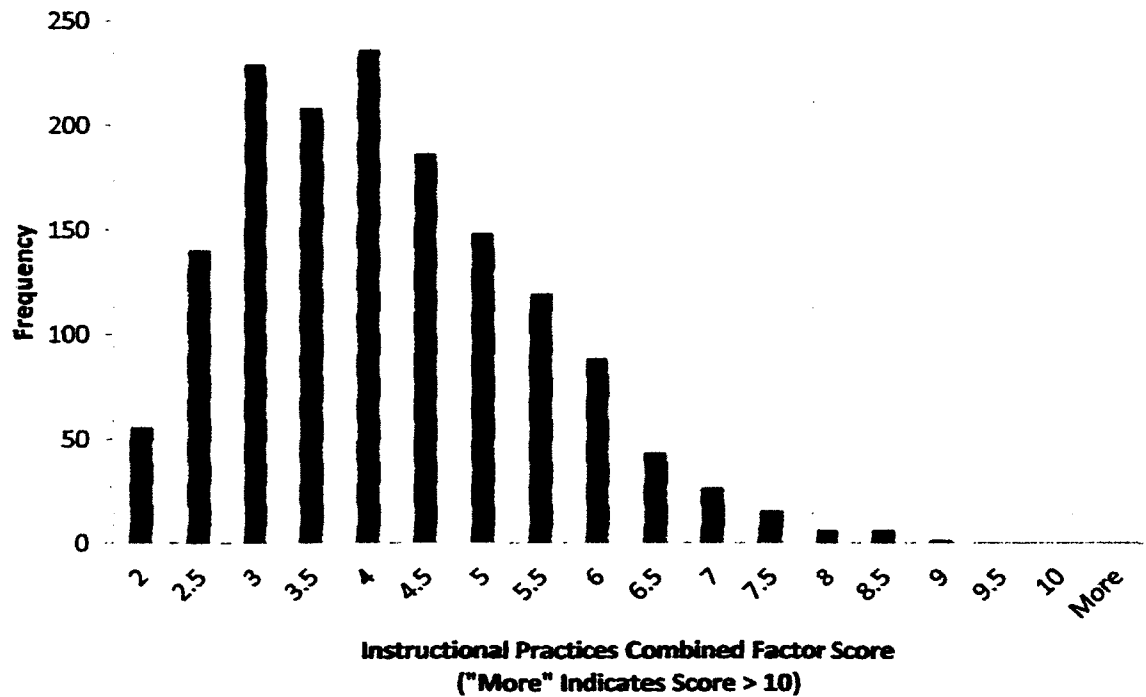


Figure 6: Combined Instructional Practices Frequency Histogram

The difference between each faculty members' beliefs and their practices in each course is also of interest, so the faculty beliefs factor was scaled up by a multiple of two (to match the range of the combined practices factor) and the combined practices factor was subtracted from it. The result is presented as Figure 7:

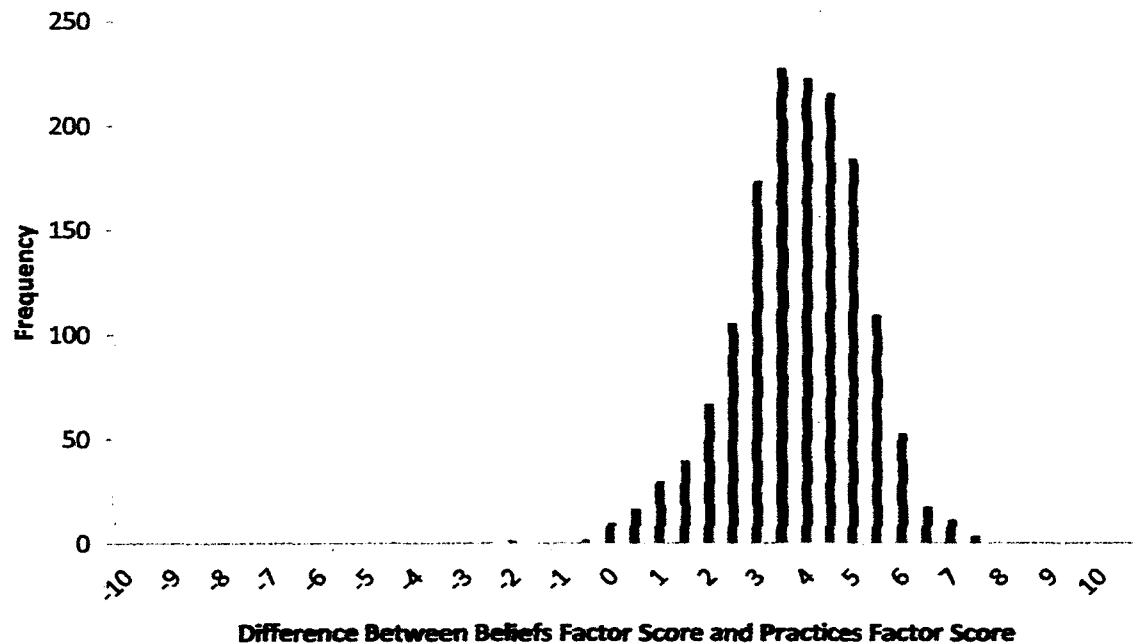


Figure 7: Difference Between Beliefs and Practices Frequency Histogram

As the majority of faculty responded more positively to the items regarding their beliefs about instructional internet use than they did to the items regarding their practice, the histogram representing the differences is almost entirely positioned on the positive side of zero. This is a potentially meaningful finding, which will be discussed in the next chapter.

Regression Analyses

The first set of regressions was multi-linear, and was performed in an attempt to correlate each of the three factors with demographic variables. In each case, the factor was the dependent variable and all institutional and individual demographic variables were included as independent variables, as were each course's format, level, and engineering discipline.

For the first factor, use of internet resources to deliver instruction, three demographic variables were correlated to a statistically significant degree (see Table 9),

and a plot of the values predicted by the regression results compared with the actual results is included as Figure 8:

Table 9

Use of Internet Resources for Content Delivery Regression Coefficients

<u>Variable</u>	<u>Coefficient</u>	<u>Standardized Coefficient</u>	<u>p-value</u>
(Constant)	-6.346		
Undergraduate Population (in thousands)	.005727	.081	.002
Acceptance Rate	-.003	-.086	.001
Year Born	.004	.063	.016

Notes: $R^2 = .017$ ($ps < .05$).

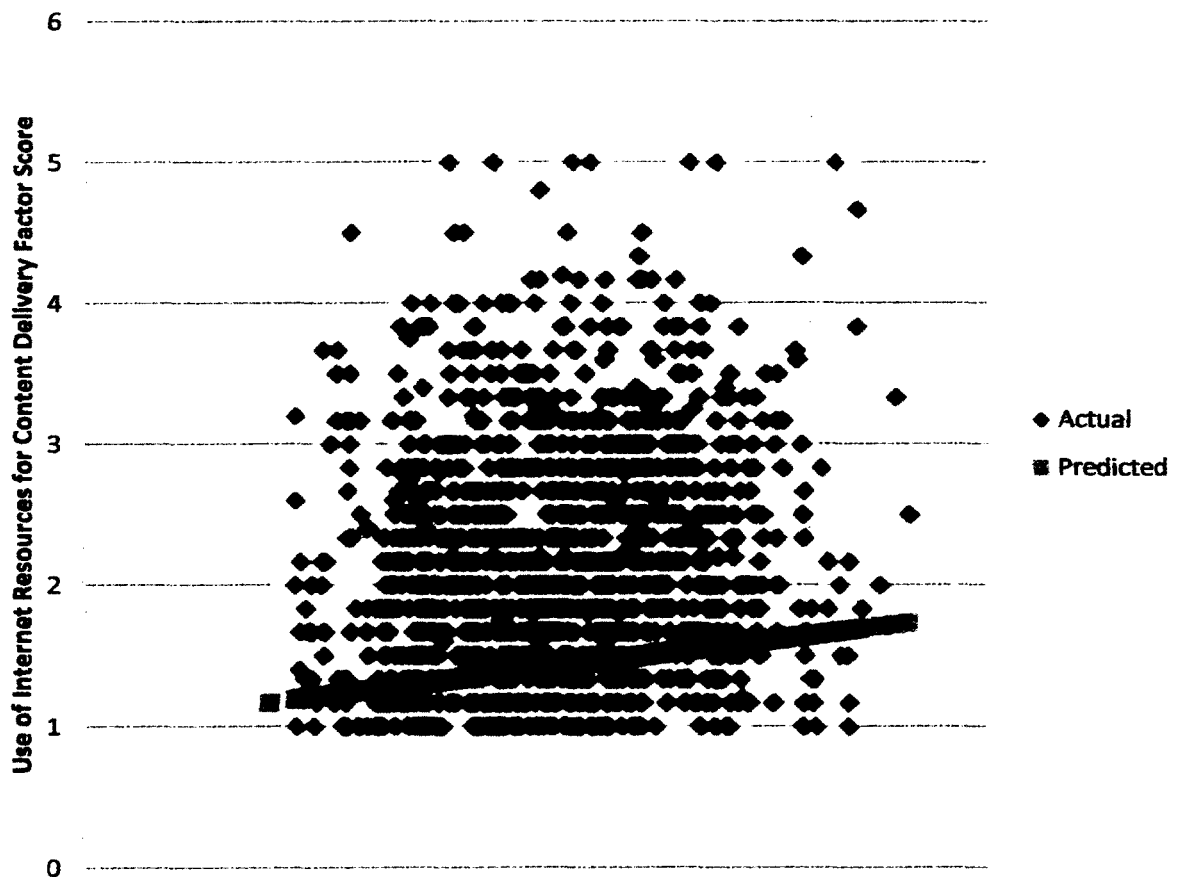


Figure 8: Use of Internet Resources for Content Delivery: Actual vs. Predicted

The regression model based on just demographic variables has very limited predictive value, so the third factor, faculty beliefs about the usefulness of internet

resources, was then included as an independent variable. This caused the variable representing a professor's age to drop out of the model, replaced by the faculty beliefs factor (see Table 10). A plot of the values predicted by the regression model compared to the actual values is again included (see Figure 9):

Table 10

Use of Internet Resources for Content Delivery Regression Coefficients (with Predictive Beliefs Factor)

<u>Variable</u>	<u>Coefficient</u>	<u>Standardized Coefficient</u>	<u>p-value</u>
(Constant)	.469		
Undergraduate Population (in thousands)	.00558	.078	.001
Acceptance Rate	-.003	-.087	<.001
Faculty Beliefs Factor Score	.477	.311	<.001
<i>Notes: $R^2 = .109$ ($ps < .05$).</i>			

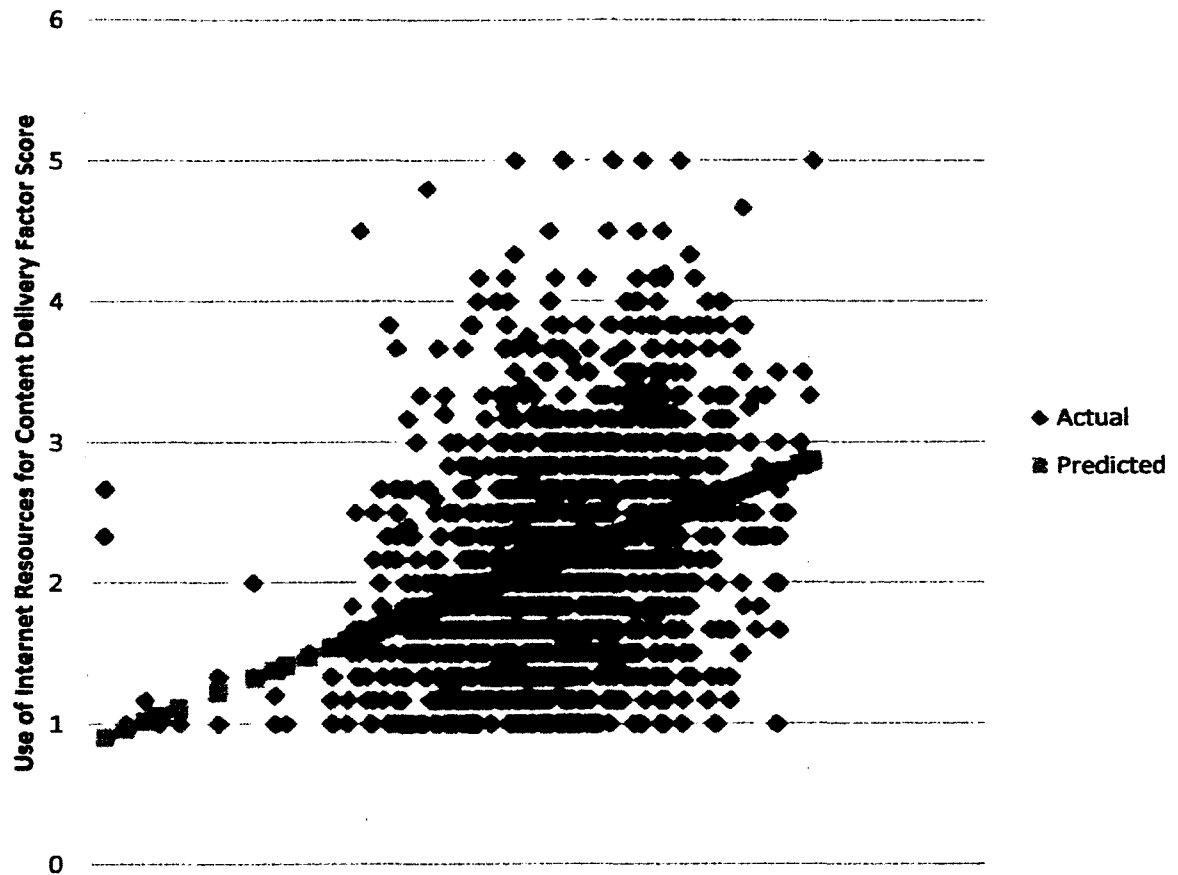


Figure 9: Use of Internet Resources for Content Delivery: Actual vs. Predicted (with Predictive Beliefs Factor)

An identical analysis was run for factor two, guiding students' internet research, both without the faculty beliefs factor as an independent variable (Table 11, Figure 10), and with it included (Table 12, Figure 11):

Table 11

Guiding Students' Internet Research Regression Coefficients

<u>Variable</u>	<u>Coefficient</u>	<u>Standardized Coefficient</u>	<u>p-value</u>
(Constant)	1.481		
Gender	.156	.088	<.001
Electrical Eng. Professor?	-.112	-.056	.026
Systems Eng. Course?	.224	.067	.007
Lecture Course?	-.342	-.196	<.001
Course Level (Soph/Jr/Sr)	.124	.136	<.001
<i>Notes: $R^2 = .080$ ($ps < .05$).</i>			

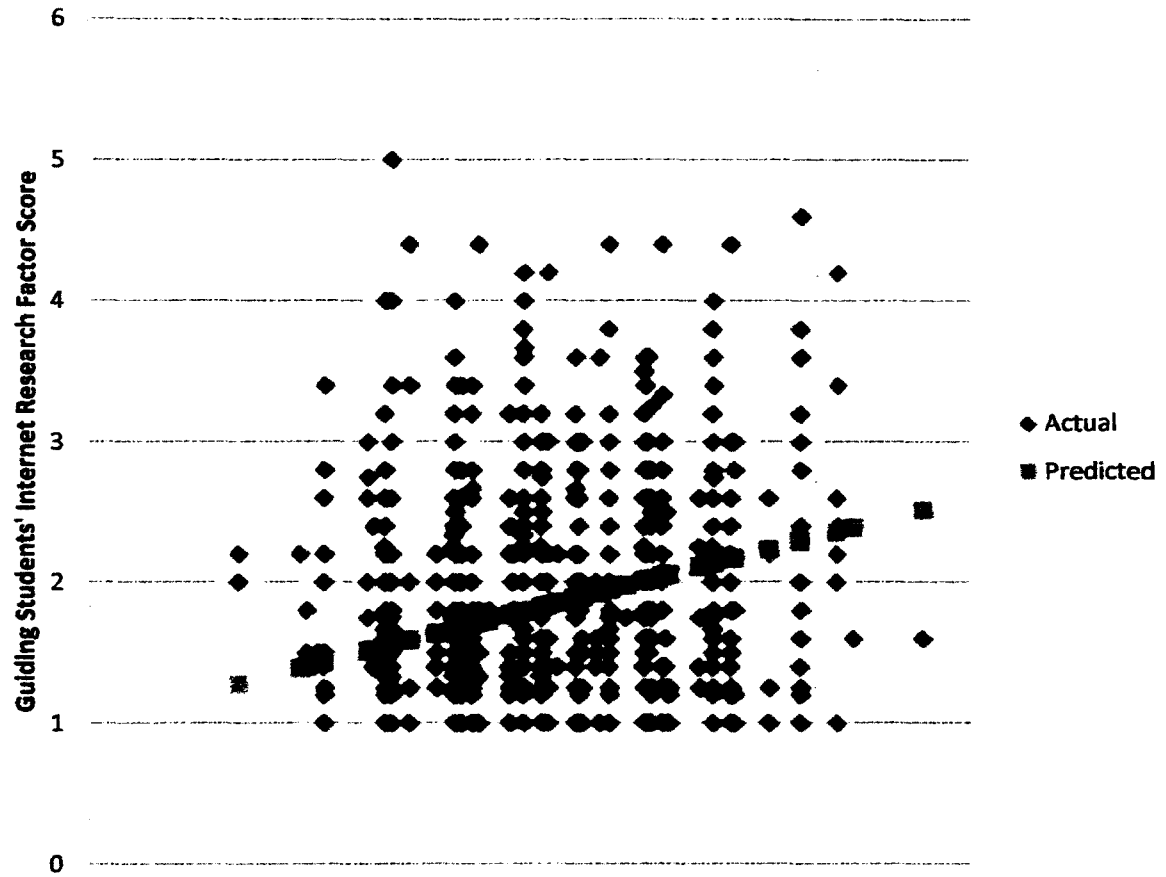


Figure 10: Guiding Students' Internet Research: Actual vs. Predicted

Table 12

Guiding Students' Internet Research Regression Coefficients (with Predictive Beliefs Factor)

<u>Variable</u>	<u>Coefficient</u>	<u>Standardized Coefficient</u>	<u>p-value</u>
(Constant)	.090		
Undergraduate Population (in thousands)	.003604	.058	.017
Civil Eng. Professor	-.163	-.082	.001
Geological Eng. Course?	-.282	-.084	.001
Lecture Course?	-.322	-.184	<.001
Faculty Beliefs Factor Score	.372	.274	<.001
Gender	.105	.059	.015
Course Level (Soph/Jr/Sr)	.125	.137	<.001

Notes: $R^2 = .163$ ($ps < .05$).

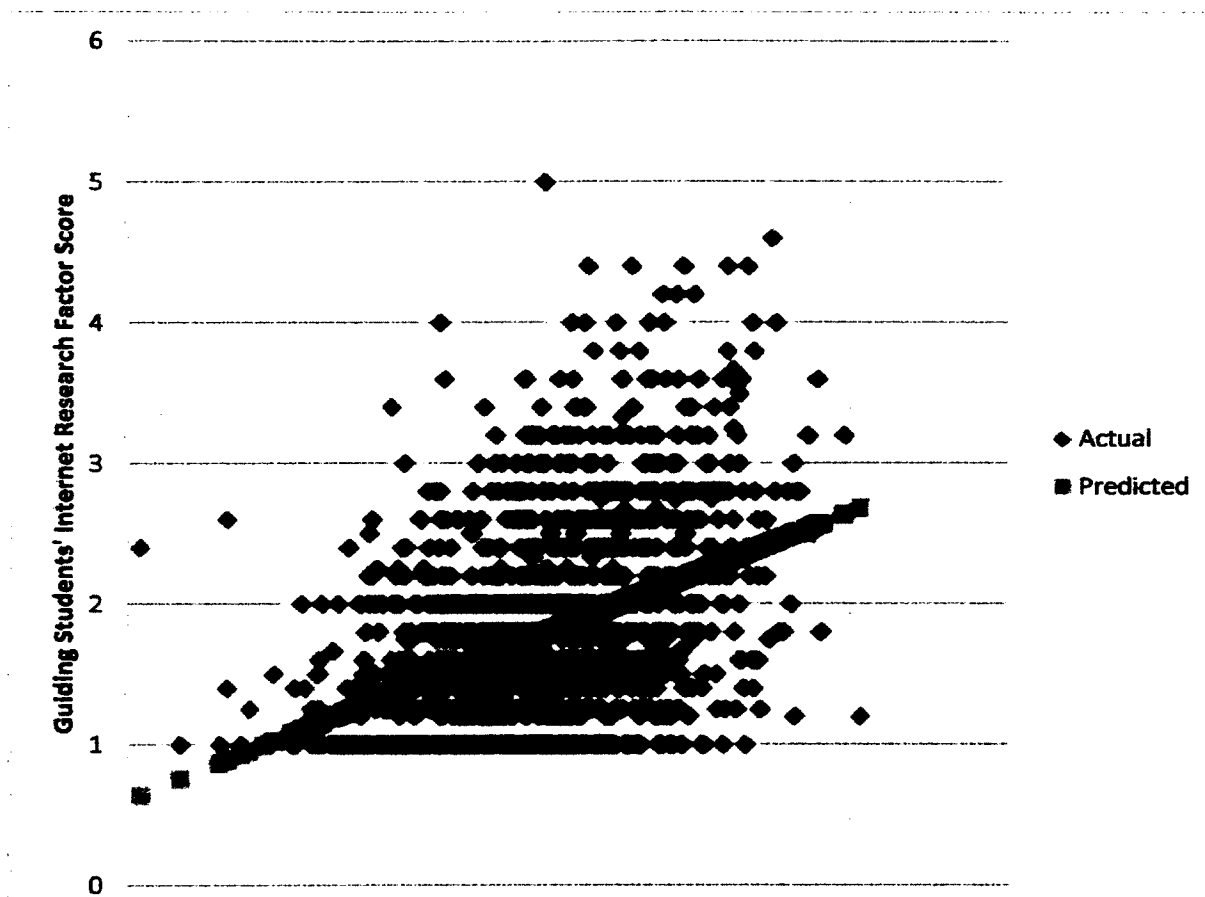


Figure 11: Guiding Students' Internet Research: Actual vs. Predicted (with Predictive Beliefs Factor)

Both regression models for factor two include several engineering discipline variables that do not have a large number of respondents and do not immediately make sense as to why they would correlate with the factor in question. This raises the possibility of type one errors; these variables may be included in the model because of a particularly skewed small sample within several different engineering disciplines. In an effort to minimize type one errors, a more robust measure of instructional practices was again created by summing scores from the two factors related to practices. Another multi-linear regression was performed using the sum of factors one and two as the dependent variable, with all demographic and course characteristic variables again included as independent variables. The resulting model is shown in Table 13, a

comparison between the actual values and the values predicted by the model is shown in

Figure 12:

Table 13

Faculty Practices (Combined Factors) Regression Coefficients

<u>Variable</u>	<u>Coefficient</u>	<u>Standardized Coefficient</u>	<u>p-value</u>
(Constant)	4.190		
Gender	.207	.065	.011
Undergraduate Population (in thousands)	.008633	.077	.003
Acceptance Rate	-.005	-.081	.002
Lecture course?	-.440	-.140	<.001

Notes: $R^2 = .036$ ($ps < .05$).

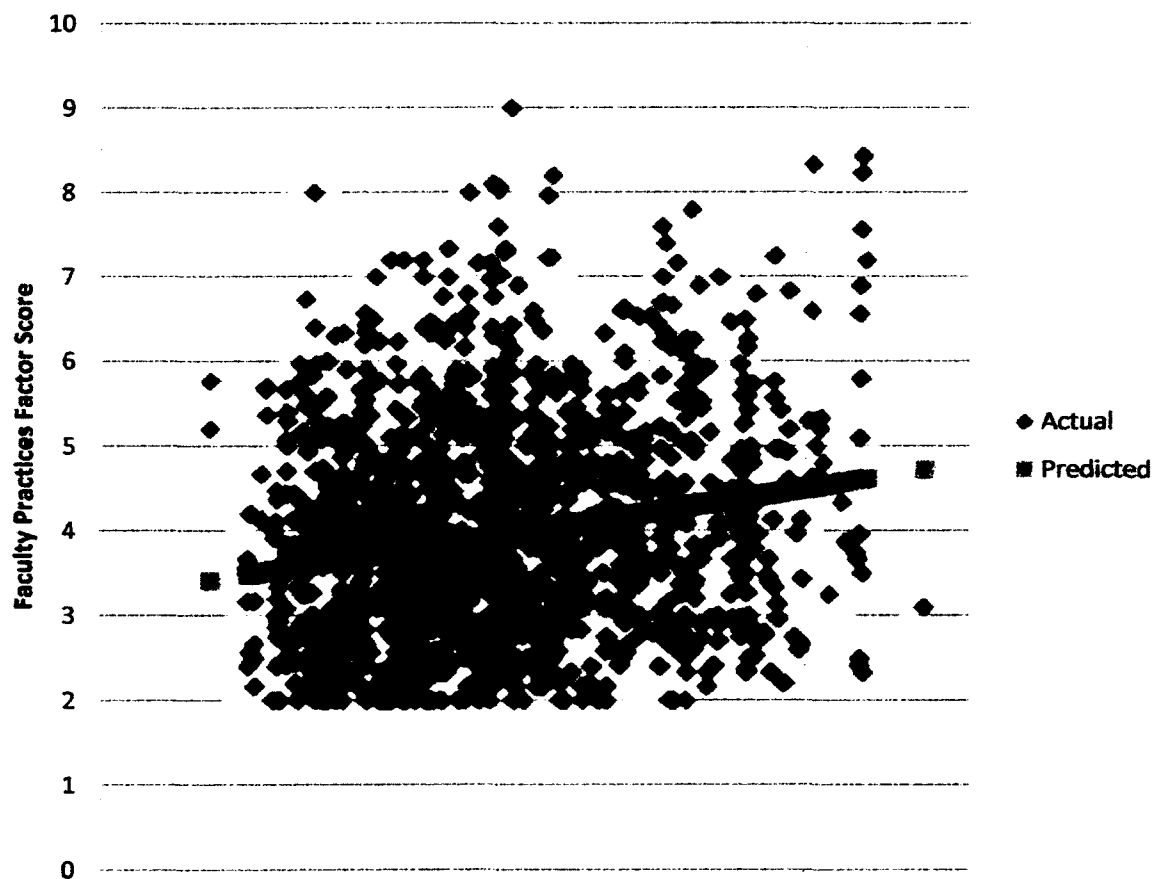


Figure 12: Faculty Practices (Combined Factors): Actual vs. Predicted

The model predicting the behavior of the sum of the two practice-related factors

appears to reflect the most significant parts of the models representing the two component factors. The variables with the strongest correlations or that appear in multiple models remain, and those with small sample sizes that only appeared in one of the previous models have fallen out of this analysis. The instructional beliefs factor was then included as an independent variable, yielding the model described in Table 14 and displayed in Figure 13:

Table 14

Faculty Practices (Combined Factors) Regression Coefficients (with Predictive Beliefs Factor)

<u>Variable</u>	<u>Coefficient</u>	<u>Standardized Coefficient</u>	<u>p-value</u>
(Constant)	1.107		
Faculty Beliefs Factor Score	.868	.359	<.001
Undergraduate Population (in thousands)	.008816	.078	.001
Acceptance Rate	-.005	-.082	.001
Lecture course?	-.371	-.120	<.001
<i>Notes: $R^2 = .159$ ($ps < .05$).</i>			

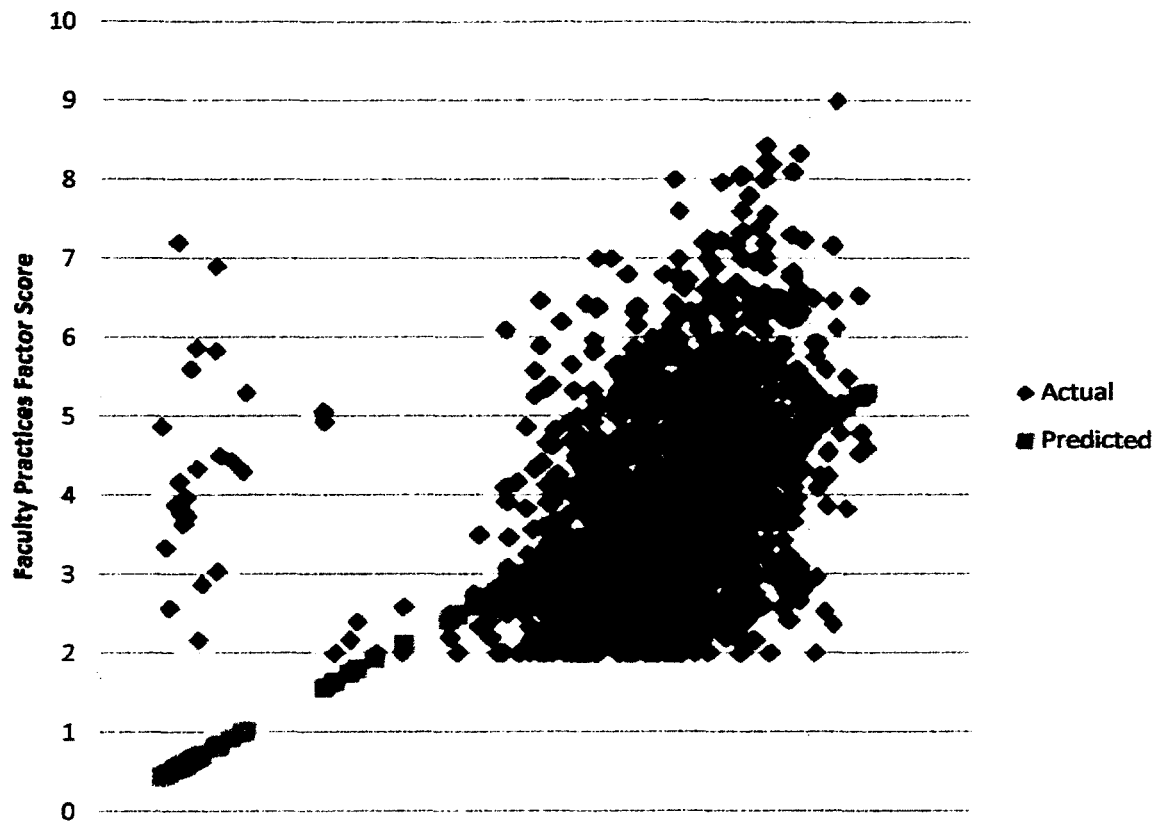


Figure 13: Faculty Practices Factor Score: Actual vs. Predicted (with Predictive Beliefs Factor)

As in the other models, adding the faculty beliefs factor improves the predictive value measurably. In this case, gender falls out of the model and is replaced by the faculty beliefs factor, indicating that the two are correlated and that gender was acting as a proxy for the faculty beliefs factor in the initial model. This existence of this correlation is confirmed below.

Finally, the last multi-linear regression was performed in order to identify demographic and course characteristic variables that correlate with the third factor, faculty beliefs about the usefulness of internet resources. The factor score was the dependent variable, while demographics and course characteristics were again included as independent variables. The resulting model is shown in Table 15, and a comparison between actual and model-predicted values is shown in Figure 14:

Table 15

Faculty Beliefs About the Usefulness of Internet Resources Regression Coefficients

<u>Variable</u>	<u>Coefficient</u>	<u>Standardized Coefficient</u>	<u>p-value</u>
(Constant)	3.501		
Gender	.154	.118	<.001
African-American Professor?	.317	.071	.004
Native English Speaker?	.102	.080	.001
Aerospace Eng. Prof?	-.214	-.065	.009
Aerospace Eng. Course?	-.298	-.053	.033
Construction Eng. Course?	-.147	-.095	<.001

Notes: $R^2 = .040$ ($ps < .05$).

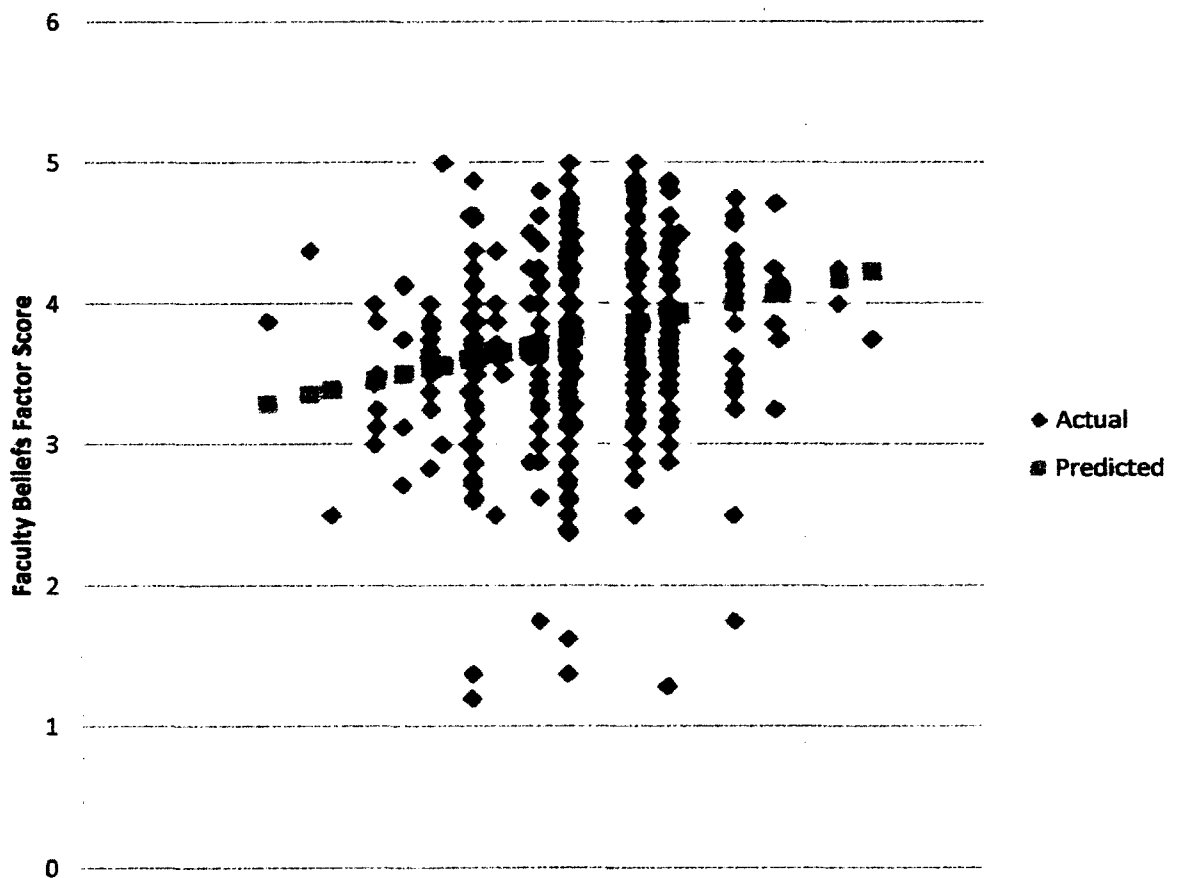


Figure 14: Faculty Beliefs About the Usefulness of Internet Resources: Actual vs. Predicted

This model also has some small-sample variables appearing as statistically significant (African-American professor?, aerospace engineering professor?, aerospace engineering course?, construction engineering course?) that may represent type one errors

in the analysis. However, given that both aerospace engineering faculty and aerospace engineering courses showed up as significant may indicate that there is something about that discipline that explains a correlation with faculty beliefs regarding instructional internet usage.

Despite the relatively high degree of statistical significance of each of the regression models above, they have limited predictive value. Because of the large variation and seemingly large degree of randomness in the data, none of these models are able to explain more than approximately 16% of the variation in each factor, and the faculty beliefs factor must be included as an independent variable to be able to explain even that much (see Table 16):

Table 16

Regression "Goodness of Fit" Data

<u>Regression Model</u>	<u>R²</u>
Use of Internet Resources for Content Delivery (without Faculty Beliefs Included)	.017
Use of Internet Resources for Content Delivery (with Faculty Beliefs Included)	.109
Guiding Students' Internet Research (without Faculty Beliefs Included)	.080
Guiding Students' Internet Research (with Faculty Beliefs Included)	.163
Combined Instructional Practices	.036
Combined Instructional Practices (with Faculty Beliefs Included)	.159
Faculty Beliefs about the Usefulness of Internet Resources	.040

These results indicate that the demographic data collected is only minimally effective at explaining the variation in the three instructional factors found, and that specification error is a significant problem. Characteristics of university faculty that were not measured in this study are responsible for shaping their beliefs and practices regarding instructional internet use, and the absence of this data limits the conclusions that can be drawn from the predictive data that was collected.

Internet Adopters and Internet Resisters. Although the distributions of each factor do not show any of the multi-modal characteristics that would clearly indicate the presence of distinct archetypes, it is still possible to identify those faculty members on the extreme low and high ends of the practices and beliefs distributions as internet resisters and adopters, respectively.

Since both the distribution of the beliefs factor (Figure 6) and the distribution of the combined practices factor (Figure 7) approximate normal distributions, all values were converted to standard scores (z-scores) to more easily facilitate comparison. Initially, those faculty members who had z-scores greater than one on both of the above factors were classified as internet adopters, and those with z-scores less than negative one on both factors were classified as internet resisters. Two binomial logistic regressions were then performed, one to attempt to identify internet adopters based on demographic variables, and one to attempt to identify internet resisters. While several variables tested out as statistically significant in each case, the most accurate model resulting from each regression was one that predicted zero internet adopters and zero internet resisters.

The initial decision rule regarding the classification of internet adopters and internet resisters was exceptionally conservative, identifying only 67 courses being taught by adopters and 89 by resisters, out of 1499 courses that had enough data to classify. This very small number of outliers could have contributed to the failure of the logistic regression, so the decision rule was relaxed to classify any professor with z-scores greater than 0.8 as an adopter, and any with z-scores less than -0.8 as a resister. This increased the number of courses taught by adopters and resisters to 109 and 126, respectively. Another pair of logistic regressions was performed, with the same result: both models

failed to predict any adopters or resisters. The decision rule was then even further relaxed with adopters having z-scores over 0.6 and resisters having z-scores less than -.06, identifying 171 courses taught by adopters and 192 by resisters. The regressions again failed to predict the existence of any adopters or resisters.

Finally, the requirement regarding the faculty belief factor was eliminated, and only the professors' practices were considered. Those faculty members with z-scores greater than one on the combined practices factor were classified as adopters, and those with z-scores less than negative one were classified as resisters. This decision rule identified 250 courses taught by internet adopters and 267 by internet resisters. Again, the regression failed to predict any resisters or adopters. The decision rule was relaxed one more time to set the z-score cutoff at ± 0.6 for the combined practices factor; the best regression models were still ones that predicted zero adopters and resisters.

The lack of results in attempting to identify internet adopters and internet resisters from the entire sample is likely due to the amount of statistical noise created by the large number of high-variance respondents that are not adopters and resisters. To eliminate this concern, another analysis was performed excluding all those respondents that were not classified as adopters or resisters. Returning to the original decision rule – classifying adopters and resisters as those with z-scores outside ± 1 on both the beliefs and combined practices factors – yields the model outlined in Table 17:

Table 17

Internet Adopters & Resisters: Logistic Regression Coefficients (z-scores outside ± 1)

<u>Variable</u>	<u>B</u>	<u>Degrees of Freedom</u>	<u>p-value</u>
Private/Public	1.312	1	.017
Setting: Urban		2	.023
Suburban	.896		
Rural	-1.104		
Total Population	<.001	1	.003
Undergraduate Population	<.001	1	.002
Gender	-1.313	1	.014
Lecture Course?	1.184	1	.050
(Constant)	-.655	1	

This model explained 30.5% (Nagelkerke R^2) of the variance between internet adopters and internet resisters, and correctly identified 73.5% of the sample (41 out of 64 taught by adopters, and 70 out of 87 by resisters). Although being able to identify internet adopters from among a sample of adopters and resisters is not as useful as being able to identify them from within the entire sample, it does show that there are measurable differences between the two groups, which is an important finding. Also note that this model is unusual in that it includes both the institution's total population and its undergraduate population, despite the fact that they are highly correlated with one another. When either is removed from the model, however, the other ceases to be statistically significant and the model's predictions become much less accurate. Possible explanations for this include the effects of statistical bias caused by a type two error when one of the two variables is excluded, or the presence of a higher order effect that is better represented by both population variables than by either one alone.

For the sake of comparison, another logistic regression was performed using the z-score cutoff of ± 0.8 to classify adopters and resisters. The resulting model is presented in Table 18:

Table 18

Internet Adopters and Resisters: Logistic Regression Coefficients (z-scores outside ± 0.8)

<u>Variable</u>	<u>B</u>	<u>Degrees of Freedom</u>	<u>p-value</u>
Setting: Urban		2	.005
Suburban	1.061		
Rural	-.131		
Total Population	<.001	1	.001
Undergraduate Population	<.001	1	.001
Acceptance Rate	-.022	1	.005
Gender	-1.452	1	.001
(Constant)	1.979	1	.

This model explains 20.4% of the variation (Nagelkerke R^2), and is correct in identifying adopters and resisters 65.4% of the time (62 out of 107 taught by adopters and 89 out of 124 by resisters). It is not surprising that this model is not as accurate in its predictions as the previous one, given that the greater the differences between the two groups are required to be, the more measurable those differences become. However, it is a positive result that most of the variables present in the first model are also present in the second, including the unusual pairing of population variables.

Different Courses as Different Archetypes

Since each of the 438 faculty members who responded regarding more than one course responded about courses of different levels, and course level is a variable that causes some variation within the three measured factors, all factor scores were reduced to standard scores (z-scores) based on the mean and standard deviation for courses at that grade level. This helps ensure that any differences between sophomore, junior, and senior courses are controlled for and all comparisons are made on the same scale. The beliefs factor obviously does not change between courses taught by the same professor, so only the two instructional practices factors were considered for each course. In order

to create a single measure to represent instructional internet practices, the two practices factors were again summed for each course, and reduced to a z-score based on the mean and standard deviation of all courses at each level. Finally, the range of the combined practices z-scores among the courses taught by each professor was calculated. The distribution of these ranges is shown in Figure 15:

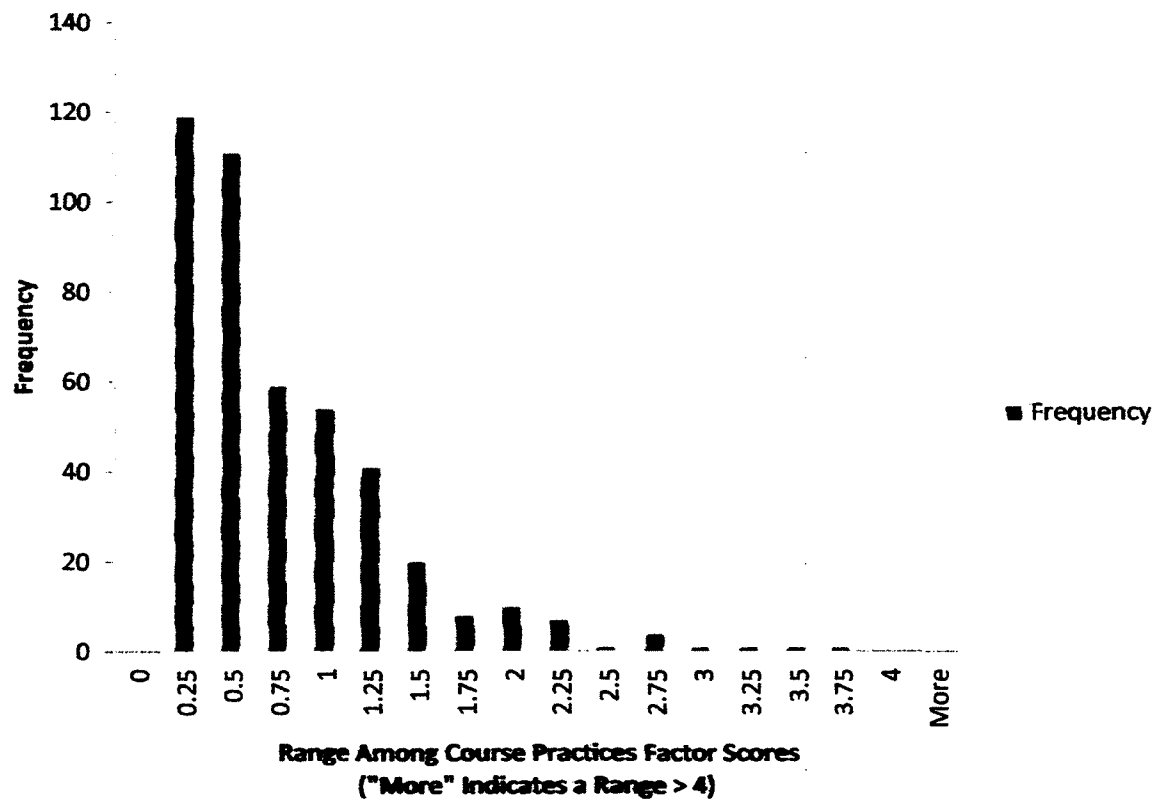


Figure 15: Variance of Course Practices Frequency Histogram

Based on the distribution above, the 35 faculty members whose range in their course practices were at least 1.5 were identified as those who taught courses in distinctly different ways with regard to instructional internet use. A binary logistic regression was not able to predict who fell into this high variance group based on demographic variables, as the resulting regression model predicted all faculty would be in the low variance group. However, the faculty beliefs factor was identified as a statistically significant

variable in identifying those faculty who showed a high variance in their instructional practice. The high-variance group reported a mean of 3.94 for their instructional beliefs, while the low variance group reported a mean of 3.76. An independent-samples t-test confirms that this difference is significant, with a p-value of 0.005. This indicates that those professors who believe the internet is a useful teaching resource are more likely to show a wider range of internet presence in their different courses. The instructional practice range for each of these 35 faculty members (sorted from greatest range to smallest) is shown graphically in Figure 16:

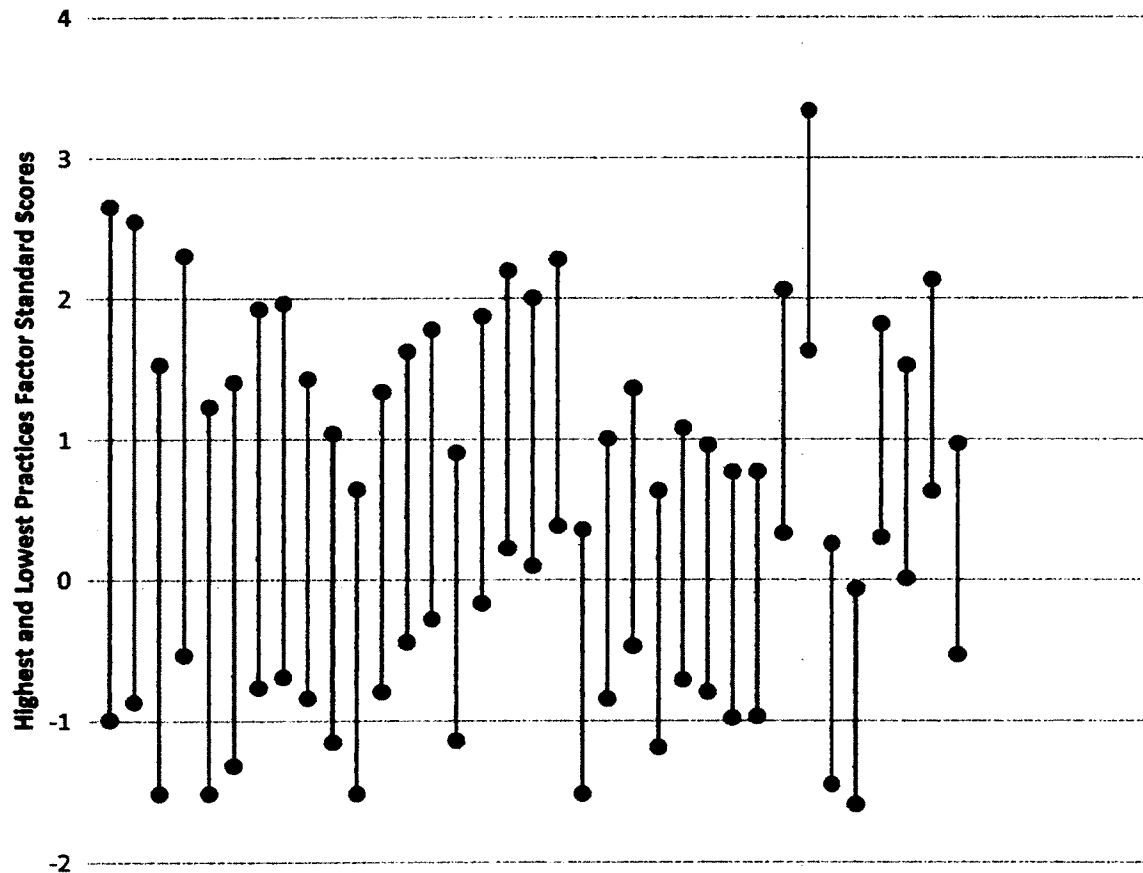


Figure 16: Range of Practices for High Variance Faculty

Chapter Five

Discussion

This chapter will discuss the findings of the study, their placement within the relevant literature and conceptual models, and their implications and limitations. For the sake of completeness, a brief review of the methodology will be provided. Then each of the three research questions will be addressed, as well as their connection to the theoretical frameworks used. Implications for policy and directions for further research will then be discussed, followed by a review of the limitations of the study.

Methodological Overview

This study attempts to answer the following research questions:

1. What is the current state of instructional internet use in undergraduate engineering classrooms nationwide, as measured by the presence and degree of integration of the technology component of the TPACK framework?
2. Do the three faculty archetypes (internet resister, internet user, and internet adopter) apply across the nationwide population? Is another model more appropriate?
3. What personal and institutional factors correlate with the extent of technology integration in professors' courses?

To do this, a three-part survey instrument was developed to assess each participant's beliefs and practices regarding instructional internet use. The three parts of the survey consisted of a demographic section consisting of 10 items, a 16 question section inquiring about respondents' beliefs about the effectiveness of the internet as a tool for teaching and learning, and a section that asked 23 questions about their instructional practices in

each of their courses. The survey was distributed electronically to all tenured and tenure-track engineering faculty in the United States, a total of 24,252 people.

Once responses were collected, a factor analysis was performed to identify constructs that represented different aspects of faculty members' beliefs and practices regarding instructional internet use. The analysis revealed three significant factors: use of internet resources in delivering instruction, guiding students' internet research, and faculty beliefs about the usefulness of internet resources. The first two factors both represented aspects of professors' instructional factor, so at times they were summed to create a single measure of instructional internet practices.

Frequency histograms were then created and examined to determine the distribution of faculty members' beliefs and practices regarding internet use in their courses. The distributions produced in the study were compared to those predicted by theory to assess the applicability of the conceptual models.

Finally, multi-linear regressions were performed to find any correlations between demographic variables and the three constructs produced by the factor analysis. In addition, logistical regressions were performed to attempt to predict a faculty members' instructional archetype based on their demographic variables and course characteristics.

TPACK and the Three Factors

The first factor, use of internet resources for content delivery, had a mean value of 2.17 and a median of 2. With a possible range of one to five, this indicates that the majority of responding faculty members are on the lower half of the scale for this factor. The fact that most faculty are hesitant to use internet resources to deliver content on a regular basis implies that the technology knowledge piece of the TPACK model is

present, but certainly not integrated with content and pedagogical knowledge. A score of two on this factor – the most common result – corresponds to a professor reporting that he or she uses each internet resource listed once per month or less. While technological knowledge in this case only represents the understanding of how to use instructional internet technology (which most engineering faculty presumably have), technological pedagogical knowledge, technological content knowledge, and technological pedagogical content knowledge all require an understanding of how that technology interacts with pedagogy and course content (Mishra & Koehler, 2006). The large number of relatively low scores on this factor indicate that while professors are comfortable using internet resources to deliver instruction occasionally, most lack the knowledge or comfort level required to integrate them into their courses on a regular basis.

The scores on the second factor, guiding students' internet research, were even lower, with a mean of 1.79 and a median of 1.6. In this case, it is not clear that the technological knowledge component is even present. The lowest score possible is a one, corresponding to faculty members reporting that they never take any of the actions listed to support internet-based research by students. Considering the large number of professors who scored at one or close to it, it seems reasonable to conclude that many faculty members simply do not have the technological knowledge required to guide students' internet research - or the willingness to use that knowledge, at least. This is an important finding, as developing internet research skills is critically important for any student; a common refrain in the field of educational technology is that the important skill in the internet age is not finding information, but filtering information (Dani & Koenig, 2008; Hennessy et al., 2007; Roberts & McInnerney, 2007). The fact that engineering

faculty are unable or unwilling to support students as they develop these skills is problematic, and will be addressed in the discussion of policy implications later in this chapter.

Scores on the third factor, faculty beliefs about the usefulness of internet resources, were noticeably higher than those on the first two factors. The third factor had a mean of 3.78 and a median of 3.75. This factor is also different because it addresses what faculty believe, rather than what they actually do, which at least partially explains the higher scores. This shows that while they do not always demonstrate technological knowledge, or the ability to integrate it with pedagogy or content, professors do see the value of the internet with regards to teaching and learning. This is also an important finding, as it highlights the gap between what faculty members are doing and what they believe they should be doing. This gap is essentially an invitation for professional development, which will also be discussed among the policy implications later in the chapter.

Faculty Archetypes

In order to conclusively support the idea of distinct faculty archetypes, each representing a different approach to instructional internet use, there would need to be some sort of multi-modal effect present in the factor distributions showing each faculty member clustered with others of the same archetype. This is clearly not the case for the factors found in this study. In fact, both the faculty beliefs factor and the combined instructional practices factor have distributions that approximate normal. This shows that, at least according to this survey instrument, there are no distinct archetypes. Instead, professors' instructional internet use is spread out over a wide spectrum of approaches,

with the majority falling somewhere in the middle ground between extreme internet adopters and extreme internet resisters.

This finding leads to two possible conclusions. The first is the obvious one: that this study shows that the faculty archetype model (Lehman & Kohl, 2013) does not apply to engineering faculty throughout the country. This is certainly possible, given that the archetype model was developed based on a study of only seven faculty members at a single university. And considering that the university in question is at the extreme teaching end of the teaching institution versus research institution spectrum, it would not be altogether surprising if faculty there were unusual in their approach to teaching. If the archetype model is not appropriate for the nationwide sample, however, it would be worth exploring to what extent it is generalizable. It is possible that there are other, similar teaching institutions where faculty do fall into the distinct archetypes, and further study could identify under what conditions the model holds true.

The other possible conclusion is that the survey was not able to measure patterns of instructional internet use precisely enough to identify the three archetypes. This is also possible, as Lehman and Kohl (2013) used in-depth interviews to identify faculty members' archetypes rather than a survey instrument. The 39 quantitative items in the survey may simply not have been able to delve deep enough to detect differences between the archetypes. If this is the case, further study with either a more detailed survey instrument, or preferably a series of interviews, would be able to detect the differences and classify professors' behavior more precisely.

One piece of the faculty archetype model does remain true when extended to a national sample: the idea that individual faculty members sometimes take dramatically

different approaches to their instructional internet use in different courses. In the archetype model, some faculty will teach as a different archetype in different classes (Lehman & Kohl, 2013). While identifying distinct archetypes was not possible in this case, it is still possible to examine the range of instructional approaches that faculty use in their courses based on the two instructional practices factors identified in this study. Of the 438 faculty who reported on more than one course, 35 of them – just under 8% - were identified as professors who showed a dramatic difference in their instructional internet use from one course to the next. Interestingly, those 35 faculty members also scored significantly higher on the faculty beliefs factor. This may be because those professors who are stronger believers in technology are more likely to teach in a technology-centric way that is much different than a course taught using the traditional model, or there may be something unique about these professors and their approach to pedagogy that facilitates the greater variation. Unfortunately there was little data collected in this study that is specific to professors who taught multiple courses, but it could be a promising future line of inquiry.

Predicting adopters and resisters. While no distinct archetypes could be identified, it is still to be expected that professors who scored the highest on the three internet usage factors will teach as internet adopters, and those that scored the lowest will teach as internet resisters. In this way, we can classify a certain fraction of the population as adopters and a certain fraction as resisters and determine if there are any measureable differences between them and the rest of the sample.

Unfortunately, due to statistical noise and the lack of distinct archetypes, logistic regression analyses were unable to predict which courses were taught by internet adopters

and which were taught by internet resisters based on the provided demographic variables. Five different decision rules were used to classify adopters and resisters, and in each case the regression converged on a model that predicted zero adopters and zero resisters. However, much of the statistical noise can be removed by disregarding those courses not taught by adopters or resisters. This does eliminate the possibility of being able to identify adopters or resisters from among the entire sample, but by regressing adopters and resisters against each other without the massive middle group, measurable differences emerge. Teaching at a public institution, teaching in a suburban setting (compared to urban), teaching at a large institution, and teaching a lecture-based course all made it more likely for a professor to teach a course as an internet adopter, while teaching in a rural setting (compared to urban) and being female made it more likely to teach a course as a resister. Some of these factors make intuitive sense: faculty at large, public institutions generally have larger class sizes, which are often an incentive to introduce a greater online component to a course, and lecture-based courses generally have more flexibility for the introduction of internet resources than labs or discussion sections. On the other hand, the reasons for the significance of gender and setting variables are not immediately clear; further inquiry could potentially offer an explanation.

Predicting Factor Scores

Three multi-linear regressions were used to find correlations between the demographic variables and each of the three instructional internet use factors. While there were several variables that emerged as statistically significant in each case, all of the standard coefficients are less than 0.2, so the practical significance is minimal at best. The model predicting the use of internet resources for content delivery yielded an R^2 of

0.02, the one predicting guidance of students' internet research yielded an R^2 of 0.08, and the one predicting faculty beliefs yielded an R^2 of 0.04. In each case, the model accounts for less than 10% of the variation in the factor, making the models essentially useless as predictive tools given the specified input variables.

The regression results improve slightly for the two instructional practices factors if the faculty beliefs factor is included as an independent variable. This is expected, as each professor's beliefs should, in theory, influence their practice. The faculty beliefs factor has a standardized coefficient of .31 with respect to the use of internet resources for content delivery factor, and .27 with respect to the guiding students' internet research factor. The regression models including the beliefs factor are more predictive than those without, as R^2 increases to 0.11 for the model predicting factor one, and 0.16 for the model predicting factor two. While including the beliefs factor creates models that are no longer meaningless in their predictions, it does require that self-reported data be collected from the professor before the model can be used. Specification error is still a significant problem, as none of the demographic variables correlate strongly with any of the three instructional internet use factors.

Possibilities for Further Research

There are several avenues for further research that have been opened up by this study. The first would be investigating the reason why the faculty archetype model proved to be inapplicable to this study. It is possible that the archetype model is dependent on some characteristic of the small, teaching institution at which it was developed and therefore its generalizability would be limited. It is also possible that the model is widely generalizable, but the survey instrument in this study was not sensitive

enough to successfully differentiate the three archetypes. A deeper inquiry into the practices of a number of faculty members at a range of institutions could reveal why this study failed to fit the conceptual framework.

There is also an opportunity to explore the backgrounds and attitudes of faculty members in order to identify some variables that correlate with the three instructional internet factors developed in this study. There was significant specification error in the regression models used to predict factor scores; none of the demographic, institutional, or course characteristic variables collected in this study correlated meaningfully with any of the three factors. Again, a deeper inquiry involving a range of faculty members could uncover variables or characteristics that do have strong correlations with behavior regarding instructional internet use.

Finally, the most open-ended line of research would be into the characteristics of those professors who teach different courses with dramatically different approaches. This study was able to identify those faculty members whose practices vary the most significantly, and was also able to show that they had measurably higher scores on the faculty beliefs factor than the rest of the sample, but any further inquiry was beyond its scope. There are opportunities for both qualitative and quantitative examinations of their beliefs, characteristics, and backgrounds to identify what makes them different from the vast majority of professors.

Implications for Policy

There are two major implications for higher education policy that emerge from this study, and both are related to professional development. First, the distributions of the three instructional internet factors showed that the vast majority of faculty score much

higher on the factor related to beliefs than they do on either factor related to practice. This means the majority of faculty are not using internet resources in their courses as much as they would like to, or as much as they think to be ideal. Because faculty have so many obligations and responsibilities, professional development is often not a high priority (Brutkiewicz, 2010; McQuiggan, 2012). However, in this case there is an identified, measured desire on the part of the faculty to increase their use of the internet for teaching and learning. This is something that most universities can, and should, take advantage of.

The second policy implication is in regards to remedying a deficiency that is far too prevalent in engineering faculty. The scores on the guiding students' internet research factor were mostly below two, meaning most faculty provide little to no support at all to students as they go through the process of learning how to find accurate and reliable information on the internet. As this has become an essential skill both in industry and in academia, it could be considered negligent for faculty to leave students to learn it on their own. Professional development could ultimately be the solution to this problem, but considering the overwhelming number of exceptionally low scores on this factor, professional development initiatives would likely have to start at a very basic level.

Limitations

There are several limitations to this study that could affect the validity of the results. The first, and potentially most problematic, is the possibility of non-response bias. While steps were taken to verify that the sample was representative of the population in terms of demographics, there may be other underlying beliefs or characteristics that could influence whether or not a recipient completes the survey or not.

For instance, it is possible – or perhaps probable - that professors who believe the internet is a useful tool for teaching and learning would be more likely to respond to a survey about instructional internet use, causing the scores on questions regarding beliefs about internet use to be significantly higher than the actual population mean. Follow-up interviews with selected participants could help assess the effects of non-response bias, if any, but that is beyond the scope of this study at this time.

An additional limitation is the dependence on self-reporting by the faculty themselves. While asking them to report on both what they do in their instructional practice and what they believe are best practices should mitigate some of the idealization of their practice, self-reporting is still not as reliable or unbiased as an independent assessment.

The broadest limitation of this study, however, is the inability to determine causality. While factor analyses and regression tools will describe which variables cause faculty to group together and how different faculty members' characteristics are associated with internet use, the statistical methods used will not reveal which variables *cause* a change in internet use. Similarly, this study does not attempt to answer the question of why certain faculty are more or less likely to make use of the internet in their courses. The difference between knowing which variables correlate with one another and which variables cause a change in others is a subtle but critically important distinction, and none of the analytics in this study are capable of addressing the question “why?”

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Appendix A

Instructional Internet Use Survey

Q1.1 Please read the following research participant assent form.

Q1.2 Research Participant Assent Form

For the research study entitled: Engineering, Teaching, and Technology: A Nationwide Examination of Instructional Internet use Among Engineering Faculty.

I. Purpose of the research study Alexander Lehman is a PhD candidate in the School of Leadership and Education Sciences at the University of San Diego. You are invited to participate in a research study he is conducting. The purpose of this research study is to assess engineering faculty members' implementation of internet-based instructional resources, and to evaluate which changes to traditional engineering pedagogy have been most embraced in this context.

II. What you will be asked to do If you decide to be in this study, you will be asked to complete the following survey. Your participation in this study will take a total of 10 minutes.

III. Foreseeable risks or discomforts This study involves no more risk than the risks you encounter in daily life.

IV. Benefits While there may be no direct benefit to you from participating in this study, the indirect benefit of participating will be helping to identify effective course models and teaching strategies that may improve your students' academic experience.

V. Confidentiality Any information provided and/or identifying records will remain confidential and kept in a locked file and/or password-protected computer file in the researcher's office for a minimum of five years. All data collected from you will be coded with a number or pseudonym (fake name). Your real name will not be used. The results of this research project may be made public and information quoted in professional journals and meetings, but information from this study will only be reported as a group, and not individually.

VI. Compensation You will receive no compensation for your participation in the study.

VII. Voluntary Nature of this Research Participation in this study is entirely voluntary. You do not have to do this, and you can refuse to answer any question or quit at any time. Deciding not to participate or not answering any of the questions will have no effect on any benefits you're entitled to, like your health care, or your employment or grades. You can withdraw from this study at any time without penalty.

VIII. Contact Information If you have any questions about this research, you may contact either: 1) Alexander Lehman, Visiting Professor of Engineering, Doctoral Candidate Email: alehman@sandiego.edu Phone: 619-260-6745 2) Dr. Fred Galloway, Professor of Leadership Studies Email: galloway@sandiego.edu Phone: (619) 260-7435

Q1.3

☐ I have read the assent form and agree to participate in this research project. (1)

Q2.1 The following questions help identify the characteristics of the subject population in terms of both demographics and professional experience. This information is important; your time and consideration is much appreciated.

Q2.2 In what year were you born?

Q2.3 What do you consider your ethnicity to be?

- ☐ White (non-Hispanic) (1)
- ☐ African American/Black (2)
- ☐ Asian (3)
- ☐ Hispanic/Latino (4)
- ☐ Pacific Islander (5)
- ☐ Native American (6)
- ☐ Mixed ethnicity (7)
- ☐ Other (8)

Q2.4 What is your gender?

- ☐ Male (1)
- ☐ Female (2)

Q2.5 Was English your first language?

- ☐ Yes (1)
- ☐ No (2)

Q2.6 With which engineering discipline do you most identify yourself?

- ☐ Aerospace, Aeronautical, or Astronautical Engineering (1)
- ☐ Agricultural Engineering (2)
- ☐ Architectural Engineering (3)
- ☐ Biomedical/Medical Engineering (4)
- ☐ Chemical Engineering (5)
- ☐ Civil Engineering (6)
- ☐ Computer Engineering (7)
- ☐ Construction Engineering (8)
- ☐ Electrical Engineering (9)
- ☐ Geological/Geophysical Engineering (10)
- ☐ Industrial Engineering (11)
- ☐ Manufacturing Engineering (12)
- ☐ Materials Engineering (13)
- ☐ Mechanical Engineering (14)
- ☐ Mining and Mineral Engineering (15)
- ☐ Nuclear Engineering (16)
- ☐ Systems Engineering (17)
- ☐ Other Engineering discipline (18)
- ☐ Multiple Engineering disciplines (19)
- ☐ I do not consider myself an engineering professional (20)

Q2.7 As of December 2013, how many years had you been teaching at the college or university level (at any institution)? Enter 0 if you had not taught at the college or university level as of December 2013.

Q2.8 As of December 2013, how many years had you been teaching at your current institution? Enter 0 if you had not taught at your current institution as of December 2013.

Q2.9 How many college- or university-level engineering courses did you teach during the 2013 calendar year?

Q2.10 Which of these most closely describes your job title?

- ☐ Professor (1)
- ☐ Associate Professor (2)
- ☐ Assistant Professor (3)
- ☐ Other tenured or tenure-track faculty (4)
- ☐ Non-tenure-track faculty (5)
- ☐ Non-faculty position (6)

Q2.11 During the 2013 calendar year, did you teach any courses intended primarily for any of the following student groups? (Check all that apply)

- ☐ Second-year (sophomore) engineering majors (1)
- ☐ Third-year (junior) engineering majors (2)
- ☐ Fourth-year (senior) engineering majors (3)

Answer If How many college- or university-level engineering courses did you teach during the 2013 calendar ... **Text Response Is Equal to 0**

Q2.12 Are you currently teaching a college- or university-level engineering course?

- ☐ Yes (1)
- ☐ No (2)

If No Is Selected, Then Skip To End of Survey

Q3.1 Please answer the following questions considering only the course you taught intended primarily for second-year (sophomore) engineering majors in the 2013 calendar year. If you taught more than one course that fits the criterion, choose the one that met most recently and answer considering that course only.

Q3.2 This course was intended for students in which engineering major?

- ☐ This course was intended for multiple engineering majors (19)
- ☐ Aerospace, Aeronautical, or Astronautical Engineering (1)
- ☐ Agricultural Engineering (2)
- ☐ Architectural Engineering (3)
- ☐ Biomedical/Medical Engineering (4)
- ☐ Chemical Engineering (5)
- ☐ Civil Engineering (6)
- ☐ Computer Engineering (7)
- ☐ Construction Engineering (8)
- ☐ Electrical Engineering (9)
- ☐ Geological/Geophysical Engineering (10)
- ☐ Industrial Engineering (11)
- ☐ Manufacturing Engineering (12)
- ☐ Materials Engineering (13)
- ☐ Mechanical Engineering (14)
- ☐ Mining and Mineral Engineering (15)
- ☐ Nuclear Engineering (16)
- ☐ Systems Engineering (17)
- ☐ Other Engineering major (18)

Q3.3 Which format best describes this course?

- ☐ Direct instruction (lecture) (1)
- ☐ Lab (2)
- ☐ Discussion section (3)
- ☐ Other (4)

thorough
internet
research with
your students?
(13)

Q3.5 How often did students present their work in a multimedia format (photographs, music, video, etc.)?

- ☐ Never (1)
- ☐ Occasionally; less than once per month (2)
- ☐ 1-3 times per month (3)
- ☐ 1-2 times per week (4)
- ☐ 3+ times per week (5)
- ☐ Not Applicable (6)

Q3.6 How often did students send you links to online content related to course concepts?

- ☐ Never (1)
- ☐ Occasionally; less than once per month (2)
- ☐ 1-3 times per month (3)
- ☐ 1-2 times per week (4)
- ☐ 3+ times per week (5)
- ☐ Not Applicable (6)

Q3.7 When students asked for assistance over email or other electronic means, how frequently did you refer them to see you in person (in class, office hours, etc)?

- ☐ 0-24% of the time (1)
- ☐ 25-49% of the time (2)
- ☐ 50-74% of the time (3)
- ☐ 75-100% of the time (4)
- ☐ Not Applicable (5)

Q3.8 When students were required to perform research on the internet, how frequently did you provide links to suggested information sources? (Answer not applicable if students were never required to research on the internet).

- ☐ 0-24% of the time (1)
- ☐ 25-49% of the time (2)
- ☐ 50-74% of the time (3)
- ☐ 75-100% of the time (4)
- ☐ Not Applicable (5)

Q3.9 In this course, what percentage of assigned problems were from a published textbook, without any modification?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q3.10 In this course, what percentage of assigned problems were modified versions of problems from a published textbook?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q3.11 In this course, what percentage of assigned problems were from an unpublished source (written by you, another faculty member, etc)?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q3.12 In this course, what percentage of assigned problems were students to complete online?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q3.13 In this course, what percentage of assigned problems were students to complete during class time?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q3.14 Did assigned problem sets count for the same percentage of the overall course grade as they did previous times you taught this course? (Answer not applicable if you had not taught this course previously).

- ☐ Yes, they counted the same (1)
- ☐ No, they counted more than in previous semesters (2)
- ☐ No, they counted less than in previous semesters (3)
- ☐ Not applicable (4)

Q4.1 Please answer the following questions considering only the course you taught intended primarily for third-year (junior) engineering majors in the 2013 calendar year. If you taught more than one course that fits the criterion, choose the one that met most recently and answer considering that course only.

Q4.2 This course was intended for students in which engineering major?

- ☐ This course was intended for multiple engineering majors (19)
- ☐ Aerospace, Aeronautical, or Astronautical Engineering (1)
- ☐ Agricultural Engineering (2)
- ☐ Architectural Engineering (3)
- ☐ Biomedical/Medical Engineering (4)
- ☐ Chemical Engineering (5)
- ☐ Civil Engineering (6)
- ☐ Computer Engineering (7)
- ☐ Construction Engineering (8)
- ☐ Electrical Engineering (9)
- ☐ Geological/Geophysical Engineering (10)
- ☐ Industrial Engineering (11)
- ☐ Manufacturing Engineering (12)
- ☐ Materials Engineering (13)
- ☐ Mechanical Engineering (14)
- ☐ Mining and Mineral Engineering (15)
- ☐ Nuclear Engineering (16)
- ☐ Systems Engineering (17)
- ☐ Other Engineering major (18)

Q4.3 Which format best describes this course?

- ☐ Direct instruction (lecture) (1)
- ☐ Lab (2)
- ☐ Discussion section (3)
- ☐ Other (4)

thorough
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(13)

Q4.5 How often did students present their work in a multimedia format (photographs, music, video, etc.)?

- ☐ Never (1)
- ☐ Occasionally; less than once per month (2)
- ☐ 1-3 times per month (3)
- ☐ 1-2 times per week (4)
- ☐ 3+ times per week (5)
- ☐ Not Applicable (6)

Q4.6 How often did students send you links to online content related to course concepts?

- ☐ Never (1)
- ☐ Occasionally; less than once per month (2)
- ☐ 1-3 times per month (3)
- ☐ 1-2 times per week (4)
- ☐ 3+ times per week (5)
- ☐ Not Applicable (6)

Q4.7 When students asked for assistance over email or other electronic means, how frequently did you refer them to see you in person (in class, office hours, etc)?

- ☐ 0-24% of the time (1)
- ☐ 25-49% of the time (2)
- ☐ 50-74% of the time (3)
- ☐ 75-100% of the time (4)
- ☐ Not Applicable (5)

Q4.8 When students were required to perform research on the internet, how frequently did you provide links to suggested information sources? (Answer not applicable if students were never required to research on the internet).

- ☐ 0-24% of the time (1)
- ☐ 25-49% of the time (2)
- ☐ 50-74% of the time (3)
- ☐ 75-100% of the time (4)
- ☐ Not Applicable (5)

Q4.9 In this course, what percentage of assigned problems were from a published textbook, without any modification?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q4.10 In this course, what percentage of assigned problems were modified versions of problems from a published textbook?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q4.11 In this course, what percentage of assigned problems were from an unpublished source (written by you, another faculty member, etc)?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q4.12 In this course, what percentage of assigned problems were students to complete online?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q4.13 In this course, what percentage of assigned problems were students to complete during class time?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q4.14 Did assigned problem sets count for the same percentage of the overall course grade as they did previous times you taught this course? (Answer not applicable if you had not taught this course previously).

- ☐ Yes, they counted the same (1)
- ☐ No, they counted more than in previous semesters (2)
- ☐ No, they counted less than in previous semesters (3)
- ☐ Not applicable (4)

Q5.1 Please answer the following questions considering only the course you taught intended primarily for fourth-year (senior) engineering majors in the 2013 calendar year. If you taught more than one course that fits the criterion, choose the one that met most recently and answer considering that course only.

Q5.2 This course was intended for students in which engineering major?

- ☐ This course was intended for multiple engineering majors (19)
- ☐ Aerospace, Aeronautical, or Astronautical Engineering (1)
- ☐ Agricultural Engineering (2)
- ☐ Architectural Engineering (3)
- ☐ Biomedical/Medical Engineering (4)
- ☐ Chemical Engineering (5)
- ☐ Civil Engineering (6)
- ☐ Computer Engineering (7)
- ☐ Construction Engineering (8)
- ☐ Electrical Engineering (9)
- ☐ Geological/Geophysical Engineering (10)
- ☐ Industrial Engineering (11)
- ☐ Manufacturing Engineering (12)
- ☐ Materials Engineering (13)
- ☐ Mechanical Engineering (14)
- ☐ Mining and Mineral Engineering (15)
- ☐ Nuclear Engineering (16)
- ☐ Systems Engineering (17)
- ☐ Other Engineering major (18)

Q5.3 Which format best describes this course?

- ☐ Direct instruction (lecture) (1)
- ☐ Lab (2)
- ☐ Discussion section (3)
- ☐ Other (4)

thorough
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(13)

Q5.5 How often did students present their work in a multimedia format (photographs, music, video, etc.)?

- ☐ Never (1)
- ☐ Occasionally; less than once per month (2)
- ☐ 1-3 times per month (3)
- ☐ 1-2 times per week (4)
- ☐ 3+ times per week (5)
- ☐ Not Applicable (6)

Q5.6 How often did students send you links to online content related to course concepts?

- ☐ Never (1)
- ☐ Occasionally; less than once per month (2)
- ☐ 1-3 times per month (3)
- ☐ 1-2 times per week (4)
- ☐ 3+ times per week (5)
- ☐ Not Applicable (6)

Q5.7 When students asked for assistance over email or other electronic means, how frequently did you refer them to see you in person (in class, office hours, etc)?

- ☐ 0-24% of the time (1)
- ☐ 25-49% of the time (2)
- ☐ 50-74% of the time (3)
- ☐ 75-100% of the time (4)
- ☐ Not Applicable (5)

Q5.8 When students were required to perform research on the internet, how frequently did you provide links to suggested information sources? (Answer not applicable if students were never required to research on the internet).

- ☐ 0-24% of the time (1)
- ☐ 25-49% of the time (2)
- ☐ 50-74% of the time (3)
- ☐ 75-100% of the time (4)
- ☐ Not Applicable (5)

Q5.9 In this course, what percentage of assigned problems were from a published textbook, without any modification?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q5.10 In this course, what percentage of assigned problems were modified versions of problems from a published textbook?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q5.11 In this course, what percentage of assigned problems were from an unpublished source (written by you, another faculty member, etc)?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q5.12 In this course, what percentage of assigned problems were students to complete online?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q5.13 In this course, what percentage of assigned problems were students to complete during class time?

- ☐ 0-24% (1)
- ☐ 25-49% (2)
- ☐ 50-74% (3)
- ☐ 75-100% (4)
- ☐ Not Applicable (5)

Q5.14 Did assigned problem sets count for the same percentage of the overall course grade as they did previous times you taught this course? (Answer not applicable if you had not taught this course previously).

- ☐ Yes, they counted the same (1)
- ☐ No, they counted more than in previous semesters (2)
- ☐ No, they counted less than in previous semesters (3)
- ☐ Not applicable (4)

Sharing online
content
recommended
by students is a
valuable use of
class time. (38)

☐ ☐ ☐ ☐ ☐ ☐

Courses
utilizing online
recorded
lectures are as
effective in
teaching
engineering as
those where in-
class time is
dedicated to
lecture. (39)

☐ ☐ ☐ ☐ ☐ ☐

Online
simulations are
as effective at
showing
phenomena as
live
demonstrations.
(40)

☐ ☐ ☐ ☐ ☐ ☐

Including
multimedia
content
(photographs,
music, video,
etc.) in class
time improves
student
learning in
engineering
courses. (41)

☐ ☐ ☐ ☐ ☐ ☐

Including
multimedia
content
(photographs,
music, video,
etc.) in class
time improves
student
engagement in

☐ ☐ ☐ ☐ ☐ ☐

engineering
courses. (42)

Researching an
engineering
topic on the
internet is a
valuable
learning
experience for
students. (43)

Engineering
faculty should
teach students
how to
thoroughly
search for
information on
the internet.
(44)

Engineering
faculty should
teach students
how to identify
reliable sources
on the internet.
(45)

It is better for
faculty to
provide links to
reliable
information
sources than
for students to
do their own
search. (46)

Student access
to online
solution
manuals is a
problem in
engineering
courses. (47)

Students
become

☐ ☐ ☐ ☐ ☐ ☐

☐ ☐ ☐ ☐ ☐ ☐

☐ ☐ ☐ ☐ ☐ ☐

☐ ☐ ☐ ☐ ☐ ☐

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dependent when they are allowed to use internet resources to complete engineering coursework. (48)						
Courses built around online content are more effective at teaching engineering than courses built around a textbook. (49)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Online resources have changed how faculty should assess student learning. (50)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Q6.2 Is there anything else you would like to add?