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Information Systems Education Journal

How to Teach Emotional Intelligence Skills in IT Project Management

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Abstract

High emotional intelligence ("EQ") is considered one of the greatest strengths of an alpha project manager, yet undergraduate project management students are not directly trained in EQ soft skills such as communication, politics and teamwork. This article describes examples of active learning exercises implemented in an undergraduate IT project management course to improve students' EQ skills in project management scenarios. Instruction emphasized the interplay of hard and soft skills in project management. In-class activities were designed to show students how to skillfully interact with peers and stakeholders on an IT project. This research provides examples of pedagogical interventions that involved students in their own learning and forced them to constructively engage with each other and with the material. This research contributes to the literature by demonstrating how to implement suggestions from research directly into pedagogy. Additionally, this research provides a set of activities that can be used to increase the EQ of students in a project management course. Based on the results from this study, the interventions worked as intended. Students reported higher EQ, critical thinking, and communication skills after completing the course.

Keywords: emotional intelligence, IT project management, soft skills, skills transference, active learning

1. INTRODUCTION

After more than 50 years of developing and deploying information systems, projects continue to fail. While the technologies have evolved and changed enormously over that time period, one factor remains consistent: people. People are the greatest threat to IT project success. Stakeholders make or break a project. Year after year, the CHAOS Report measures project success by whether a project meets scope, time and cost budgets. However, people estimate, control and ultimately determine the success or failure of those projects (Hastie & Wojewoda, 2015).

Undergraduate education in IT project management tends to spend more time teaching hard skills like time and scope estimation, requirements elicitation, and how to build Gantt charts, and less time on soft skills like how to work in teams and manage stakeholders at multiple levels of the organization (Cowie, 2003; Jewels & Bruce, 2003; Tynjälä, Pirhonen, Vartiainen & Helle, 2009). Even the Project Management Institute's ("PMI") Project Management Body of Knowledge ("PMBOK") acknowledges that soft skills are important but has little room for it. For example, the 5th edition PMBOK added a new knowledge area for stakeholders, but arguably, only three of the ten knowledge areas directly relate to people skills.

To improve the chances of project success, better trained project managers are needed. In order to prepare students for roles in project management, we need to improve their interpersonal "soft skills" and their emotional intelligence. However, while this goal is important, it definitely requires a more holistic approach to project management education.

In this paper, we present a review of the relevant literature and explore an active learning approach that was applied in a project management classroom. This approach was designed to improve student learning in the area of emotional intelligence. We present the details of this approach, the results from the classroom, and the implications to teaching and learning IT project management in an undergraduate college class.

2. LITERATURE REVIEW

Sufficient research exists to explain what skills IT project managers need and what skills lead to more successful projects. Known as "alpha" project managers, the top 2% most effective project managers plan and communicate significantly more than the other 98%, and they are better communicators (Crowe, 2006). Communication and the ability to prioritize tasks are soft skills. These skills are even more acute and demanded in agile teams, where clients are more directly involved in product development (Cockburn & Highsmith, 2001).

The question then becomes, how can we teach these skills? For the most part, project management classes tend to focus on the PMBOK material presented on PMI's certification exams, mostly because soft skills are difficult to measure with standardized tests (De Piante, 2010; Scott, 2010). Additionally, EQ skills are difficult to teach via traditional lectures, because they are typically learned from experience. Therefore, an active learning approach may be more effective. In this section, we briefly review the research on soft skills vs. hard skills and active learning.

IT Project Management

Project management is an increasingly important topic in information systems education and practice, in part because many studies have shown that project success is far from assured and that having a bad project manager can greatly increase the risk of failure (Poston & Richardson, 2011). In order to train effective project managers, we need to ensure they have the soft skills that industry demands (Mitchell, Skinner, & White, 2010; Pazhani & Priya, 2012; Poston et al., 2011). However, these soft skills are not usually covered in a project management classroom, in no small part because they are not easy to teach or learn, and they are not a primary focus of the PMI exams. Yet their presence can greatly enhance the chances of success for a project.

Teaching Soft Skills versus Hard Skills

Generally speaking, the skills that define the most successful project managers would be categorized as "soft" skills, whereas the PMI exams measure more of what are generally considered "hard" skills, or skills and knowledge in a very specific area (Pazhani, et al. 2012). Although hard skills and soft skills represent different types of knowledge, they need to be balanced effectively. Hard skills are often aligned more clearly, though not exclusively, as explicit knowledge. Explicit knowledge can be recorded and disseminated more easily via text than its counterpart, tacit knowledge. Soft skills are more aligned with tacit knowledge, though again not exclusively. Tacit knowledge is generally harder to convey via text. Tacit knowledge must frequently be acquired by doing, rather than by reading, and this problem extends well beyond academia. The difference and difficulty in capturing and conveying tacit knowledge have been noted in the literature on knowledge management as well (Crane & Bontis, 2014; Herschel, Nemati, & Steiger, 2001).

Soft skills are as critical to project management as hard skills, but unlike hard skills, instruction of soft skills is most effective when taught in context in a more holistic way (Adams & Morgan, 2007). Active learning is one way to convey these important soft skills to students and allow them to see them in action.

Active Learning

Active learning is generally defined as learning that actively engages the students in the learning process (Zheng & Li, 2016). In numerous studies, it has been shown that engaging students in the learning process can improve learning outcomes, especially where soft skills are concerned (Adams & Morgan, 2007). It has also been shown that active learning approaches can help students master difficult concepts, particularly when students have little professional experience on which to draw (Connolly & Lampe, 2016; Reinicke & Clark, 2010).

In addition to successful applications in IS classrooms in general, active learning principles have been used to teach project management (Davidovitch, Parush, & Shtub, 2006; Gan Kok Siew, Joshi, Lending, Outlay, Quesenberry & Weinberg 2014). However, despite a plethora of professional project management education websites, books and articles on the importance of soft skills training, very little research describes how to implement active learning in a formal college class to train students in soft skills (Cowie, 2003; Tynjälä, et al. 2009). This research presents specific, measurable, assignable, realistic, and time-related ("SMART") activities appropriate for an undergraduate project management class to improve students' emotional intelligence and soft skills.

3. CLASSROOM INTERVENTION

These interventions were applied in an undergraduate course on IT Project Management at a 4-year, regional senior campus linked to a Research One institution in the Southeast United States. The course is a required part of an Information Management & Systems ("IM&S") curriculum within the College of Arts & Sciences. Before taking this class, students learn skills in relational databases, technical presentation and communication, data warehousing, social informatics, and introductory programming. Of special note is the fact that almost half the students in the IM&S program earn a health informatics minor, 40% study a business administration minor and 10% receive other minors. The demographics of the IM&S students are more diverse than typical IT programs, being evenly split between men and women. They are often first-generation, non-traditional students with limited professional IT experience.

Originally, material in this class was taught in a standard lecture format with PowerPoint slides interspersed with audience discussion. The course schedule followed the book chapters in sequence, which closely parallel the PMBOK (Schwalbe, 2010). In addition to a group project and in-class quizzes, students completed a midterm and a final exam. Students reported difficulty with the midterm and final exam format due to the amount of material to recall. Students struggled with the group project because they did not practice with the material during class, and they had difficulty applying the concepts.

Additionally, group members sometimes expressed frustration with the group project due to personality conflicts that impeded productivity. Such conflicts are not uncommon in groups (Tuckman et al. 1977), and it can be argued that these are a part of the learning experience for students. However, more harmonious groups are much more likely to succeed, especially in short term projects (Richards, 2009; Matta et al 2011). Students enjoyed the in-class discussions but often appeared distracted or bored during lectures (e.g., browsing Facebook, completing other class homework, or texting).

To improve student outcomes, this class was redesigned based on principles from active learning pedagogy, as more fully described in the exercises below. First, the material was divided into four cohesive and related units to improve student memory by reducing cognitive load. These units were titled introduction and project selection, triple constraint, people, and finishing touches. Rather than a midterm and final, students completed four unit exams. These exams were not comprehensive, but they required students to apply concepts to new, unfamiliar problems. The group project remained the same. A graphic syllabus of the course is shown in Figure A.3. in the Appendix.

Class enrollment was limited to 24 students. It met twice per week for 75 minutes in an active learning classroom. The chairs and tables in this room are modular and moveable. A picture of the room is shown in Figure A.2. in the Appendix. The nature of the room encouraged movement, small group work and collaboration. The instructor had one year of previous experience teaching classes in active learning classrooms on campus. This experience provided a basis for the interventions described.

Five Stages of Team Development

The class as a whole was treated as one big project team, with the end goal to learn project management. Although students were eventually divided into teams of four for the group project, students were free to assemble and reassemble the room in any formation during class activities. Based on this premise, Tuckman's five-stage model of team development can be seen occurring throughout the semester. This model has five stages, which generally occur in sequence: forming, storming, norming,

performing and adjourning (Tuckman, B.W. & Jensen, M.A.C., 1977).
During forming, team members get to know each other but do very little productive work. In storming, "people test each other, and there is often conflict" (Schwalbe 2010, p. 385). After beginning to work together, the team builds norms and a common understanding in the "norming" stage. The actual project work is done during performing when the team focuses on the task at hand. Finally, during adjourning, the team breaks up. The following sections illustrate how these stages manifested throughout the class.

Icebreakers
On the first day of class, students were challenged to learn everyone's name. To help students learn names and to overcome their reticence on the first day of class, they completed a "People Bingo" activity towards the end of the class period. An example Bingo card is provided in Table A.2. in the Appendix. To complete the exercise, students were tasked with finding one person in class who fit in each cell (Peterson, 2015). Students became so engrossed with this exercise, that they did not notice the class period end for 15 minutes. The items in the bingo cells may be modified to match the class makeup as needed.

Throughout the semester, students were verbally quizzed on random classmates' names to check for recall. Recall was always close to 100%. Learning names is integral to team forming (Tuckman, 1977). It "humanizes learning, builds community, and positively impacts students' wellbeing" (O'Brien, Leiman & Duffy, 2014).

Class Rules for Discussion
On the first day of class, students completed a brief questionnaire on Socrative, an online quiz tool (similar to iClicker technology). The questionnaire asked about students' experience with discussion-based classes, what they considered an "ideal discussion," and what the rules for class discussions should be. Then, the class was divided into 4 or 5 ad hoc groups. Each group agreed on one or two rules for class discussions and wrote the rule on the board in their own words. The class then met as a whole to discuss the rules that everyone should follow during discussions. These rules are presented in Figure A.1. in the Appendix.

In this exercise, students often assume "everybody knows" what the rules mean, even though that is not necessarily true. To flesh out these assumptions, students were asked to describe concrete examples of following or not following the rules. For example, physically show us what "being attentive" looks like. This exercise helped to improve "storming" and begin the "norming" process for the group (Tuckman et al. 1977), and it was students' first of many experiences where they were introduced to the idea that not everyone thinks like they do. Students were challenged to confront assumptions and talk about their similarities and differences.

Creative Expression
Throughout the semester, student activities involved drawing or writing on the whiteboards distributed throughout the room. This practice became such a habit, that during the particularly difficult lesson on dependencies, one student brainstormed his personal mental map on the board next to his seat without any prompting. His diagram was so useful, that he was asked to explain it to the class. The ability to draw one's thinking "aloud" to others is exceptionally useful in IT teams, particularly on projects. The student's illustration is shown on Figure A.4. in the Appendix. Teaching a topic to someone else improves both participants' learning, and in many cases, is the best way to learn material in a meaningful way (Argyris, 1991).

Requirements Gathering Process
Gathering and interpreting useful requirements is tricky even for experienced analysts (Robertson & Robertson, 2013). To introduce students to this idea, students worked in pairs. Everyone was asked to imagine his or her perfect wedding or Super Bowl party. Each student interviewed his or her partner to gather the partner's requirements for the event and to write them down on a piece of paper. Students felt fairly confident about their lists. Then, to simulate a real project, students' lists were swapped with a pair across the room or at another table. Then, they were asked to plan the event described by the requirements, but many found they couldn't. They did not have enough information.

This exercise helped students understand why requirements need to be specific and measurable. Students learned how to interview a stakeholder, actively listen, and probe for better information. During the class discussion, students drafted questions they should have asked to clarify requirements. For example, most students wrote "food" without specifying what kind and how much. It also brought students closer together and improved their emotional intelligence, in that they began to realize that they need to explain what their communication means in clear and specific terms. This exercise laid the groundwork

for the norming process to transition into performing (Tuckman et al. 1977).
A second activity to teach students about EQ in project management was a story puzzle. Each student was given a random snippet on a slip of paper, where each snippet was part of a well-known fairy tale story with slight modifications to make it slightly less obvious. In this case, the story of Snow White was modified by deleting words such as "the magic mirror", "Snow White" and "dwarves". The class worked as a team to make sense of the storyline and to build a mental model of the final product. This exercise was harder than it seemed, because pieces were missing, as often happens on real projects. Even once students identified the story as Snow White, they did not put the events in the correct order. It was about 75% correct, which is good enough for the first prototype of most IT systems, particularly in agile environments with limited resources and tight time constraints (Ambler, 2003).

Cost Estimating
People are notoriously bad at estimating activity costs and durations, but they do slightly better when they work as a group (Schwalbe, 2010). Students worked together to estimate the cost to host their personal Super Bowl party. Despite the familiar theme of the task, students' estimates were excessive. They estimated it would cost between $32 and $180 per person to host a Super Bowl party. (In 2011, Americans spent on average $118 to host a Super Bowl party (Statista 2012).) Despite their gross overestimations, the act of working together in a small group to create cost estimates improved their understanding of the task. To complete the exercise, students had to listen and respond to peers and to research and support their contributions with facts.

Dealing with Stakeholders
Stakeholders can make or break a project (Schwalbe, 2010). Two class activities specifically focused on dealing with stakeholders. The first exercise taught students how to assess stakeholders' power and interest on a project. The class was divided into one of two roles: stakeholder or project team. Each stakeholder was given a job title and how he or she felt about the project (resistant, unaware, supportive, leading, or neutral). Stakeholders chose their level of interest and power based on their job title, while the project team designed a plan to assess the stakeholders. In this exercise, the project under development was to replace an existing electronic health record ("EHR") system in a hospital. The example cards given to students for this exercise are shown in Table A.3. in the Appendix. Stakeholders roleplayed their assigned jobs, while the project team was tasked with interviewing the stakeholders. Stakeholders' roles were kept secret from the project team, but stakeholders could talk amongst themselves. The project team then categorized the stakeholders into a power/interest grid based on their findings before the class debriefing.

A second stakeholder exercise focused even more directly on reading people's emotions. This exercise was loosely based off "The Dating Game" from the TV show "Whose Line Is It Anyway?". Half the class was assigned to the project team, while the other half observed. Each team member received a "secret identity." Each identity was a unique emotion-based role that described how the team member felt about the project. These roles are provided in Table A.4. in the Appendix. The project team then met to discuss the project's status. For this exercise, it was helpful to choose a charismatic, outspoken student to lead the meeting to prevent the exercise from stalling. After the meeting, the rest of the class tried to identify the emotions they observed.

Note that these exercises required a full class period to perform and debrief. "The debriefing is the most important part of the role-play" (Nickerson, 2007, p. 3). During debriefing, students solidify what they learned from the exercise by discussing what happened, what it means, and how they will use it in their careers. Roleplay can increase empathy and understanding, which are vital to increased EQ (Nickerson, 2007). Students found these activities interesting and engaging, which are key components of active learning.

Utility and Risk Management
Risk is a complicated concept. To help students assess their understanding of risk, they first rated their personal risk preference on a risk utility graph on the whiteboard (averse, neutral or seeking). Curiously, most students ranked themselves partway between seeking and neutral. This exercise prepared the class to discuss the differences between risk strategies. Students' risk strategy rankings are shown in Figure A.5. in the Appendix.

To test these risk preferences, students played a short game of "Deal or No Deal" using an Excel spreadsheet (Sloman, 2009). Most students quickly discovered that when money is involved (even pretend money), they are far more risk-averse than they initially thought, although one student switched to risk-seeking. All students agreed that their risk assessment would change, depending on the circumstances.

Regular Assessment

At the end of each class period, students completed a minute paper on Socrative (Stead, 2005). The minute paper asked students what they learned for the day and if they had any additional questions. The minute paper is a useful yet seldom-used tool to gauge whether students have learned the day's material, to encourage students to reflect on what they've learned, and to solicit questions that can be researched and discussed at the next session.

Adjourning

On the last day of class and to celebrate the end of the semester, we took a group photo of the class. Remarkably, students did not find it unusual and they did not need prompting to complete the exercise. Class adjourned on a positive note.

4. STUDENT LEARNING OUTCOMES

To gauge the effects of these interventions on student learning outcomes, at the end of the semester, students were asked to complete a brief survey on Survey Gizmo. Seventeen out of the 24 students completed the survey, or about 70% response rate. The survey was optional and anonymous and unrelated to students' final grades. Out of these respondents, 70% said it was the first class where they were encouraged to move furniture. The other 30% had taken another active learning class, which is unsurprising because the active learning classrooms had been in use across campus for at least two years.

Students were asked to identify what skills they feel confident they can do and to rank these skills by order of importance to their career. Students felt most confident about critical thinking and interpersonal skills (83.3%), followed by team building (77.8%), effective communication and organizational skills (66.7%), and leadership skills and project leadership (61.1%). Students then ranked the skills from most to least important as follows: (1) critical thinking, (2) interpersonal skills, (3) team building, and (4) effective communication.

Students were asked to compare this class to other classes on campus as to amount of material, retention of material, use of lecture or in-class activities, usefulness, and interest. Most students ranked the course above the mean in terms of more material, retention, in-class activities, usefulness, and interesting. As a control, students were asked "what is a critical path". Two-thirds of students correctly identified it as the longest path through the schedule, and one-third identified it as the shortest path. Even in industry, there is some debate on this issue (LePage, 2013).

As shown in Table A.1. in the Appendix, students reported that the classroom format and in-class activities were useful, engaging and improved their learning. It should be noted that when asked if the class should be taught in a "standard format" the students overwhelmingly agreed that the active format was better (56.3% either disagreed or strongly disagreed that a standard classroom would be better, while only 18.8% felt that a standard classroom would be better). Additionally, only 13.3% of the students felt that a lecture would have been a better way to learn the material, while 60% agreed that the active learning environment was better.

The students also noted significant learning of the soft skills that the intervention was designed to improve. One student commented, "I have learned more skills in this class than any other course I have taken during my tenure in college." Another student wrote "Be prepared to interact and learn in a different way." "Take full advantage of everything that the classroom has to offer."

Students noticed that they had to step up their game in this environment. The class format put the onus to learn on the students. As one student wrote, "This type of class puts the responsibility to learn a little more on the student. You must be engaged and willing to participate to get the full effect of this kind of class."

The intimate classroom arrangement improved students' learning and increased communication skills. Students felt more comfortable talking to and interacting with peers. As one student wrote, "Don't be nervous about public speaking, because by the time you're done with that class, you'll be comfortable to talk in front of your whole class." Plus, they got to know their classmates better. One student said that it "shares similarities to real world meeting rooms." It "made presentations and group work more fun and interactive." When asked what they would change about the room, the most frequent suggestions were nothing, to use round tables instead of rectangular ones, and to have a bigger room.

Students' most significant learning experiences included communicating with others, emotional intelligence, critical thinking, group discussions, hands on activities, drawing pictures to help understand, role playing games, and team work exercises. Students' least interesting or least useful learning experiences were not having group discussions every day and anything with math formulas. One student wrote "I cannot recall an experience during the semester which was not useful."

One student appreciated that "getting to put your individual ideas on the board and learning from each other made learning seem more fun and interesting, because every student had a different point of view on a specific subject." When students have serious fun, their brains are more engaged in the task. They are more likely to experience higher order thinking, to retain difficult concepts, and to make vital mental connections (Willis, 2006).

Considering the small sample size and the potential bias of self-reports, these results should be viewed as a qualitative proof of concept, in that students recognized the usefulness and importance of the active learning interventions. Although these activities worked in this class one semester, it is possible they may not work in all project management classes. Future studies could assess students' soft skills pre- and post-intervention of these activities with a more rigorous survey instrument and compare results across different classrooms to test their effects.

5. CONCLUSION

Project management is one of the fastest growing positions for IT/IS professionals. Employers "need students to understand problem solving, interviewing clients and developing solutions to problems involving technology" (Janicki, Cummings, & Kline, 2014, p. 66). This research presented an active learning method to increase students' soft skills and emotional intelligence in a project management classroom. Based on the evidence collected in the classroom, this approach engaged the students in the learning process and improved interpersonal skills.

Conveying tacit skills and emotional intelligence are not as straightforward as increasing standard skill sets, and we believe that the intervention presented in this paper can be applied to other classrooms to aid student learning. This research presented ways to incorporate these skills into the curriculum without sacrificing quality. As we improve the EQ of future project managers, we expect to see more IT projects succeed.

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Appendix

Table A.1. Survey Results

Rate your agreement with the following statements.	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
I would recommend this class be taught in a normal classroom in the future	6.3%	12.5%	25%	25%	31.3%
I learned more in the active classroom compared to my other classes	43.8%	18.8%	25%	0%	12.5%
Because of the furniture arrangement, I was forced to participate in class more	53.3%	20%	20%	6.7%	0%
The classroom kept me on my toes	37.5%	37.5%	18.8%	0%	6.3%
I would have preferred a more traditional lecture format to learn the material	13.3%	0%	26.7%	20%	40%
I felt that I came to class prepared	31.3%	43.8%	18.8%	6.3%	0%
After class, I found it useful to go back and review the materials we created together	18.8%	43.8%	18.8%	12.5%	6.3%
I will use the concepts and skills we learned in class in my future career	43.8%	37.5%	18.8%	0%	0%
The active learning classroom was fun	43.8%	43.8%	12.5%	0%	0%
I felt challenged by this class	31.3%	37.5%	12.5%	6.3%	12.5%
Every day was an adventure	31.3%	18.8%	37.5%	0%	12.5%
I would have understood the material better if we had had lectures every day	12.5%	18.8%	25%	18.8%	25%
Project managers must have emotional intelligence and soft skills to succeed	62.5%	31.3%	6.3%	0%	0%

Figure A.1. Discussion Rules

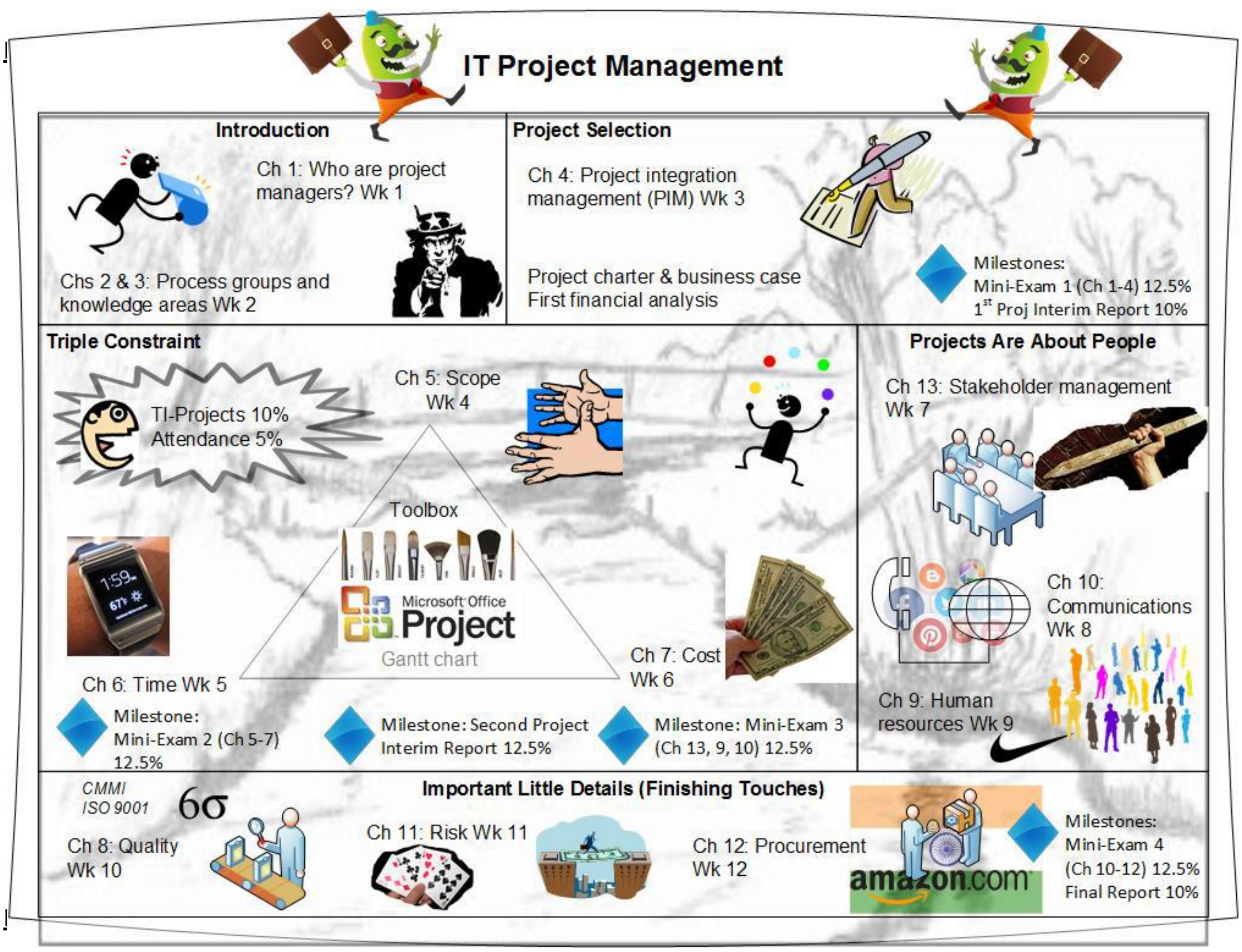
- Don’t talk while someone else is talking.
- Think before you speak.
- Everyone should participate.
- Respect everyone’s ideas.
- Be engaged in the discussion.
- Be attentive.

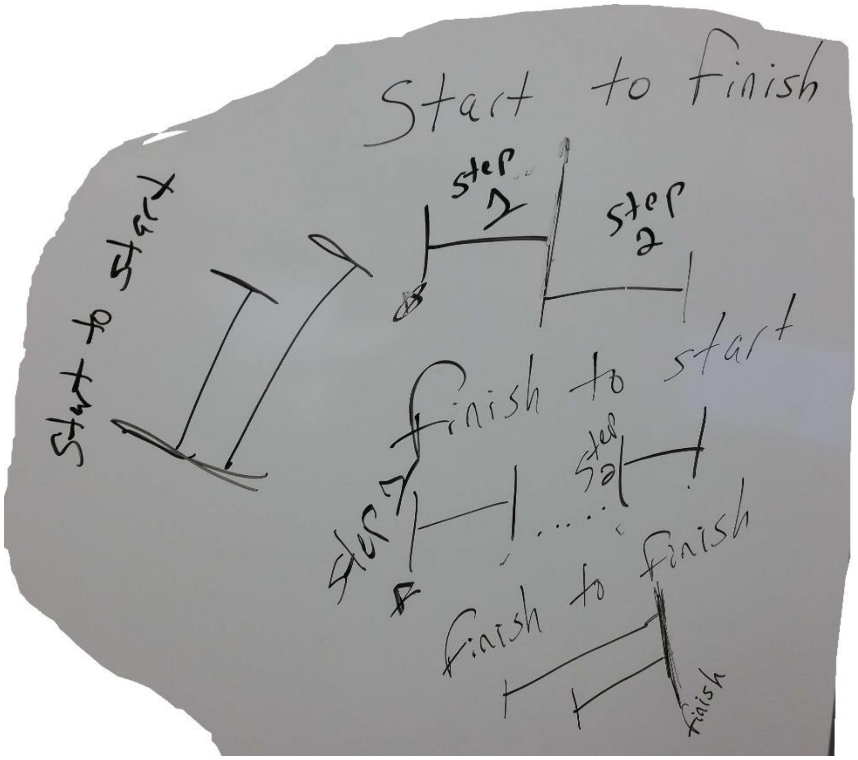
Table A.2. Icebreaker Bingo

Has a pet	Wears glasses or used to wear glasses	Wearing blue today	Has an iPhone or iPad	Wildcard
Pays for TV cable	Did an internship	Prefers Android	Prefers online classes	Works in an IT department
Owns a Roku or other TV on demand device	Graduating next fall semester	Something about me	Has lived on campus	Likes to clean house or organize messes
Wildcard	Taken an online class	Graduating this spring semester	Worked in retail	Does work “just-in-time” (not early)
Prefers in-person class	Attended community college	Wildcard	Shopped Black Friday sales	Works in a healthcare setting

Figure A.2. Active Learning Classroom

Figure A.3. Graphic Syllabus




Start to finish
step 1
step 2
Start to start
finish to start
step 1
step 2
finish to finish
finish

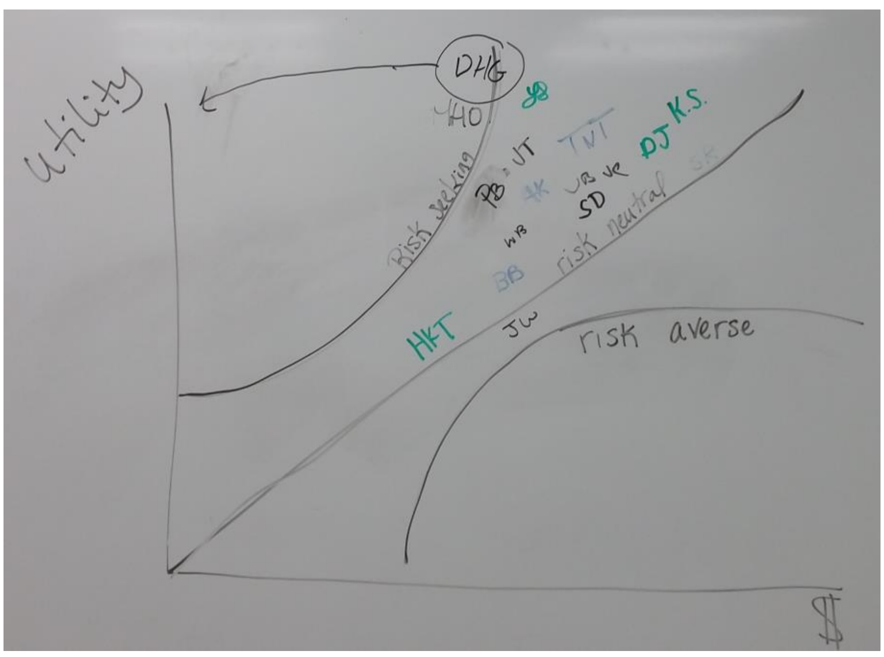

utility
DHG
Risk seeking
risk neutral
risk averse
$

Table A.3. Stakeholder Exercise to Build Power/Interest Grid

New Patient Interest: _________ Power: _________ Resistant	***New Physician*** Interest: _________ Power: _________ Unaware	***Hospital CIO*** Interest: _________ Power: _________ Supportive
Current EHR Vendor Interest: _________ Power: _________ Resistant	***IT Staff Person*** Interest: _________ Power: _________ Leading	***State Legislature*** Interest: _________ Power: _________ Unaware
New EHR Vendor Interest: _________ Power: _________ Leading	***Department Administrative Assistant*** Interest: _________ Power: _________ Resistant	***Head Shift Nurse*** Interest: _________ Power: _________ Neutral
Physician About to Retire Interest: _________ Power: _________ Neutral	***X-Ray Technician*** Interest: _________ Power: _________ Leading	***Billing Specialist*** Interest: _________ Power: _________ Neutral

Table A.4. Stakeholder Exercise Related to Emotional Intelligence

Ecstatic that project is ahead of schedule	Angry that project is behind schedule	Preoccupied with another project because the other project manager makes more demands on my time
Concerned that no one takes me seriously when I speak in meetings	Frustrated because too much work has left no time for family	Worried because kids are sick at home without a sitter
Happy, no matter what goes wrong - unflappable	Apathetic – I don't care what happens because nobody listens anyway	Scared I'll be fired any day because I feel like an imposter here
Sad about a death in the family	Sick with flu-like symptoms and I took lots of cold medicine	Confused about what I'm supposed to be doing on this project

Reboot: Revisiting Factors Influencing Female Selection of the CIS Major

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Abstract

A concern among many universities, this study reflects and continues research on the changing attitude and intent of selecting a Computer Information Systems major. Focusing on the gender gap for selection of major for women in this field, studies indicate instrumental beliefs and subjective norms can influence behavior and indicate how selection is influenced in undergraduate major selection. Experiential beliefs, overall image, job accessibility, and educational cost (workload) have been shown to influence academic path selection. Salient referents including family, friend, professors, and advisors have also been shown to indicate intent on selection of an academic major. The combination of these factors with respect to intent may be changing over time, and this study reconstructs survey questions and analyzes the difference in responses between the original research and this study. Comparison of student responses have indicated factors that females utilize to select undergraduate majors could be moving. All salient referents, personal image, genuine interest, overall attitudes toward the CIS major, and the intent of females to ultimately choose a CIS major showed significant differences between the studies. With these findings, this study discusses and recommends additional research to find what additional factors may be a work when selection of an undergraduate major by females is being completed.

Keywords: Information Systems, Gender, Theory of Reasoned Action, Subjective Norm, Behavioral Intention, Undergraduate Major, Career.

1. INTRODUCTION

Research models studying why female participation is lacking in choosing a Computer Information Systems major has long been an area of study for the academic community. Job availability, family influence, and genuine interest have, in the past, been proven to be significant when females choose an academic major (Ahuja, 2002; Banerjee et al., 2012; Kuechler, McLeod, & Simkin, 2009; Zhang, 2007). However, even though extensive study has been performed as to why females are not choosing the Computer Information System (CIS) major, many academic programs are still having difficulty attracting females to CIS programs (Nielsen, von Hellens, Pringle, & Greenhill, 1999). In 2007, Dr. Wei Zhang performed a study and developed a model to determine the factors influencing female participation in the CIS major. This study recreates Dr. Zhang's previous survey and compares the results to determine if significant factors in 2007 still hold true today. Although different methods and studies have been performed, results and methods have varied with varying outcomes (Ahuja, 2002; Banerjee et al., 2012; Randall, Reichgelt, & Price, 2003; Zhang, 2007). We feel the comparison between Dr. Zhang's 2007 study and our survey provide the best opportunity to help administrators of CIS departments better understand which factors may be changing, and help attract and retain more female students. For this study, Information Systems will include related fields of study including Computer and Management Information Systems.

As this study seeks to gather evidence about selection of a major by females, the overall gender landscape inside the greater IS community is changing. Factors such as social image, overall aptitude, and job related beliefs have been found to influence female participation in the IS major (Croasdell, McLeod, & Simkin, 2011; Zhang, 2007). Joined with subjective norms like advisors and professors, and experiential factors such as genuine interest can determine overall interest and intent to major in the IS field (Adya & Kaiser, 2005; Croasdell et al., 2011). With IS gender inequality prevalent within the business environment, the business community overall is concerned with creating and cultivating more opportunities for females globally (Ahuja, 2002). Some studies suggest barriers, including gender, have negative effects on retention in the IS filed where, historically, lower-level positions and pay are held by females (Igbaria, et al., 1990). As firms are competing for talent to find new ways to diversify workforce, technology, and product, influencing females to choose an IS major could help firms become more competitive and balance gender induced effects between colleges and the overall business community (Nielsen et al., 1999). The research question asks: Are factors influencing female selection of the IS major changing over time?

This study begins with a detailed review of previous studies determining selection of an IS major by undergraduate females. A discussion of the survey instrument, methodology and analysis of results follows this review. Concluding discussion with results of the study will cover if factors influencing female selection of an IS major are changing.

2. BACKGROUND

Many institutions and researchers try to determine what attitudes (job availability, social image, and interest) and subjective factors (family, professors, other students) influence how students determine a major (Croasdell et al., 2011; Kuechler et al., 2009; Zhang, 2007). Ahuja (2002) concluded the need to study this subject "because women drop out of computer career pipelines at several different points and the entire variance cannot be placed in one place." Many researchers have concluded the need for longitudinal studies to determine what the causal issues may be (Ahuja, 2002; Banerjee et al., 2012; Kuechler et al., 2009). The Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980) have provided the foundation of many frameworks developed within the research (Croasdell et al., 2011; Zhang, 2007). The framework used by Zhang (2007) (Appendix A, Figure 1) is broken down into job, image, cost, and experiential related beliefs, and subjective norms involving family, fellow students, advisors and professors.

Job Related Beliefs

Job availability across literature is studied extensively with respect to female major selection (Croasdell et al., 2011; Kuechler et al., 2009; Turner & Bowen, 1999; Zhang, 2007). The concerns about jobs after graduation significantly influence how women choose an undergraduate major (Croasdell et al., 2011; Zhang, 2007). Even as the job market has improved after the dot.com bubble, and the most recent economic downturn, institutions "cannot expect IS enrollments to self-heal as the IS job market recovers" (Zhang, 2007). Even with demand for workers of both genders in the IS field, all job-related beliefs are sometimes not considered a priority by women when determining an undergraduate major (Croasdell et al., 2011; Zhang, 2007; Brooks, 2014). In some literature, job availability is a significant factor in the job category and job availability strongly influences females in major selection (Zhang, 2007), while Kuechler et al. (2009) provides support that job related beliefs is the only major factor attributable to major selection. (Croasdell et al., 2011). Therefore, we hypothesize (see Appendix 2, Table 1):

Hypothesis 1a: There will be no significant difference between Job Availability Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 1b: There will be no significant difference between Job Security Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 1c: There will be no significant difference between Job Salary Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Image Related Beliefs
Literature has shown how social and personal image relate to why women select a major. Croasdell et al. (2011) describes social image as thinking "business people look up to or respect IS professionals", and personal image as a "fear that IS professional are "geeks" or "nerds". In keeping with this description, research has indicated more of a preference by women to focus on social image over personal image. On issues that would determine major selection, women have shown they are "influenced by the opinions of the person surrounding them" (Zhang, 2007) than that of a personal image belief. Croasdell et al., 2011 came to the same conclusions finding that female social image was more important than that of personal image stating "females feel that societal views are more important" in selecting a IS major. Findings by Kuechler et al. (2009) and Banerjee et al. (2012) supported the personal image belief that women do not necessarily see the IS filed as 'geeky' or 'nerdy'. Therefore, we hypothesize (see Appendix 2, Table 1):

Hypothesis 2a: There will not be a significant difference between Personal Image Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 2b: There will not be a significant difference between Social Image Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Cost Related Beliefs
Cost related beliefs, not to be confused with financial costs, are those which create more academic problems for participants in the major than those who choose another path (Zhang, 2007). Earlier research has determined that inclusion of instrumental beliefs, such as academic cost associated with aptitude (Lowe & Simons, 1997), the workload required for the major (Cohen & Hanno, 1993), and the overall difficulty in the courses and the chosen degree (Adams, Pryor, & Adams, 1994) can influence a student's choice of major and was therefore included in previous research. Female aptitude in computer usage, how much work the major may require, and the difficulty of the major and curriculum may be found to be not significant factors in costs associated with major determination (Croasdell et al., 2011; Varma, 2010; Zhang, 2007). Early studies have shown that overall cost related beliefs by women and "perceived difficulty of the IS curriculum or IS major, workload, and aptitude – were not statistically significant." Research following the Zhang (2007) study continue to support a logic that women who associate themselves with the IS major consider themselves to have the aptitude to succeed. But, as studies have progressed, an opinion about a IS degree by females continues to be seen as being too technical and more difficult (Kuechler et al., 2009). Studies also indicate that women who choose to not major in CIS considered themselves not very good at the major, or consider the workload to be excessive (Croasdell et al., 2011). Therefore, we hypothesize (see Appendix 2, Table 1):

Hypothesis 3a: There will be no significant difference between Difficulties of the Curriculum in undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 3b: There will be no significant difference between Difficulties of the Major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 3c: There will be no significant difference between in Workload in undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 3d: There will be no significant difference between in Aptitude toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Experimental Beliefs
As one of the overarching themes among literature, genuine interest by females in Information Systems is a determining factor in major selection (Cohen & Hanno, 1993; Croasdell et al., 2011; Downey, McGaughey, & Roach, 2011; Kuechler et al., 2009; Nielsen et al., 1999; Zhang, 2007). In recent studies, "interest in the major was by far the most important factor influencing one's attitude toward one's choice of major" (Downey et al., 2011; Nielsen et al., 1999). Interest in the subject to determine a choice of major was found to be statistically significant indicating females showed much less interest in IS overall (Zhang, 2007). Additionally, interest in a career choice can be formative very early in life. Some studies have indicated relationships between interest level and gender

stereotypes, early adolescent counseling, and family education level (Adya & Kaiser, 2005). Even though they show interest with technology in general, women have a genuine lack of interest in IS (Banerjee et al., 2012) and that "genuine interest" is a key determinant in the choice of a university major" (Croasdell et al., 2011). Therefore, we hypothesize (see Appendix 2, Table 1):

Hypothesis 4: There will not be a significant difference in Genuine Interest between undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Salient Referents/Subjective Norms
Previous research has indicated any choice of major or college curriculum could possibly be influenced by family, friends, peers, advisors and professors. Ayda et al. (2005) found, "career choice is directly influenced by role models, gender stereotypes…and that career role models primarily emerge from family-mothers, fathers, and siblings-and to a lesser degree, from among peers, teachers, and counselors." Females relied more on subjective norms, with family playing a significant role on female major selection (Croasdell et al., 2011). Gender stereotypes by professors (Zhang, 2007) and overall lack of female professors in the IS field (Croasdell et al., 2011) continue to indicate a lack of influence from professors and advisors. Therefore, we hypothesize (see Appendix 2, Table 1):

Hypothesis 5a: There will not be a significant difference between Family Influence toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 5b: There will not be a significant difference between Fellow Student Influence toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.

Hypothesis 5c: There will not be a significant difference between Advisor Influence toward the CIS major in undergraduate female students in 2007 when compared to undergraduate

Hypothesis 5d: There will not be a significant difference between a Professor's Influences toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.

3. RESEARCH METHOD

Survey Design
For this study, a replication of a survey questions, based on previous research, was prepared and submitted to the Institutional Review Board (IRB) and included questions derived from Zhang's (2007) study. The survey was administered to students at a medium sized university in the southeast United States. Approval was given to submit the survey to undergraduate students enrolled in an introductory Information Systems classes during the Spring 2015 semester. Some survey items were identical to those used in Zhang's (2007) research study and was given to business students who may or may not have declared a business major. Additional questions were added to collect demographic data from participants, such as gender. Because of the sensitivity of demographic data, unique and random identification codes were used to protect participant's anonymity when accessing the survey.

Participation was voluntary and the survey was administered online through surveymonkey.com. Survey items were rated on a seven-point scale from strongly disagree to strongly agree. The results were analyzed to determine if significant differences exist between studies. A list of the survey items measuring instrumental beliefs and salient referents can be found in Appendix A and include: job availability, job security, job salary, personal image, social image, difficulty of the major, difficulty of the curriculum, workload, aptitude, genuine interest, family, other students, professors, and advisors.

Participants
To test the survey and operationalize the thesis question, participants were recruited from a required undergraduate introductory IS course taken by all business majors at a medium sized university in the Southeast United States. The course is typically taken by students prior to COB admission and official major declaration. All students enrolled in the introductory IS course were invited to participate on a voluntary basis, but only female responses were used for analysis. Extra credit was offered as an incentive for participation.

A total of 440 students were invited to participate in the survey. A total of 293 (or 67.0 %) students voluntarily participated in the survey which included 118 (or 41.3%) female students. The participation level reached expectations and provided sufficient responses to perform an analysis of the results. A breakdown of the gender participation results is shown in Appendix C, Table 2.

4. ANALYSIS & RESULTS

Analysis and Results

To determine the differences between the two studies, T-tests were performed to analyze the sample means and standard deviations of the current survey, and the reported results of Zhang's (2007) survey. Table 3 in Appendix D contains the results of the t-test analysis between the different factors Dr. Zhang had determined from his TRA methodology.

Results of the t-test comparison of the surveys would indicate that there is not a significant difference between job related beliefs among females. All job-related constructs of job availability (JA: $t= -0.65$, $p= 0.52$), job security (JSE: $t= -0.62$, $p= 0.54$), and job salary (JSA: $t= -0.51$, $p= 0.61$) indicate there is no significance between the two studies.

Cost related beliefs were not statistically different across surveys. In the four categorized factors, females in both studies were statistically the same when it came to overall difficulty concern of the major (DIFM: $t= -0.82$, $p= 0.41$), difficulty of curriculum (DIFC: $t= -0.06$, $p= 0.96$), overall workload (W: $t= 0.00$, $p= 1.00$), and aptitude (APT: $t= 1.32$, $p= 0.19$).

With image related beliefs, there are some discrepancies between the studies. My analysis shows a significant difference between the personal image factor (PI: $t= 2.87$, $p < 0.01$) and the finding of Zhang's 2007 study. The social image factor (SI: $t= -0.84$, $p= 0.40$) results found no significant difference between the two studies.

Experimental beliefs, notably the student's genuine interest in the IS major and area of study, was found to be significantly different. Female students responded to having a substantially lesser amount of interest in the IS field as compared to the previous study (INT: $t= 2.36$, $p < 0.05$).

Attitude and interest were found to be significant different in how women choose the IS major. Attitudes were significantly different to the prior study (A: 3.91, $p < 0.01$), as well as intentions to choose a IS major (I: $t= 6.13$, $p < 0.01$).

The results indicate that the salient referents and subjecting norms for the IS major are significantly different from the previous study. The results indicate females attending the mandatory CIS introductory class at disagreed that family (REF1: $t= 3.38$, $p < 0.01$), students (REF3: $t= 3.87$, $p < 0.01$), advisors (REF4: $t= 5.45$, $p < 0.01$), and professors (REF5: $t= 3.76$, $p < 0.01$) played a role in a determination of selecting a IS major.

The results of the hypotheses can be seen in Appendix E, Table 4.

5. DISCUSSION & CONCLUSION

Discussion

There were considerable differences between the studies overall. Zhang's (2007) study found that females were statistically influenced by family, professors, the overall difficulty of the curriculum, job availability, and genuine interest. In this study, some factors remained constant, such as influences of job availability and difficulty of the curriculum. However, there were differences in general interest and subjective norms that need to be addressed and further studied to better understand why women are leaving the CIS major.

Overall, the results of the analysis seem to indicate job related factors is consistent over time. Scores from both studies indicate females in both time periods believe jobs would be available, pay well, and have good security in the IS field. Zhang's (2007) study provides evidence to suggest only job availability influenced females when choosing a IS major. This study supports Zhang's (2007) findings. Job availability can be viewed as a major selection criteria considering the recovering US economy from the 2008 recession, and the availability of jobs across all sectors of the economy.

There was a significant difference for one image related belief between the studies. Personal image showed a significant difference. Women in Zhang's (2007) study were more concerned with being viewed as geeky or nerdy when associated with an IS major. Smartphones were introduced in the mid 1990's, entered mainstream usage in 2001, and attained widespread popularity in 2007 with the introduction of Apple's IPhone (McCarty, 2011); around the same time Zhang was initiating research and after the original study (Sarwar & Soomro, 2013). Since then, technology has integrated itself more than ever into the everyday lives of students (Sarwar & Soomro, 2013). The finding of the current research study could support the belief that increased usage of technology has reduced the geeky or nerdy image associated with the IS major. The model adopted by Zhang (2007) which included the personal image factor may need to be modified to reflect the changing perceptions included in Zhang's (2007) TRA model. The removal of this factor may help simplify the model and facilitate the addition of new constructs used to measure women's intentions to major in IS. The social image construct remained consistent with the previous study and evidence suggest female students felt the IS major was a respectable career choice.

Female perceptions associated with the overall cost of an IS major did not significantly change related to: difficulty of the major and curriculum, workload, and aptitude. Zhang's (2007) results indicated that difficulty of the curriculum was a significant factor in determining females' attitude toward selection of a IS major. The current studies research would support his conclusions, and support earlier literature that indicated women find the IS major a technical and more difficult major than available alternatives (Croasdell et al., 2011). All factors involved in the cost construct were remarkably similar with the prior study, except for the aptitude factor. The questions, "I find myself good at CIS courses," and "I have the aptitude required for a CIS concentration' both scored lower compared to the previous findings. Although not statistically significant, females' aptitude (APT: $t= 1.32$, $p < 0.20$) about the major fell from the previous study but held as a neutral response (A: Mean =3.91). This could be an indication of an overall lack of knowledge about the IS major. Future research studies should be performed to investigate whether or not current efforts to educate students about the CIS major is having the desired effect.

The experimental factor of genuine interest along with the subjective norms of family, other students, professors, and advisors was found to be significantly different than the previous study. Previously, Zhang (2007) found genuine interest, along with the subjective norms of family and professor influence, to be a significant factor in selecting an IS major. This study has findings supporting genuine interest as being a reason females select a IS major, but the results show that fewer females interested in the IS major. Additionally, this study has findings supporting that subjective norms are less of a factor for women at as this small southern university then those in the previous study. The mean response level from all subjective factors, along with the interest factor, were below those of Zhang's (2007) study. The lack of interest could be a result of family influence, education, or gender stereotypes in earlier formative years as recommended by earlier studies (Adya & Kaiser, 2005). With a diminishing lack of interest by females in the IS major, and a decrease in influence from family and professors, additional study is needed to determine if IS departments would benefit more from tangible relationships with elementary and high school establishments.

Conclusion

In conclusion, the results would indicate that factors affecting a female's intention to choose an IS major have at least moved, if not changed, over time. The factors proven to not be a significant in a female's choice of major in Zhang's (2007) earlier study remained consistent. However, all significant factors, except for a woman's perception of the difficulty of the IS curriculum and job availability, differed from the previous study. In the Theory of Reasoned Action model used by Zhang (2007), most constructs are used to develop an attitude toward the IS major, and when combined with subjective norm, develop an overall intention to choose a CIS major. As can be seen in Appendix F, Table 5, and reported earlier, both overall intent and attitude toward the CIS major by females in my study were significantly lower. These results would indicate that the factors explaining the lack of women majoring in Information Systems could be changing over time.

Across the many factors identified in the earlier study, mean response rates declined among females. This lead to over an overall decrease in both attitude and intent to major in IS. Other studies should be performed to determine if the limitations of this study, such as geographic location or homogeneity of the student sample, altered this study's results. Results of this study indicate additional research should be performed to determine if the overall model and factors are unique to the IS major, or if these factors apply to alternative majors as well. Because previous literature has supported interest in the IS major to be a significant reason women choose to major in the field (Adya & Kaiser, 2005; Banerjee et al., 2012; Downey et al., 2011; Kuechler et al., 2009; Zhang, 2007), future research should be performed to determine what factors influence interest in the IS major. Additional studies could also be performed to determine if interest in the IS field is lost prior to arrival at post-secondary institutions.

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Editor's Note:

This paper was selected for inclusion in the journal as a EDSIGCon 2016 Distinguished Paper. The acceptance rate is typically 7% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2016.

Appendix A

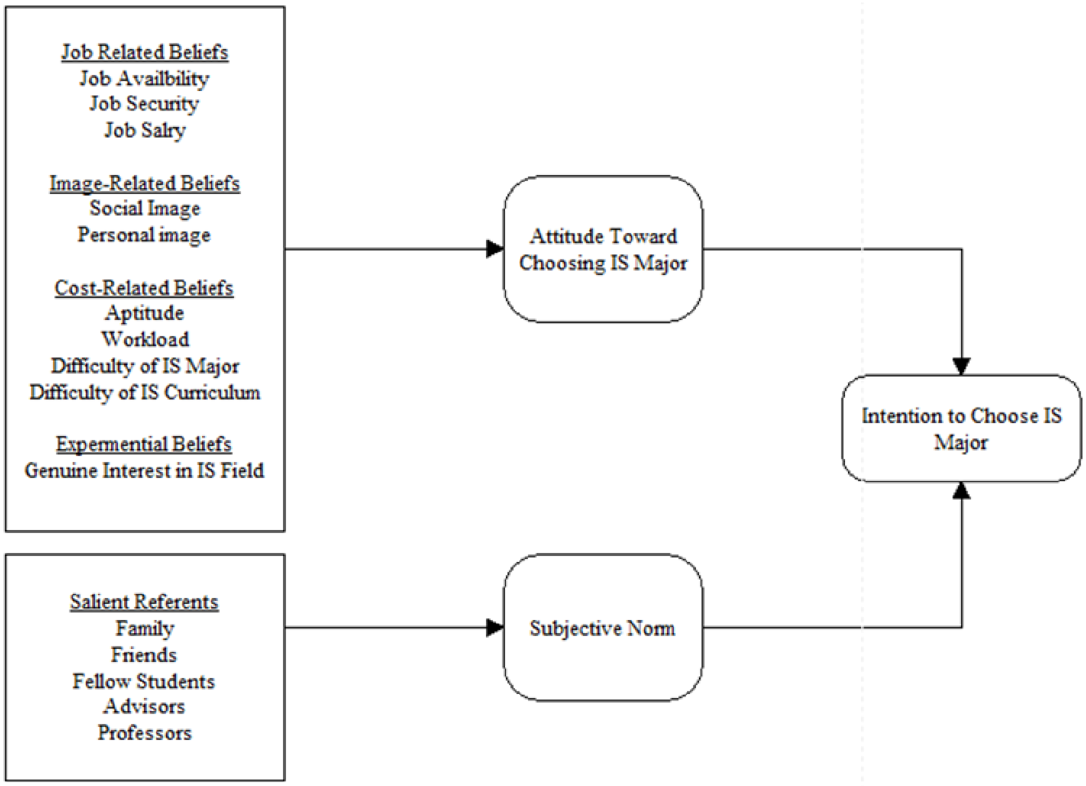

Figure 1: The TRA Framework

Source: Zhang, 2007

Appendix B

Table 1: Hypotheses Summary Table

Hypotheses Summay Table — *Hypotheses Test Results*

Name	Symbol	Text	Name	Symbol	Results
H1a	JA	There will be no significant difference between Job Availability Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H1a	JA	Supported
H1b	JSE	There will be no significant difference between Job Security Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H1b	JSE	Supported
H1c	JSA	There will be no significant difference between Job Salary Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H1c	JSA	Supported
H2a	PI	There will not be a significant difference between Personal Image Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H2a	PI	Not Supported
H2b	SI	There will not be a significant difference between Social Image Beliefs between undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H2b	SI	Supported
H3a	DIFC	There will be no significant difference between Difficulties of the Curriculum in undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H3a	DIFC	Supported
H3b	DIFM	There will be no significant difference between Difficulties of the Major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H3b	DIFM	Supported
H3c	W	There will be no significant difference between in Workload in undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H3c	W	Supported
H3d	APT	There will be no significant difference between in Aptitude toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H3d	APT	Supported
H4	INT	There will not be a significant difference in Genuine Interest between undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H4	INT	Supported
H5a	REF1	There will not be a significant difference between Family Influence toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H5a	REF1	Not Supported
H5b	REF3	There will not be a significant difference between Fellow Student Influence toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H5b	REF3	Not Supported
H5c	REF4	There will not be a significant difference between Advisor Influence toward the CIS major in undergraduate female students in 2007 when compared to undergraduate	H5c	REF4	Not Supported
H5d	REF5	There will not be a significant difference between a Professor's Influences toward the CIS major in undergraduate female students in 2007 when compared to undergraduate female students in 2015.	H5d	REF5	Not Supported

INT = Genuine Interest; REF1 = Family subjective norm; REF3 = Fellow Students subjective norm; REF4 = Advisor subjective norm; REF5 = Professor subjective norm; JA = Job Availability; JSE = Job Security; JSA = job salary; PI = Personal Image; SI = Social Image; DIFC = Difficulty of CIS Curriculum; DIFM = Difficulty of CIS Major; W= Workload

Appendix C

Table 2: Survey Respondents by Gender

Gender	Male	Female
# of Respondents	167	118
Percentage of Total	58.50%	41.30%

Appendix D

Table 3: T-test 2014 Survey Results vs. 2007 Survey Results

	2007 Results		2014 Results		Difference		
Factor	Mean1	SDev1	Mean2	SDev2	Mean Diff	t-Stat	Sig
JA	4.53	5.01	4.86	1.40	0.33	-0.65	0.517
JSE	4.56	4.77	4.86	1.36	0.30	-0.62	0.538
JSA	4.49	4.69	4.73	1.28	0.24	-0.51	0.610
PI	3.60	3.30	2.59	1.24	-1.01	2.87	0.005*
SI	4.16	4.41	4.52	1.01	0.36	-0.84	0.404
DIFC	4.69	5.02	4.72	1.13	0.03	-0.06	0.956
DIFM	3.94	4.31	4.30	1.37	0.36	-0.82	0.412
W	4.53	4.73	4.53	1.26	0.00	0.00	0.998
APT	4.46	4.10	3.91	1.28	-0.55	1.32	0.190
INT	4.72	4.16	3.69	1.50	-1.03	2.36	0.020*
REF1	3.23	2.96	2.11	1.33	-1.12	3.38	0.001*
REF3	3.58	3.00	2.25	1.46	-1.33	3.87	0.000*
REF4	3.77	3.15	1.98	1.09	-1.79	5.45	0.000*
REF5	3.82	3.21	2.44	1.53	-1.38	3.76	0.000*
A	4.11	3.80	2.52	1.46	-1.59	3.91	0.000*
I	3.72	3.05	1.73	1.15	-1.99	6.13	0.000*

2007 Results from (Zhang, 2007)   N(2007) = 49; N(2014) = 118

* denotes significance

INT = Genuine Interest; A = Attitude toward choosing CIS major; REF1 = Family subjective norm; REF3 = Fellow Students subjective norm; REF4 = Advisor subjective norm; REF5 = Professor subjective norm; JA = Job Availability; JSE = Job Security; JSA = job salary; PI = Personal Image; SI = Social Image; DIFC = Difficulty of CIS Curriculum; DIFM = Difficulty of CIS Major; W= Workload; I = Intention to Choose a CIS Major

Appendix E

Table 4: Hypotheses Test Results

Hypotheses Test Results

Name	Symbol	Results
H1a	JA	Supported
H1b	JSE	Supported
H1c	JSA	Supported
H2a	PI	Not Supported
H2b	SI	Supported
H3a	DIFC	Supported
H3b	DIFM	Supported
H3c	W	Supported
H3d	APT	Supported
H4	INT	Supported
H5a	REF1	Not Supported
H5b	REF3	Not Supported
H5c	REF4	Not Supported
H5d	REF5	Not Supported

INT = Genuine Interest; REF1 = Family subjective norm; REF3 = Fellow Students subjective norm; REF4 = Advisor subjective norm; REF5 = Professor subjective norm; JA = Job Availability; JSE = Job Security; JSA = job salary; PI = Personal Image; SI = Social Image; DIFC = Difficulty of CIS Curriculum; DIFM = Difficulty of CIS Major; W= Workload

Appendix F

Table 5: T-test results 2007 to 2014 for Attitude and Intent

	2007 Results		2014 Results		Difference		
Factor	Mean1	SDev1	Mean2	SDev2	Mean Diff	t-Stat	Sig
A	4.11	3.80	2.52	1.46	-1.59	3.91	0.000*
I	3.72	3.05	1.73	1.15	-1.99	6.13	0.000*

2007 Results from (Zhang, 2007) N(2007) = 49; N(2014) = 118
* denotes significance
A = Attitude toward choosing CIS major; I = Intention to Choose a CIS Major

Appendix G

The following questions were asked and responses were given using a seven-point Likert scale with response categories from Strongly Disagree to Strongly Agree. Strongly Disagree was given a rating of 1 and Strongly Agree was given a rating of 7. Each response was equally weighted.

Intention to Choose CIS as Major	
I1	I intend to choose CIS as a major
I2	It is likely that I will choose CIS as a major
Attitude toward CIS major	
A1	Choosing a CIS major seems like a good idea to me
A2	It will be wise for me to choose CIS as a major
Salient Referents	
REF1	My family wants me to choose CIS as a major
REF3	Other students recommended a CIS major to me
REF4	My advisor recommended a CIS major to me
REF5	My professors think that I should make CIS my major
Job Availability	
JA1	If I choose a CIS major, there will be jobs available for me when I graduate
JA2	If I choose a CIS major, there will be plenty of job opportunities for me when I graduate
Job Security	
JSE1	If I choose a CIS major, there will always be a great market demand for people like me
JSE2	If I graduate with a CIS major, my job security will be high
Job Availability	
JSA1	I can get a high paying job if I graduate with CIS as my major
JSA2	My starting salary will be satisfying if I graduate with CIS as my major
Personal Image	
PI1	Choosing a CIS major would make me look like a computer geek
PI2	CIS professionals are nerds
Social Image	
SI1	Businessmen look up to CIS professionals
SI2	If I choose CIS as my major, I would have a respectable career
SI3	The business world treats CIS professionals with great respect
Difficulty of CIS Curriculum	
DIFC1	To me, CIS courses are intensive
DIFC2	I think CIS courses are challenging
DIFC3	I think CIS courses are demanding
Difficulty of CIS Major	
DIFM1	A CIS concentration would be difficult for me
DIFM2	If I choose CIS as my major, it will take a long time for me to complete it
Workload	
W1	If I choose CIS as my major, I will have to spend a lot of time studying for it
W2	If I choose CIS as my major, it will take a long time for me to complete it
Aptitude	
APT1	I find myself good at CIS courses
APT2	I have the aptitude required for a CIS major
Genuine Interest in CIS major	
INT1	I like CIS
INT2	I find computers and information technologies interesting
INT3	I have a true interest in the CIS subject

Parental Perceptions and Recommendations of Computing Majors: A Technology Acceptance Model Approach

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Abstract

Currently, there are more technology related jobs then there are graduates in supply. The need to understand user acceptance of computing degrees is the first step in increasing enrollment in computing fields. Additionally, valid measurement scales for predicting user acceptance of Information Technology degree programs are required. The majority of existing research regarding methods for increasing enrollment focus on subjective measures that are often invalid or invalidated. This research study adapts a well-known, validated and established user acceptance of information technology model (TAM) developed by Davis in 1989. The TAM model was adapted to understand factors for the acceptance of information technology and was based on the long standing Theory of Reasoned Action from behavioral psychology. This work adapts TAM to explore factors that influence parents' decision to recommend Information Technology as a Major to their children. Since parents have a high degree of influence over the major selection of their children, determining factors for recommending IT as a major can assist IT programs in improved marketing to increase enrollment. In this work, we hypothesize that perceived usefulness (PU) and perceived ease of use (PEoU) will impact a parent's likelihood of recommending IT as a major to their children. Results revealed parent's perception of the perceived usefulness of IT (PU) affected their willingness to recommend IT as a major to their children; conversely, parents were not concerned with the ease of use of IT (PEoU). Implications include improved marketing of IT programs to parents by focusing on the usefulness of IT as a discipline.

Keywords: Technology Acceptance Model, Computer Science, Information Technology, Enrollment

1. INTRODUCTION

Within the last decade there has been improbable technology development and advancement; specifically in the fields of mobile computing (Chung, Chen, & Kuo, 2015; Iqbal & Bhatti, 2015; Shaikh & Karjaluoto, 2015; Turban, King, Lee, Liang, & Turban, 2015). Today, technology is part of almost every organization. As such, worldwide there is surging demand for computing professionals in both the private and the public employment sectors. However, there is not enough supply of computing professionals to meet the current demands. Additionally, there is a deficiency in student enrollment into computing degrees which is also compounding the need for computing professionals (Bullen, 2007; Wong, 2015a). Researchers Granger, Dick, Luftman, Slyke and Watson (2007) believe that there is a negative image about the computing fields that is often portrayed by students, parents, and advisors. Finally, Wong (2015a) suggests that students' perceptions of the computing fields are ill-informed and future research is needed.

Considering that parents are one of the main influences on a student's career path and college major, it is important to understand parents' perceptions and acceptance of computing in order for researchers, educators, and organizations try to augment the supply of computing professionals. As such, it is important to find out what parents believe about computing fields such as information technology. It is also important to understand parents' acceptance of computing fields as their beliefs and acceptance may have a major impact on students' decision regarding majoring in a computing discipline. Understanding parent's beliefs and acceptance of computing disciplines would further aid in recruiting students into computing disciplines.

There are several ways to assess people's beliefs and acceptance of technology. However, the Technology Acceptance Model (TAM) is one of the most valid and accepted ways to assess the acceptance of technology. Despite the widespread use of the TAM in practice, there has not been an adaptation of the model into the context of computing disciplines. This study seeks to further adapt the TAM constructs into understanding parental acceptance towards higher education computing degrees and career opportunities. Specifically, we aim to uncover factors that influence a parent's intention to recommend IT as a major to their children. In this work, we hypothesize that perceived usefulness (PU) and perceived ease of use (PEoU) will impact a parent's likelihood of recommending it as a major to their children. Results revealed parent's perception of the perceived usefulness of it (PU) affected their willingness to recommend it as a major to their children; conversely, parents were not concerned with the ease of use of it (PEoU). Implications include improved marketing of it programs to parents by focusing on the usefulness of it as a discipline.

This work has practical implications for higher education institutions, faculty, and computing degree programs by uncovering factors that can help assist with improving marketing/recruiting efforts to increase enrollment within computing disciplines. The remainder of this paper is structured as follows: background/review of the literature, the methodology, results, and conclusion.

2. BACKGROUND

Computing Opportunities and Need for Increase Enrollments

Information technology is a broad field that deals with the design, development, analysis, implementation and management of information and technology. The information technology field is one of the most dynamic fields of study that is responding to the upsurge of affordable technology as well as the explosion of free or inexpensive data through the internet. Currently, the building of a new industrial paradigm around the Internet of Things (IoT) calls for information technology managers and professionals to support new growth in new ways, which will form the core of Industry 4.0. As such, information technology worldwide has become a primary driver of economic development and a tool for more effective communication within and across national borders. For example, China's Internet Plus plan will "integrate mobile Internet, cloud computing big data, and the Internet of Things with modern manufacturing, to encourage the healthy development of e-commerce, industrial networks, and Internet banking, and to get Internet-based companies to increase their presence in the international market" (China Daily, 2015).

Almost every business is affected by technology. Technological advances such as the internet have significantly influenced the way businesses function and communicate. Worldwide, information technology has become a primary driver of economic development and a tool for more effective communication within and across national borders. As information technology continues to provide new possibilities and opportunities for businesses globally, the need for information technology related professionals also grows.

Job growth in the information-technology fields is expected to be far stronger than average for the foreseeable future. Specifically, the U.S. News and World Report's Best Jobs Report (2016) lists several information technology related positions within the top 100 best jobs. They expect 50,900 new information technology manager positions by the year 2022. Additionally, a recent study by the

McKinsey Global Institute projects a need for more than 1.5 million more managers and information technology analysts with both analytical and technical skills (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh, and Byers, 2011).

The American Computing Association's Career News (2016) reports "In just a few years, there will be 1.8 million jobs unfilled in our nation because the U.S. doesn't have enough individuals trained with the necessary technical skills, including the ability to program, to fill them." Furthermore, Moore (2016) states that "The United States faces a global competitiveness crisis that, if not addressed, will put our nation at a strategic disadvantage for decades to come. In just a few years, there will be 1.8 million jobs unfilled in our nation because we don't have enough individuals trained with the necessary technical skills to fill them."

An applied data mining research study conducted by Wimmer, Powell, Kilgus and Powell (2015) using Bureau of Labor Statistics (bls.gov) to determine which skills will be most in demand in the next decade can assist higher education in designing relevant curriculum. Their website, BLS.gov, provides information about occupations, including growth rates, median salaries, and job descriptions. Results reveal that information technology terms are among the top 50 terms used in job descriptions for the top-growing jobs, as defined by number of new positions projected.

Finally, information technology is consistently ranked as a career field in high demand. A CNN Money article titled "5 jobs with the biggest pay hikes" reported that pay raise rates for IT workers outpaced all other professions. It was also reported that "unemployment among IT workers is among the lowest in the nation" (Christies, 2013).

Why the large amount of projected computing jobs?
There are several reasons as to why there is a large amount of projected computing jobs. Two of the most obvious reasons are the mobile computing market and the Internet of Things (China Daily, 2015; Chung et al., 2015; Iqbal & Bhatti, 2015; Shaikh & Karjaluoto, 2015; Turban, et al., 2015).

In previous years, there was an increase in demand for web developers. However, that has shifted to mobile application developers as mobile phones have seamlessly integrated into everyone's daily lives. Businesses want native iOS apps for the iPhone and iPad, or several other Google Android-based apps for other cell phone manufacturers. Businesses need to connect to their customer to increase or maintain sales. As such, developing a mobile app for businesses to connect to their customers is essential. Hence, the increase in computing jobs.

Additionally, the Internet of Things has manufacturers embedding computers into appliances like refrigerators, ovens, water heaters, and daily products. These embedded computers send data across the Internet, and this data is stored in databases. The data creates a demand for database administrators, data scientists and software developers. Furthermore, when things go wrong with the embedded computers, people will need technical support. As such there is an increase in demand for people with advanced computing skills.

Technology Acceptance Model
There are several studies have proposed frameworks to identify and investigate the determinants of technology acceptance. Specifically, Fishbein and Ajzen (1975) developed the theory of reasoned action (TRA) model and Ajzen (1985) later developed the theory of planned behavior (TAB) model (Chen, Gillenson & Sherrell, 2002; Prieto, Miguelanez, & Penalvo, 2014). These two models provided the foundation for Davis, Bagozzi, and Warshaw (1989) to develop the Technology Acceptance Model (TAM). The TAM hypothesizes perceived ease of use (PEU) and perceived usefulness (PU) influence a person's acceptance of a new technology (Davis, 1989).

Originally, TAM was developed for determining user acceptance towards a computer system. However, over the years, TAM has been validated and widely utilized, adapted or extended within a variety of different contexts (Osswald, Wurhofer, Trosterer, Beck, & Tscheligi, 2012; Wong, 2015b). For example, TAM was extended for predicting information technology usage in the car (Osswald et. al., 2015), measuring the mobile acceptance among teacher (Prieto et al., 2014), understanding, analyzing and evaluating the acceptance of eLearning systems from the perspective of students in Ireland and Vietnam (Tri Tran & Glowatz, 2014), examining faculty use of learning management systems in higher education institutions (Fathema, Shannon & Ross, 2015) understanding cross cultural context for online shopping adoption (Ashraf, Thongpapanl, & Aul; 2014). As such, the TAM has consistently gained theoretical and empirical validity for predicting technology acceptance of users and decision makers (Ajzen 1991). Today, the TAM is one of the most prominent models for information technology acceptance research (Venkatesh et al. 2003; Wirtz & Göttel, 2016).

3. METHODOLOGY

The research method was based on adapting the technology acceptance model to determine parents' perceptions of perceived usefulness and perceived ease of use and whether their perceptions affected their views on recommending IT as a major for their children. While TAM focuses on actual system use as the independent variable, this work focuses on the likelihood of recommending Information Technology as a major Parents have a high degree of influence on a child's major selection; therefore, understanding factors for parents recommending IT as a major can help to market IT programs. The survey had 14 questions, 6 measuring PU, 6 measuring PEoU, and 2 measuring behavioral intention, willingness to recommend IT as a major. Appendix A lists the survey questions which were adapted from (Davis, 1989) changing "Chart Master" to "Information Technology" and adding "For my Child" to measure parent's perceptions of IT as a major toward their children. The survey was collected by paid respondents online and administered using the Qualtrics survey platform. All respondents were required to be parents in order to proceed with the survey.

Several demographic factors were collected on the data sample. Specifically, there were 50 participants with a median age of 35-44 years. A total of 83% were white, 9% black, 4% Asian, 2% American Indian/Native Alaskan, and 2% were other. Additionally, 72% of the participants were male. Education levels varied with 53% having a 4 year degree, 14% a 2 year degree, 11% a professional degree, 11% some college, 9% high school, and 2% less than a high school education.

Most of the participants worked in business and finance (31%), computing and IT (26%), or were listed as other (26%), followed by health and medical (7%), engineering (6%), and homemaker (4%). 64% of respondents had taking a computing course. Most lived in a suburban area (53%), followed by urban (31%), then rural (16%). The median household income was $50,000 to $59,000. Figure 1 shows the distribution of the median household income.

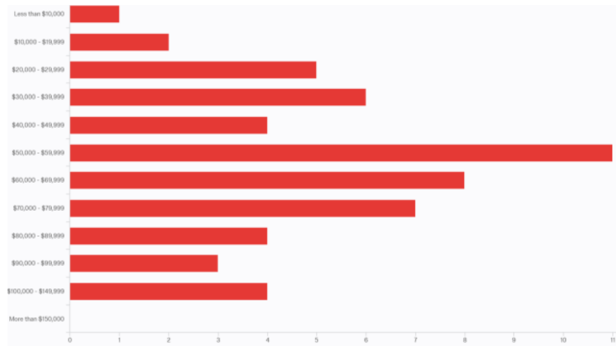

Figure 1 – Median Household Income

The research model is illustrated in Figure 2. From Figure 2, we generate 2 hypotheses:

- H1: Perceived Usefulness positively affects Intent to Recommend IT as a Major
- H2: Perceived Ease of Use positively affects Intent to Recommend IT as a Major.

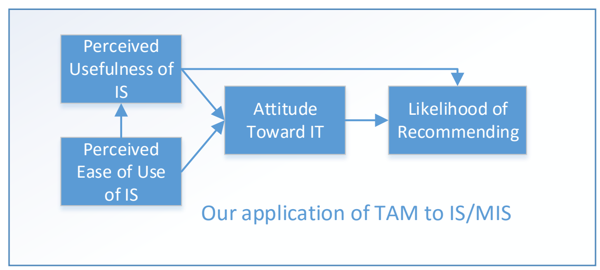

Figure 2 – Research Model Based on TAM

4. RESULTS

The first part of the analysis was performed using Structural Equation Modeling (SEM) using AMOS software. A confirmatory factor analysis revealed that 1 PU variable and 3 PEoU variables did not load at acceptable levels. It is also noted that the second question on behavioral intention was negative, which we expected since it was opposite the first question (not recommend). Advancing to the structural equation model, all remaining questions were significant to their latent construct at $p<.001$. In our tested model, we employed 2 exogenous constructs, perceived usefulness (PU) of IT and perceived ease of use (PEoU) of IT These constructs gauge a parent's perceptions of PU and PEoU as it applies to their children. We apply 1 endogenous construct, intent to recommend IT as a major to their child or children. Variables to measure our latent constructs come from the TAM survey in the Appendix. Our SEM is detailed in Figure 3.

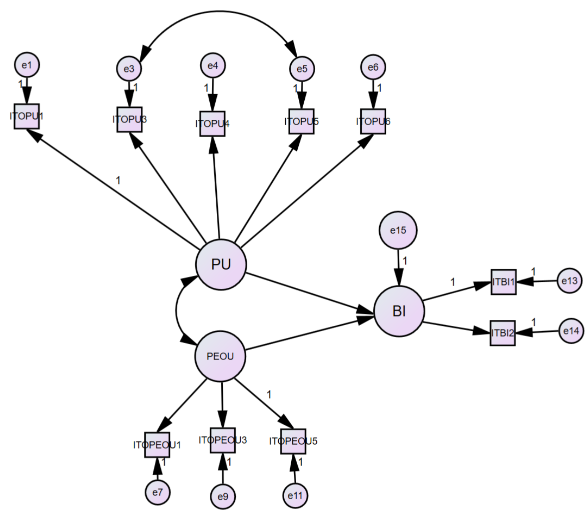

Figure 3 – Structural Equation Model in AMOS

Factorial invariance was tested using a procedure recommended by Byrne, Shavelson, and Muthén (1989). Hence, a non-significant Chi-square is preferable as it indicates that the predicted model is congruent with the observed data. A p value > 0.05 indicates we should accept the model. According to (Thacker, Fields & Tetrick, 1989), the closer Chi-square to the degrees of freedom, the better. Results from our study show Chi-square =29.75, degrees of freedom = 31, and p = 0.53 indicating we accept the model and progress to measuring how our model fits the data.

CMIN/DF was reported as 0.96 which is less that the upper bound of 5. Goodness of fit index (GFI) was 0.879 where 1 is perfect fit and 0 is no fit thus indicating an acceptable model fit with a good model fit being > 0.9. Similarly, root mean squared error of approximation (RMSEA) was 0.000 indicating a good approximate fit (Gefen, Rigdon, & Straub, 2011).

Regarding hypothesis 1 and 2, the results show support of hypothesis 1 that a parent's perception of the perceived usefulness of IT affects their willingness to recommend IT as a major to their children. The model estimates that as PU increases by 1, intent to recommend increases by 1.042 with a standard error of .435 with p < 0.05. Hypothesis 2 was not supported with p = .395. Based on these results, parents are not concerned with how easy IT is but concerned with the usefulness of IT O'Lander (1996) studied factors that influenced high-school students' attitudes towards computing and found that enthusiasm of computing, perceived abilities, apprehensions in majoring in CS, perceptions of positive instructional influences, and perceptions of career and employment opportunities were all critical factors. In our efforts, we focus not on students but on parents. We note that perceived usefulness, such as career opportunities, are important to both students and parents. Further refining factors measuring perceived usefulness of IT as a major and targeting marketing efforts toward PU are important next steps to increasing IT enrollment.

5. CONCLUSIONS

In summary, this work hypothesized that perceived usefulness (PU) and perceived ease of use (PEoU) will impact a parent's likelihood of recommending IT as a major to their children. Results revealed parent's perception of the perceived usefulness of IT (PU) affected their willingness to recommend IT as a major to their children; conversely, parents were not concerned with the ease of use of IT (PEoU). Implications include improved marketing of IT programs to parents by focusing on the usefulness of IT as a discipline.

The research method was based on adapting the technology acceptance model constructs to determine parents' perceptions of perceived usefulness and perceived ease of use and whether their perceptions affected their views on recommending IT as a major for their children. The results indicated that parent's perception of the perceived usefulness of IT affected their willingness to recommend IT as a major to their children. Furthermore, parents were not concerned with how easy IT is but, they were concerned with the usefulness of IT.

This research is important because as it provides information that Information Technology programs should consider this in marketing programs to parents by stressing the usefulness and practical nature of IT coupled with the burgeoning demand may influence parents to recommend IT as a major to their children by increasing their perceived usefulness of IT as a major. Future research will be conducted to determine if any demographic information including, but not limited to, as age, gender, and occupation will have an effect upon the overall results.

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Appendix

Questionnaire

All questions were on a 7 point Likert scale with 1 = Strongly Agree and 7 = Strongly Disagree. Questions were adapted from (Davis, 89).

1. IT-O-PU1 Using Information Technology in his/her job would enable my child to accomplish tasks more quickly.

2. IT-O-PU2 Using Information Technology would improve my child's job performance.

3. IT-O-PU3 Using Information Technology in my job would increase my child's productivity.

4. IT-O-PU4 Using Information Technology would enhance my child's effectiveness on the job.

5. IT-O-PU5 Using Information Technology would make it easier for my child to do his/her job.

6. IT-O-PU6 My child would find Information Technology useful in his/her job.

7. IT-O-PEoU1 Learning to use Information Technology would be easy for my child.

8. IT-O-PEoU2 My child would find it easy to get Information Technology to do what he/she wants it to do.

9. IT-O-PEoU3 My child's interaction with Information Technology would be clear and understandable.

10. IT-O-PEoU4 My child would find Information Technology to be flexible to interact with.

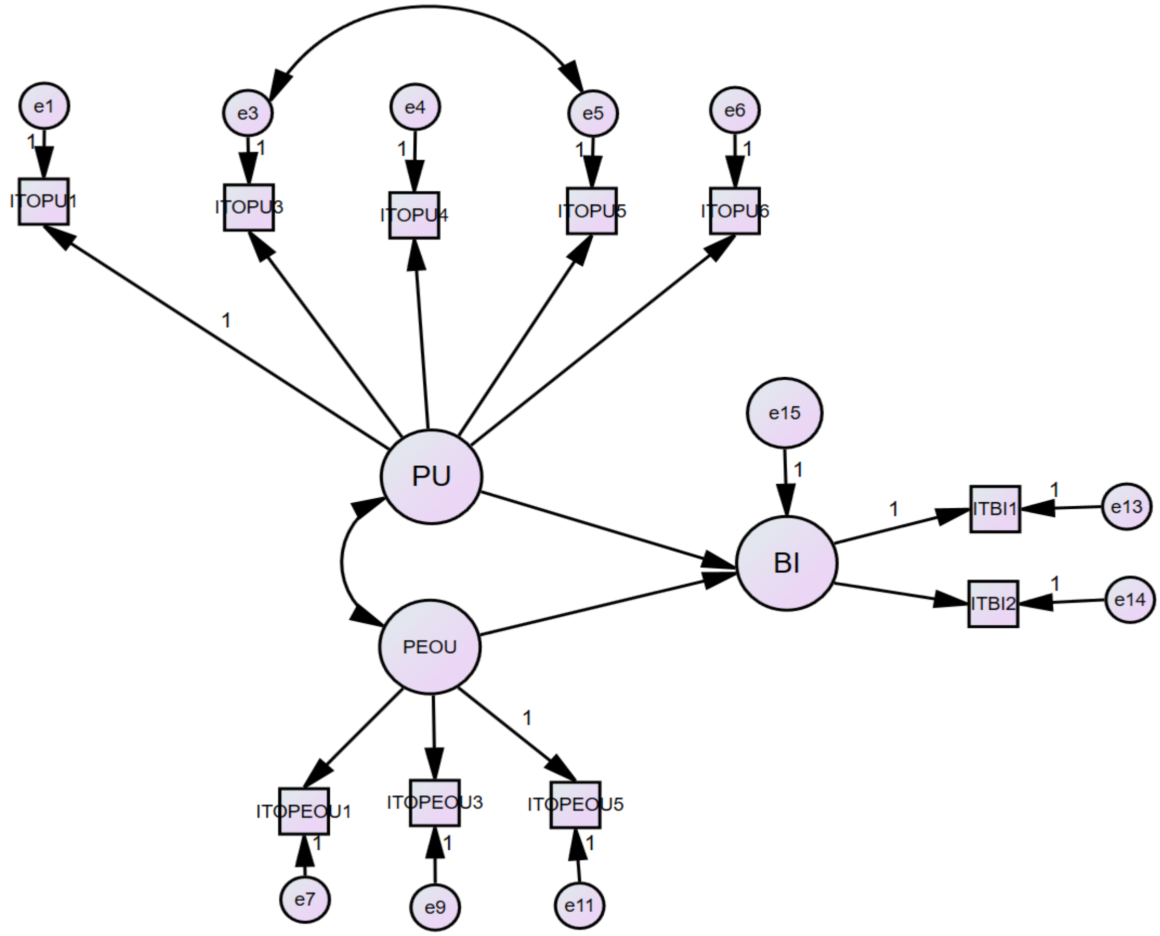
11. IT-O-PEoU5 It would be easy for my child to become skillful at using Information Technology.

12. IT-O-PEoU6 My child would find Information Technology easy to use.

13. IT-BI1 Assuming Information Technology would be available, I predict that I would recommend it as a major to my child.

14. IT-BI2 Assuming Information Technology would be available, I predict that I would NOT recommend it as a major to my child.

Figures



Big Data Analytics Methodology in the Financial Industry

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Abstract

Firms in industry continue to be attracted by the benefits of Big Data Analytics. The benefits of Big Data Analytics projects may not be as evident as frequently indicated in the literature. The authors of the study evaluate factors in a customized methodology that may increase the benefits of Big Data Analytics projects. Evaluating firms in the financial industry, the authors find that business and procedural factors, such as collaboration maturity of the organization and Big Data Analytics governance, are more important than the nuances of technology, such as hardware and product software of technology firms, in beginning to maximize the potential of Big Data Analytics in the firms. The findings of the paper will benefit educators in improving Big Data Analytics curricular programs to be current with the patterns of firms fruitfully initiating Big Data Analytics systems.

Keywords: analytics, big data, big data analytics, financial industry, methodology program.

1. BACKGROUND

Big Data is defined as aggregations of data in applications of bigness and complexity demanding advanced analytic approaches. The approaches to Big Data are described as descriptive analytics, analyzing data from the past; predictive analytics, analyzing data for prediction; and prescriptive analytics, analyzing data for pro-action (Camm, Cochran, Fry, Ohlmann, Anderson, Sweeney, & Williams, 2015). The complexity of Big Data Analytics is described in gigabytes (GB) in a massive miscellany (O'Neil, & Schutt, 2014) of structured, semi-structured and unstructured data, including objects of the Internet of Things (IOT) (Oracle, 2015); and, in the financial industry, Big Data Analytics is described in the volatility of volumetric data (King, 2015). The dimensions of Big Data Analytics are in data base management, data mining, natural language processing, social networking and statistics (Chiang, Goes, & Stohr, 2012) from disparate sources. Big Data Analytics is cited as an enhanced field of innovation (Kiron, Prentice, & Ferguson, 2015) adopted by industry in analyzing ever-increasing information sources.

The Big Data Analytics market is estimated to be $27 billion in 2016, and the market is estimated to be expanding to $50 billion in 2018 (McKendrick, 2015). Most Fortune 1000 firms (75%) are estimated to have a Big Data Analytics initiative in operation, mostly of investments of more than $10 million on projects (Bean, 2015); and most of the Fortune 1000 firms (67%) are estimated to have an edge in their industries from the investments (Mayer-Schonberger, & Cukier, 2013, & Kiron, Prentice, & Ferguson, 2015). Firms, including the financial industry, are indicated to have increasing interest in 2016 in the opportunities from prescriptive analytics (Zoldi, 2016). The majority of firms (70%)

applying real-time analytics systems are indicated to be increasing profitability and solvency from the technology in 2017 (Greengard, 2015). Big Data Analytics for decision-making is cited in the literature to be a disruptive but important transformative trend (Chen, Chiang, & Storey, 2012, & Siegel, 2015) in the 2010s, which is deserving of study.

2. INTRODUCTION

In this study, the authors are evaluating firms in the financial industry as to how they are initiating Big Data Analytics projects in the management of obstacles. To meet the demands for fruitful Big Data Analytics projects, the authors furnish a customized governance methodology of business, procedural and technical factors for decision-making on Big Data Analytics projects in the industry, enhanced from methodology on Big Data Analytics projects in the health sector (Lawler, Joseph, & Howell-Barber, 2016). Governance of Big Data Analytics projects (Kappenberger, McGrattan, & Aven, 2015) is essential in the financial industry, in order to exploit the projects for maximizing return-on-investment (ROI) (Westerman, Bonnet, & McAfee, 2014, & Baesens, 2015) but minimizing the risk of the technology. Maturity of data science initiatives is measurable by a disciplined methodology guiding managers on the impacts, processes and requirements of Big Data Analytics projects (Provost, & Fawcett, 2013). Most organizations are not integrating a governance methodology on Big Data Analytics systems (Davenport, 2014b).

The methodology can be applied by business and information systems departments of financial firms. The emphasis of the methodology is in engaging business professionals in the management of Big Data Analytics without fear of the projects or the technology. This emphasis may be helpful in insuring policies and procedures in the management of Big Data Analytics projects, systems and technologies (Baesens, 2015) in financial firms. The methodology may be helpful in insuring the performance and the stability of the technologies (Fleming, & Barsch, 2015), as in the processing of the volatile volumetric data of the industry. The methodology may be further helpful in maximizing a potential strategy (Goutas, Sutanto, & Aldarbesti, 2016) for Big Data Analytics, as strategies for the technologies are often not evident in firms (Rogers, 2015). Though levels of maturity in meeting Analytics and Big Data Analytics requirements, such as the Cross Industry Standard Process for Data Mining (CRISP-DM), are referenced in the literature (Shearer, 2000, & Ransbotham, Kiron, & Prentice, 2015), the methodology program of this study is inclusive of best-of-class practices found in current Big Data Analytics practitioner sources. The research on Big Data Analytics in the financial industry is largely limited in scholarly sources. The methodology of the authors contributes an organizational program for prudent investment in Big Data Analytics technology in the financial industry.

3. FOCUS

The focus of the authors in this study is in evaluating business, procedural and technical factors in the management of Big Data Analytics projects in the financial industry (Figure 1 in Appendix). The factors originated from an earlier study of Big Data Analytics projects in the health sector by the authors (Lawler, Joseph, & Howell-Barber, 2016) that they now particularize to projects in the financial industry. The factors are defined in Table 1 (in Appendix) and founded in the foremost practitioner sources, given the paucity of scholarly study of Big Data Analytics (Chen, Chiang, & Storey, 2012).
The methodology of this study may be helpful to information systems professors in learning the best practices of Big Data Analytics in the industry.

4. RESEARCH METHODOLOGY

The authors applied a case study of 5 firms in the financial industry, chosen from Big Data Analytics pioneers headquartered in New York State and cited in foremost practitioner publication sources in the August 2015 – February 2016 period. The financial industry is correlated to one of the sectors of the Big Data Analytics curriculum of the Seidenberg School of Computer Science and Information Systems of Pace University, defined by the authors in an earlier study (Molluzzo, & Lawler, 2015). The Big Data Analytics projects in the 5 firms were evaluated by the authors from a checklist definition instrument survey of the business, procedural and technical factors of the customized methodology program in the October 2015 – April 2016 period. The factors were evaluated by the authors on evidence to Big Data Analytics project success, on a 6-point Likert-like rating scale:

- (5) Very High Role to Project Success;
- (4) High Role;
- (3) Intermediate Role
- (2) Low Role
- (1) Very Low Role; and
- (0) No Role to Success.

These evaluations were predicated on in-depth observation of middle-management in the business and information systems organizations; informed perceptions of observation rationale; and research scrutiny of secondary studies, by the authors.

The checklist instrument of the survey was checked in the context of construct, content and face validity and content validity, measured in sample validity. The methodology of the study was dependable in proven reliability with the previous Big Data Analytics study of the authors (Lawler, Joseph, & Howell-Barber, 2016). The data from the evaluations was interpreted in Microsoft EXCEL the Mathworks MATLAB 7.10.0 Statistics Toolbox, and IBM SPSS (McClave, & Sincich, 2012) by the second author in the April – May 2016 period, as detailed in the next section and in the tables in the Appendix of this study.

5. ANALYSIS OF FINANCIAL FIRMS*

Firm 1: Consumer Lending Institution
Firm 1 is a large revenue-sized national organization that began an expanded descriptive / predictive Big Data Analytics initiative, in order to better inform on applicant consumer loans. The goal of the initiative was to integrate increased external demographic data into internal data bases to help loan officers in deciding potential loans at risk. The firm is beginning to benefit from decreased exposure to loans at risk due to increased predictive analytical interpretation of structured data.

The organization empowered its Big Data Analytics project from established features of Analytical Intuition (5.00), Analytical Maturity (5.00) and Analytical Process (5.00) evident in its headquarters. The knowledge to initiate the project was evident with data scientist staff in a Center of Excellence (5.00), partnered in Education and Training (4.00) with the loan officer staff. The management of the project was evident with existing Big Data Analytics Governance (5.00) and Data Governance (5.00) facilitated by Data Services (5.00) by the information systems staff. The project was helped with internally known predictive Software (3.00), instead of investment with Multiple Product Software Vendors (0.00) or new Product Software of the Vendor (2.00). Though Measurements of the Program (2.00) was not a feature initially on the project, the organization was formulating a Big Data Strategy (4.00) with Organizational Strategy (5.00).
Firm 1 is an example of a financial organization benefiting from Big Data Analytics in a controlled methodology, with a foundation for fruitful potential from a Big Data Analytics strategy.

Firm 2: Investment Banking Institution
Firm 2 is a large-sized regional organization that initiated a predictive Big Data Analytics project, in order to inform investment managers of impacts of new customer services. The goal of the project was to integrate increased external and internal data to help the managers learn metrics of profitable services. The firm is benefiting from insights on the services due to interpretation of structured and unstructured data.

This organization empowered its Big Data Analytics project with the existing features of a large-sized organization, such as Analytical Intuition (5.00), Analytical Maturity of Organization (5.00) and Analytical Process (5.00), as found in the prior organization. The Center of Excellence for Big Data Analytics (5.00) was evident as a leader on the project, in partnership with the investment management staff, and was funded by Executive Management Support (5.00) The new processes for interpretation of the results of the services was evident in Change Management (3.00) and Data Architecture (4.00) reviews. Therefore, this organization was focused more on immediate Measurements of Program (4.00) than in the prior organization, in order to insure that the niche project was a success, focusing less on limited Data Ethics and Privacy (3.00) requirements and less on strategic success. This project was helped more by the new Product Software of the Vendor (3.00) that enhanced the Internal Software (2.00), which was limited in interpretation of the new services.

Firm 2 is an example of a financial organization helped by existing methodology that is facilitating a Big Data Analytics project, which may be a model for other projects in a more recognized strategy.

Firm 3: Securities Trading Institution
Firm 3 is a medium-sized national organization that initiated a descriptive / predictive Big Data Analytics project, in order to monitor regulatory thresholds on trades. The intent of the project was to interpolate external data from governmental sources and internal data from securities trades to help managers learn of problematic trades. The firm is benefiting from faster information due to increased interpretation of interpolated semi structured, structured and unstructured data.

The organization enabled its project with features less evident than the functions in the prior organizations. The Analytical Process (3.00), Big Data Analytics Governance (4.00), Internal Standards (3.00), Responsibilities and Roles (3.00) and Risk Management (3.00) were less integrated on the project than in the prior large-sized organizations. The Center of Excellence for Big Data Analytics (3.00) projects was not a bona fide department in this organization, as the project was served by Cloud Methods (4.00), Multiple Product Software Vendors (3.00), and Product Software of the Vendor (3.00), but several information systems and business staff were trained in Education and Training (5.00) on the tools by the vendors. Due to criticality of immediate interpretation of on-line thresholds on trades, the Agility of Infrastructure (5.00), Data Governance (5.00) and Infrastructure of Technology (5.00) were more integrated on to the project than complimentary controls, such as Data Services (3.00), for diverse information not included on the project. Finally, this medium-sized organization was not integrating a Big Data Strategy (2.00) nor an Organizational Strategy (3.00), as the priority was the one project in the period of the study.

Financial Firm 3 is an example of an organization with limited methodological resources for a Big Data Analytics strategy, but which is investing productively in the technology.

Firm 4: Hedge Fund Institution
Firm 4 is a small-sized regional organization that invested in a predictive / prescriptive Big Data Analytics system, in order to inquire into optimal speeds of securities transactions. The objective of the system was to introduce methods for progressively speedy trading. The institution is benefiting from programmatic solutions for structured and unstructured data.

Financial Firm 4 enabled its new system with a culture of functional Analytical Intuition (4.00), Analytical Maturity of Organization (5.00) and Analytical Process (5.00), as found highlighted in the prior organizations 2 and 1. The system was enabled by exceptional Collaboration in Organization (5.00), driven by Executive Management Support (5.00), and was enabled further by extensive research of Best Practices (5.00) of Big Data Analytics systems. The Agility of Infrastructure (5.00) and the Infrastructure of Technology (5.00) were evident in success of the system. This organization was without a Center of Excellence (0.00), as selected Staffing (5.00) were knowledgeable in the Product Software of the Vendor (5.00); and this organization was also limited in Curation of Data (1.00) and even in Data Ethics and Privacy (3.00) and Data Security (3.00), and Internal Standards (2.00) of the system, as the priority was on the intricate processes of the trading. This organization was not planning a Big Data Strategy (0.00), but with the results of the limited productive system was pursuing an Organizational Strategy (3.00).

Financial Firm 4 is an illustration of an organization, as in Firm 3, investing productively but prudently in Big Data Analytics, but without expanded management for a strategy with the technology.

Firm 5: Wealth Management Institution
Firm 5 is a medium-sized regional organization that invested in a predictive / prescriptive Big Data Analytics system, in order to optimize customer portfolios. The objective of the system was to introduce models of products and services for diverse investor portfolios. The institution is benefiting from marketable models of structured and unstructured data that are contributing to increasing return-on-investment.

Firm 5 enabled its new system with evident functions of Analytical Intuition (5.00), Analytical Maturity of Organization (4.00) and Analytical Process (4.00). The firm lacked a full Center of Excellence in Big Data Analytics (3.00), but, as in Firm 3, several information systems staff in Staffing (5.00) were trained in Education and Training (5.00) on new tools by the vendor. The firm was helped by a very high maturity in oversight of Big Data Analytics Governance (5.00), Data Governance (5.00), Internal Standards (5.00), Process Management (5.00) and Responsibilities and Roles (5.00); and the consideration of Data Ethics and Privacy (5.00) and Security (5.00) was notable on this system. The Data Architecture (1.00) function was limited on the system, as the organization was initially leveraging only its internal structured data in the portfolios. Lastly, this organization was interpreting the models of products and services of the productive system into a new Organizational Strategy (5.00) without a similar Big Data Strategy (3.00), as the models involved only structured data at the conclusion of the study.

Firm 5 is an illustration of a financial organization incrementally investing in a Big Data Analytics system, with further potential of the technology to be hopefully pursued strategically.

*Firms are classified as confidential due to competitive imperatives in the sector.

6. SUMMARY ANALYSIS OF FINANCIAL FIRMS

The analysis is highlighting business factors (4.00) [summary in Table 2 and detail in Table 3 of the Appendix], the most highly rated in the study, as important to the Big Data Analytics projects. Analytical Intuition (5.00), Analytical Maturity of Organization (4.60) and Analytical Process (4.40) in decision-making were collectively important in all of the firms in the initiation of projects. The Center of Excellence (3.20), Collaboration in Organization (4.40) and Education and Training (4.00) were collectively important in all of the firms. The Center of Excellence in the large-sized organizations consisted of data scientists in information systems matrixed with the business departments of the organizations. In contrast, the mid-sized and small-sized organizations were without a Center of Excellence, but they were helped by data scientist "scrums" or "data smart" staff in the business departments managing the projects or by the vendors.

Findings in the mid-sized organizations are indicating Staffing (4.60) integrated inter-disciplinary information systems students of local universities.

The analysis of the findings is concurrently indicating procedural factors (3.94) [Tables 2 and 3] of the methodology program as important to the Big Data Analytics projects. Big Data Analytics Governance (4.00) and Data Governance (4.80) were collectively important in the decision management of most of the projects, and committees on governance were key mechanisms in the justification of needs on most of the projects. Data Ethics and Privacy (4.20) and Data Security (4.60) were important on most of the projects, given regulatory requirements
The analysis of the findings of the study is indicating technical factors (2.70) [Tables 2 and 3] as important, but as the most lowly rated in the study, they were less important than procedural and business factors. The Agility of Infrastructure (3.80), Data Services (4.00) and Infrastructure of Technology (3.60) were important on most of the projects. The factors of Internal Software (1.60), Multiple Product Software Vendors (1.20) and Product Software of Vendors (3.20) were generally not as important as other procedural and technical factors on most of the projects, and few of the organizations were fully investing in in advanced prescriptive or advanced architectural technologies, even though most of them were proliferating unstructured data into their structured systems.

Lastly, the firms in the study were focusing less on a Big Data Strategy (2.40) and more on localized Organizational Strategy (4.20), as they were pursuing silo systems essentially tactical; and they were supported with Executive Management Support (5.00).

As to the correlation of factor ratings along pairs of the firms (Table 4) in the study, the correlation of ratings associated with Firms 1 and 2 was significant statistically at the 1% significance level with a value of 0.8440; and the correlations of the ratings with the pairs of Firms 1 and 5, Firms 2 and 5, Firms 3 and 4 and Firms 3 and 5 were significant at the 1% significance level. With respective values of 0.5009, 0.5132, 0.3987 and 0.4001.

(Summary and detailed analysis of the factors in the study are in Tables 2 and 3 of the Appendix, followed by correlations between organizational pairs in Table 4 and by frequency distributions of ratings in Tables 5-8.)

7. IMPLICATIONS

The financial firms of the study are benefiting from an analytical culture that is enabling Big Data Analytics experimentation. The data governance of the projects in especially the large-sized firms is highlighting the foundational maturity of the firms to initiate Big Data Analytics projects. The inherent intuitive maturity of the firms is indicating the potential for profitable Big Data Analytics projects. This maturity is moreover positioning the organizations to pursue non-silo solutions with the technology. The implication is that the analytical maturity of an organization is a clear prerequisite to Big Data Analytics success.

The firms are enabling Big Data Analytics from either a formal center of competency excellence in Big Data Analytics, consisting of data scientists, or from an informal department, consisting of data scientists or data smart quantitative staff aligned with data management information systems staff. Importantly, most of the data scientist and data smart staff are pursuing Big Data Analytics projects in a matrix with the mostly business ownership staff (Harris, & Mehrotra, 2014), a need cited in the literature (Ransbotham, Kiron, & Prentice, 2015). The data scientists are mostly pursuing Big Data Analytics product and service solutions on business and information systems teams (Kiron, Prentice, & Ferguson, 2015), not on isolated scientist teams. The implication is that a multiplicity of skilled staffing is an important prerequisite to Big Data Analytics success.

Lastly, the authors are learning that the financial firms of the study are currently not focusing on a Big Data Analytics strategy, a concern cited in the literature (Davenport, 2014). The firms are focusing on limited silo systems that are benefiting the organizations with impactful results. The foundation of maturity for pursuing further systems in a Big Data Analytics strategy is evident however in the firms, so that the model of data science in the organizations may not be limited to silo systems (Burns, 2015). Most of them have optimal organizational structures. The implication of this finding is that in order to fully leverage the investment, a Big Data Analytics strategy will be eventually a requirement.

8. LIMITATIONS AND OPPORTUNITIES

The findings of the case study are constrained by the limited number of Big Data Analytics organizational participants. The impacts are constrained by the limited maturity of methodological processes and steps of strategy. The findings may not be generalized to the financial sector or other sectors without discretion. Nevertheless, the Big Data Analytics methodology program of this study contributes opportunities for further research. The program may be helpful to practitioners and professors pursuing study of the potential of prudent Big Data Analytics practices and technologies.

9. CONCLUSION

The financial firms of this study are benefiting in decision-making from the factors of the Big Data Analytics methodology program.

The business factors of especially Big Data Analytics maturity of the organizations, centers of competency excellence and collaboration on Big Data Analytics projects managed by business functions, and education and training of data smart staff were collectively important on the study.

The procedural factors of the methodology program of Big Data Analytics governance and data governance were also important on most of the projects on the study.

The technical factors of agility of Big Data infrastructure and the infrastructure of the Big Data Analytics technology were indicated to be important on most of the systems, but the bulk of the technical factors were less important than the procedural and business factors, as the firms were not fully investing in advanced integrated Big Data Analytics systems.

Though the firms of this study were investing in limited Big Data Analytics systems, the foundation if not the momentum for optimizing the potential to be smarter with Big Data Analytics technology strategically was indicated on the study.

The results of this study will be meaningful nevertheless in illustrating best practices in Big Data Analytics, as applied from the methodology program introduced by the authors.

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Editor's Note:

This paper was selected for inclusion in the journal as a EDSIGCon 2016 Meritorious Paper. The acceptance rate is typically 15% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2016.

APPENDIX

Figure 1: Conceptual Design of Big Data Analytics Methodology Model of Study

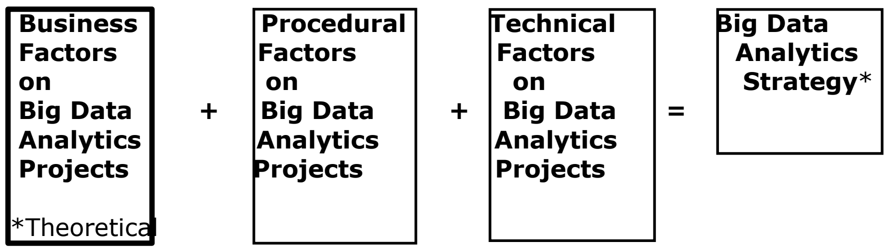

Table 1: Definition of Business, Procedural and Technical Factors of Study

The business factors in the management of Big Data Analytics projects are below:

- Agility and Competitiveness (Phillipps, 2012), Extent to which improved agility and competitiveness contributed to project success;
- Analytical Intuition (Kiron, Prentice, & Ferguson, 2014), Extent to which methods for integrating Big Data Analytics and executive intuition for management contributed to success;
- Analytical Maturity of Organization (Nott 2014, Phillipps, 2012, & Pramanick, 2013), Extent to which maturity of the organization in fundamental Analytics methods contributed to success;
- Analytical Process (McGuire, 2013), Extent to which organizational processes for integrating Big Data Analytics contributed to success;
- Big Data Strategy (Iodine, 2014, McGuire, 2013, & Phillipps, 2012), Extent to which Big Data organizational strategy, having a clearly defined Big Data Analytics subset, contributed to success;
- Budgeting for Big Data Analytics (Columbus, 2014), Extent to which funding for Big Data Analytics contributed to success;
- Center of Excellence (Phillipps, 2012, & Pramanick, 2013), Extent to which growth of Big Data Analytics with Data Analytics best practices, coordinated by a central department of Analytics staff, contributed to success;
- Change Management – Business (Bartik, 2014, Davenport, 2014a, Kiron, Prentice, & Ferguson, 2014, & Nott, 2013), Extent to which changes in business departments of the organization, in order to leverage Big Data Analytics, contributed to success;
- Collaboration in Organization (Columbus, 2014, & Lipsey, 2013), Extent to which cooperation in diverse business and technical departments on Big Data Analytics projects contributed to success;
- Control of Program (Nott, 2013, & Pramanick, 2013), Extent to which control of Big Data Analytics by the business management staff, in close cooperation with the technical staff, contributed to success;
- Data Integration (Columbus, 2014, Lipsey, 2013, Nott, 2013, Phillipps, 2012, & Pramanick, 2013), Extent to which data considered as an asset, common to the organization for accessing and repurposing by diverse business and technical staff, contributed to success;
- Education and Training (Kiron, Prentice, & Ferguson, 2014), Extent to which training of the business and technical staff in Big Data Analytics contributed to success;
- Executive Management Support (Kiron, Prentice, & Ferguson, 2014), Extent to which executive support of Big Data Analytics contributed to success;
- Measurements of Program (Lipsey, 2013, & Phillipps, 2012), Extent to which measurements of performance of the Big Data Analytics projects contributed to success;
- Organizational Strategy (Idoine, 2014, Kiron, Prentice, & Ferguson, 2014, & Nott, 2014), Extent to which integration of Big Data Analytics with organizational strategy contributed to success; and
- Specification of Use Cases (Davenport, 2014a), Extent to which use cases, including functional flows and requirements, contributed to success.

The procedural factors on the projects are below:

- Best Practices (Davenport, 2014, Kiron, Prentice, & Ferguson, 2014, & Pramanick, 2013), Extent to which application of Big Data Analytics best practices from external research contributed to project success;
- Big Data Analytics Governance (Todd, 2010), Extent to which establishment of guidelines for Big Data Analytics initiatives contributed to success;
- Curation of Data (Columbus, 2014, & Nott, 2013), Extent to which curation of Big Data for quality contributed to success;
- Data Ethics and Privacy (Nott, 2013, & Phillipps, 2012), Extent to which initiation of privacy and regulatory requirements contributed to success;
- Data Governance (Nott, 2013, Nott, 2014, & Lipsey, 2013), Extent to which existing data management methods contributed to success;
- Data Security (Columbus, 2014, & Lipsey, 2013), Extent to which initiation of processes for rigorous security of Big Data contributed to success;
- Internal Standards (Bleiberg, 2014), Extent to which governance internal processes contributed to success;
- Process Management (Lipsey, 2013, & Nott, 2013), Extent to which maintenance of processes in Big Data Analytics initiatives contributed to success;
- Program Management and Planning (Bleiberg, 2014, & Davenport, 2014a), Extent to which a centralized management team with iterative planning skills, and with executive management support, contributed to success;
- Responsibilities and Roles (Idoine, 2014, Lipsey, 2013, & McGuire, 2013), Extent to which clearly defined roles of business and technical staff engaged on Big Data Analytics projects contributed to success;
- Risk Management (Weathington, 2014), Extent to which rigorous risk management processes for Big Data contributed to success;
- Selection of Product Software from Vendor(s) (Vance, 2014), Extent to which methodological processes for project selection(s) of software from vendor(s) contributed to success; and
- Staffing (Columbus, 2014, Davenport, 2014, Lipsey, 2013, & Pramanick, 2013), Extent to which business and technical staff on Big Data Analytics projects contributed to success.

The technical factors are below:

- Agility of Infrastructure (Phillipps, 2012), Extent to which infrastructure responsiveness with Big Data contributed to success;
- Change Management – Technology (George, 2014, & Lipsey, 2013), Extent to which infrastructure operational processes for leveraging Big Data Analytics contributed to success;
- Cloud Methods (Pramanick, 2013), Extent to which cloud provider technology contributed to success;
- Data Architecture (Nott, 2014), Extent to which new Big Data organizational processes rules contributed to success;
- Data Services (Lipsey, 2013), Extent to which centralized managed Big Data services contributed to success;
- Entitlement Management (Bartik, 2014), Extent to which management of Big Data access privileges contributed to success;
- Infrastructure of Technology (Columbus, 2014, & Nott, 2013), Extent to which initiation of a scalable technology contributed to success;
- Internal Software (Vance, 2014), Extent to which internal organizational Analytics software contributed to success;
- Multiple Product Software Vendors (Columbus, 2014), Extent to which integration of external Big Data Analytics software from multiple vendors contributed to success;
- Product Software of Vendor (Vance, 2014), Extent to which integration of external Big Data Analytics software from a single vendor contributed to success;
- Usability of Technology (Lipsey, 2013), Extent to which usability of external software and internal organizational software contributed to success; and
- Visualization Tools (Phillipps, 2012), Extent to which Big Data visualization tools contributed to project success.

Table 2: Summary Analytics of Big Data Analytics Factors in Financial Firms of Study

Categorical Factors	**Means**	**Standard Deviations**
Business Factors	4.00	1.31
Procedural Factors	3.94	1.51
Technical Factors	2.70	1.62

Legend: (5) Very High in Contribution Role to Big Data Analytics Project Success, (4) High in Contribution Role to Project Success, (3) Intermediate in Contribution Role to Project Success, (2) Low in Contribution Role to Project Success, (1) Very Low in Contribution Role to Project Success, and (0) No Contribution Role to Project Success

Table 3: Detailed Analysis of Big Data Analytics Factors in Financial Firms of Study

Factors of Study	Firm 1 Mean	Firm 2 Means	Firm 3 Means	Firm 4 Means	Firm 5 Means	Summary Means	Standard Deviations
Business Factors							
Agility and Competitiveness	4.00	4.00	5.00	5.00	3.00	4.60	0.55
Analytical Intuition	5.00	5.00	4.00	4.00	5.00	5.00	0.00
Analytical Maturity of Organization	5.00	5.00	4.00	5.00	4.00	4.60	0.55
Analytical Process	5.00	5.00	3.00	5.00	4.00	4.40	0.89
Big Data Strategy	4.00	3.00	2.00	0.00	3.00	2.40	1.52
Budgeting for Big Data Analytics	5.00	5.00	5.00	4.00	5.00	4.80	0.45
Center of Excellence	5.00	5.00	3.00	0.00	3.00	3.20	2.05
Change Management – Business	2.00	3.00	3.00	1.00	3.00	2.40	0.89
Collaboration in Organization	4.00	4.00	4.00	5.00	5.00	4.40	0.55
Control of Program	5.00	5.00	4.00	2.00	5.00	4.20	1.30
Data Integration	5.00	5.00	3.00	5.00	5.00	4.60	0.89
Education and Training	4.00	4.00	5.00	2.00	5.00	4.00	1.22
Executive Management Support	5.00	5.00	5.00	5.00	5.00	5.00	0.00
Measurements of Program	2.00	4.00	4.00	3.00	4.00	3.40	0.89
Organizational Strategy	5.00	5.00	3.00	3.00	5.00	4.20	1.10
Specification of Use Case	5.00	5.00	1.00	1.00	2.00	2.80	2.05

Procedural Factors							
Best Practices	3.00	4.00	3.00	5.00	5.00	4.00	1.00
Big Data Analytics Governance	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Curation of Data	4.00	5.00	5.00	1.00	5.00	4.00	1.73
Data Ethics and Privacy	5.00	3.00	5.00	3.00	5.00	4.20	1.10
Data Governance	5.00	5.00	5.00	4.00	5.00	4.80	0.45
Data Security	5.00	5.00	5.00	3.00	5.00	4.60	0.89
Internal Standards	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Process Management	5.00	5.00	4.00	3.00	5.00	4.40	0.89
Program Management and Planning	5.00	5.00	4.00	1.00	5.00	4.00	1.73
Responsibilities and Roles	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Risk Management	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Selection of Product Software from Vendor(s)	0.00	0.00	0.00	3.00	0.00	0.60	1.34
Staffing	4.00	4.00	5.00	5.00	5.00	4.60	0.55
Technical Factors							
Agility of Infrastructure	3.00	3.00	5.00	5.00	3.00	3.80	1.10
Change Management – Technology	3.00	3.00	3.00	0.00	3.00	2.40	1.34
Cloud Methods	0.00	0.00	4.00	5.00	3.00	2.40	2.30
Data Architecture	3.00	4.00	2.00	0.00	1.00	2.00	1.58
Data Services	5.00	5.00	3.00	2.00	5.00	4.00	1.41
Entitlement Management	4.00	4.00	3.00	1.00	5.00	3.40	1.52

Infrastructure of Technology	3.00	3.00	5.00	5.00	2.00	3.60	1.34
Internal Software	3.00	2.00	1.00	0.00	2.00	1.60	1.14
Multiple Product Software Vendors	0.00	0.00	3.00	2.00	1.00	1.20	1.30
Product Software of Vendor	2.00	3.00	3.00	5.00	3.00	3.20	1.10
Usability of Technology	3.00	3.00	1.00	2.00	4.00	2.60	1.14
Visualization Tools	0.00	0.00	2.00	4.00	5.00	2.20	2.28

For ratings in Table 3 refer to Legend in Table 2.

Table 4: Correlations between Pairs of Big Data Analytics Financial Firms of Study

	Firm 1	**Firm 2**	**Firm 3**	**Firm 4**
Firm 2	0.8440**			
Firm 3	0.2100	0.2120		
Firm 4	0.0032	0.0000	0.3987**	
Firm 5	0.5009**	0.5132**	0.4001**	0.1811

****Correlation is significant at 0.01 level (2-tailed).**
(Kendall tau correlation coefficient)

Table 5: Frequency Distributions of Ratings of Big Data Analytics Financial Firms of Study
- **Business Factors of Study**

Ratings	**Overall**	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**	**Firm 5**
0	2.50	0.00	0.00	0.00	12.50	0.00
1	3.75	0.00	0.00	6.25	12.50	0.00
2	7.50	12.50	0.00	6.25	12.50	6.25
3	15.00	0.00	12.50	31.25	12.50	18.75
4	20.00	25.00	25.00	25.00	6.25	18.75
5	51.25	62.50	62.50	31.25	43.75	56.25
Total	100.00	100.00	100.00	100.00	100.00	100.00

Table 6: Frequency Distributions of Ratings of Big Data Analytics Financial Firms
- **Procedural Factors of Study**

Ratings	**Overall**	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**	**Firm 5**
0	6.15	7.69	7.69	7.69	0.00	7.69
1	3.08	0.00	0.00	0.00	15.38	0.00
2	6.15	0.00	0.00	0.00	30.77	0.00
3	16.92	7.69	7.69	38.46	30.77	0.00
4	10.77	15.39	15.38	15.38	7.69	0.00
5	56.92	69.23	69.23	38.46	15.38	92.31

Total	100.00	100.00	100.00	100.00	100.00	100.00

Table 7: Frequency Distributions of Ratings of Big Data Analytics Financial Firms of Study

- **Technical Factors of Study**

Ratings	Overall	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5
0	15.00	25.00	25.00	0.00	25.00	0.00
1	8.33	0.00	0.00	16.67	8.33	16.67
2	15.00	8.33	8.33	16.67	25.00	16.67
3	33.33	50.00	41.67	41.67	0.00	33.33
4	10.00	8.33	16.67	8.33	8.33	8.33
5	18.33	8.33	8.33	16.67	33.33	25.00
Total	100.00	100.00	100.00	100.00	100.00	100.00

Table 8: Frequency Distributions of Ratings of Big Data Analytics Financial Firms of Study

- **All Factors of Study**

Ratings	Overall	Firm 1	Firm 2	Firm 3	Firm 4	Firm 5
0	7.31	9.76	9.76	2.44	12.20	2.44
1	4.87	0.00	0.00	7.32	12.20	4.88
2	9.27	7.32	2.44	7.32	21.95	7.32
3	20.98	17.07	19.51	36.59	14.63	17.07
4	14.15	17.07	19.51	17.07	7.32	9.76
5	43.41	48.78	48.78	29.27	31.71	58.54
Total	100.0	100.00	100.00	100.00	100.0	100.00

Cloud-based Versus Local-Based Web Development Education: An Experimental Study in Learning Experience

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Abstract

This paper investigates the use of a cloud computing environment to facilitate the teaching of web development at a university in the Southwestern United States. A between-subjects study of students in a web development course was conducted to assess the merits of a cloud computing environment instead of personal computers for developing websites. The goal of using cloud being to ensure that each student had access to the same high-quality learning experience. The study also sought to determine the extent to which cloud computing could ensure efficient use of students' time through eliminating hardware and software troubleshooting. Finally, the study sought to assess the extent to which the use of cloud computing would enhance students' learning experience.

Keywords: Web Development, Cloud Computing, Learning Experience, HTML, CSS, ASP.NET, C#

1. INTRODUCTION

The web development course considered in this study is taught in-person at the junior level and exists as a required course for students within the IS department in a business college. The college has a highly structured curriculum with a strong common core. As a result, there is a reliance on this course to meet specific learning objectives to prepare students for future courses. The first half of the course covers the fundamentals of HTML, CSS, and Javascript. The second half of the course requires students to install a complex Integrated Development Environment (IDE) and then build an e-business website that features a range of HTML and CSS components along with user interaction mechanisms including forms and a database.

Currently, instructors have students install web development software on personal computers and implement their projects in a standalone environment. Collectively, faculty have observed that student experiences with installing, configuring, and maintaining a web development platform on personal computers negatively impacts academic performance. One important drawback to this approach is that some students struggle to make the software operate on their computers. Time devoted to the installation is wasted as it detracts from learning objectives.

Faculty involved with the web course believe that cloud computing environments, which offer ubiquitous access to development systems, would improve student learning outcomes and satisfaction. Thus, the purpose of this study was to measure the potential difference in learning experience in a web development course between students with and without access to cloud-based services.

2. LITERATURE REVIEW

Web

Web design is an important topic in computer science and information systems academic programs and students gain significant leverage in the job market with related skills (Ellis, 2007, Sridharan 2004). There is a broad consensus in the literature on the difficulty of teaching web development. Deshpande & Hansen (2001) referred to web development as a discipline among disciplines as it draws together skills from areas such as business, computer science, and art.

Zhang & Dang (2015) suggest that difficulties with teaching web development result from needing to possess many skills beyond traditional programming using languages such as Java & C#. Web programmers also need skills which include server controls, data validation, site navigation, session validation, database, authentication and more. Del Fabro, de Almeida & Sluzarski (2012) offered three reasons for the difficulty of teaching web development which is 1) course content, 2) required infrastructure and 3) the environment of the university. The first two items reflect on the broad set of skills required by students and the required infrastructure to provide complex development environments for students' work. The third item argues that school often consists of many relatively trivial assignments that do not reflect complexities and dependencies students would face in real-world projects.

Connolly (2011) offered a review of computer science education literature. In the review, Connolly revealed that the most common approach to teaching web development in North America is to fit all needed material into a single upper-level course. The UK differs in that programs offer web develop as stand-alone degrees with topics divided into separate and distinct courses.

The literature regarding web development is consistent in demonstrating that there is much content to be taught/learned and that this content may be too much for a single course. The literature, particularly Zhang & Dang (2015) and Fabro, de Almeida & Sluzarski (2012), is also consistent in calling for a learning environment that includes not only web programming but also the related duties of a web developer including controls, database integration, authentication, data/session validation and much more.

Cloud

While cloud computing appears to be a relatively new concept, the technology was first introduced in the 1960s (Marston et al., 2011). The concept has surfaced in such forms as Application Management Services (AMS) and Application Service Providers. There is disagreement on the definition of cloud computing due to factors such as the approach taken (Prelas Kovacevic, Spoljaric, & Hegyi, 2012). In this paper we adopt the definition offered by the National Institute of Standards and Technology (NIST) which states:

"Cloud computing is typically presented as a service model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction."

NIST's five essential characteristics of cloud computing are useful: on-demand self-service, broad network access, resource pooling, rapid elasticity and measured service. The technology and cost improvements represented by cloud computing have led to the technology being called a "genuine information technology revolution" (Morrison, 2011). Conn & Reichgelt (2013) referred to cloud computing as the "fifth major paradigm shift in computing". IT experts predict that cloud computing will be the "dominant IT service delivery model" by the end of the decade (Jararweh et al., 2014).
Universities recognize the value of cloud computing (Mircea & Andreescu, 2011). The technological concept is ranked as one of the top priorities for higher education (Lowendahl, 2012). Sultan (2010) focused on the power of cloud computing to better utilize resources and reduce risk for academic institutions.

Ercan (2010) addressed not only the ability of cloud computing to offer cost savings to support university operations, but also benefits for students and academic programs. There are examples of cloud computing being adopted for specific courses or objectives such as Lawler and Joseph (2012) who used cloud computing in an entrepreneurship program and Chen et al. (2012)

who integrated cloud computing into a set of IS and CS courses.

Grossniklaus and Maier (2012) taught on the use of NoSQL and VoltDB in the cloud, and Mrdali (2011) offered an alternative Business Intelligence course using cloud technology to create a dynamic and cost-effective learning environment. Conversely, Lawler (2011) defined a more comprehensive and structured program that leverages cloud technology to provide an education platform for teaching CS and IS.

3. METHOD

A single, overarching research question guided the design of this study: *what is the potential difference in learning experience in a web development course between undergraduate students with access to cloud-based services compared to undergraduate students with access to local computing services only*? Operationally, learning experience appeared too abstract and did not adequately establish a measurable critical success factor. Based on research by (Schiefele, 1991), more measurable elements such as time, effort, errors, experience, and grades better served as critical success factors indicative of learning experience. Accordingly, we operationalized the general research question into five specific sub-questions (Table 1). Further, the five sub-questions then informed both the identification of the study variables as well as the selection of relevant questions for the data collection instrument.

Population
The population considered in this research was limited to four-year college students in the United States enrolled in a computer information systems or equivalent degree track. We assumed that members of the population engage in at least one quarter or semester of web development study. This assumption appeared rationale upon review of existing computer information systems and equivalent curricula. Further, we assumed that web development courses involved non-trivial coding work using Microsoft technologies (e.g., ASP.NET, C#). Based on the existing curricula surveyed, such an assumption appeared to be rational.

Sample
A self-selection sampling technique, using two steps, was employed. To avoid potential sampling bias, one of us not involved in teaching the web development course issued a call for participation. Students responding to the solicitation were permitted to self-select into one of two study groups (cloud-based versus local-based). We did not purposefully filter participants based on demographics. However, diversity across the institution and within the degree track under study facilitated a student population representative of the general population.

Table 1
List of Operational Research Questions

Index	Questions
1	What is the potential difference in the time spent installing and configuring the development environment between students using a cloud-based environment compared to students using a local environment?
2	What is the potential difference in the effort spent installing and configuring the development environment between students using a cloud-based environment compared to students using a local environment?
3	What is the potential difference in the number of errors arising during installation, configuring, and usage of the development environment between students using a cloud-based environment compared to students using a local environment?
4	What is the potential difference in normative experience installing, configuring, and using the development environment between students using a cloud-based environment compared to students using a local environment?
5	What is the potential difference in the final course grades earned by students using a cloud-based development environment compared to students using a local development environment?

Two factors bound the call for participation: (a) the scope as defined by the purpose of the research; (b) volunteers possessing characteristics of the broader population. Self-selection sampling was appropriate to segment potential volunteers from the researchers (Rutherford, 2006; Salkind & Rainwater, 2003). Segmentation (or blinding) was desirable to reduce participant selection time and to ensure adequate dedication to the study once enrolled (Salkind & Rainwater, 2003). Further, despite not having the power of probabilistic sampling techniques, self-selected sampling is effective when employing experimental research designs (Rutherford, 2006).

Twenty-nine students (out of 65 total) volunteered from two sections of an undergraduate web development course. The course is a core requirement for students in the computer information systems degree program and may serve as an elective for computer science majors. The course required ten weekly development projects, a midterm, and a final project. The weekly assignments were of increasing difficulty (ranging from simple HTML to single-page web applications) and included a web-based version of the classic game, hangman, using Microsoft ASP.NET with C#.

Fourteen participants joined the cloud-based study group with the remaining 15 selecting the local-based study group. Participants remained in the self-selected study groups for the duration of the course. The sample was independent because data from one group could not influence data from the other (Huck, 2012). Lastly, the sample size was appropriate given the scope and design of the research (Creswell, 2012; Huck 2012; Salkind & Rainwater, 2003).

Table 2
Breakdown of variables

Variable Index	Variable Name	Variable Type
I0	Cloud-based	Independent-Categorical
I1	Local-based	Independent-Categorical
D0	Time	Dependent-Ordinal
D1	Effort	Dependent-Ordinal
D2	Errors	Dependent-Ordinal
D3	Experience	Dependent-Ordinal
D4	Grade	Dependent-Ordinal

Study design
Analysis of the research questions indicated that a quantitative design would be necessary (Creswell, 2012). More specifically, because the research questions inquired how two independent groups might comparatively reveal the effect of treatment (Salkind & Rainwater, 2003), we used a between-subjects experimental design. Between-subjects design facilitates applying a treatment (i.e., change in development environment) to a study group while applying a different treatment to the second study group (Bellemare, Bissonnette, & Kröger, 2014). Additionally, the research questions outlined the study variables.

Variables
The study included a single independent variable (i.e., development environment) with two levels (i.e., cloud-based and local-based), and four dependent variables (Table 2). Independent variable levels aligned with the study groups and were categorical in nature. The five dependent variables were present in both study groups and typed as ordinal. Dependent variables served as data collection elements within the study instrument and formed a basis for hypothesis testing. There was a consideration for controlling potential extraneous factors such as prior experience with development tools or retaking the course after a failing grade. However, we decided that allowing for such factors more appropriately represented the general population and had equal probability of appearing in both groups.

Data Collection
Data were collected using a web-based questionnaire instrument. The instrument consisted of nine bounded questions and a single unbounded question designed to collect data aligned with the dependent variables. The bounded questions aligned with the dependent variables (Table 2). Six of the bounded questions were Likert items with the same scale. The Likert scale ranged from strongly agree, to neutral and strongly disagree. Three of the bounded questions were multiple-choice. All multiple-choice questions were of different response scales. The last question was unbounded to allow participants to submit unfiltered feedback, but data were used only as a measure of course feedback, not as data in this study's analyses. One of us who led the course sections paired study participants with each student's final course grade.

A pilot test validated the data collection instrument as reliable and internally valid. The pilot test included five participants. Pilot participants completed the questionnaire and submitted feedback to a brief set of meta-questions. The meta-questions included elements such as length of the study instrument, clarity of questions, and wording. Additionally, pilot data were used to validate the data analysis process.

Data analysis

The data were ordinal as such represent ordered categories (Huck, 2012). Interval and ratio data types were ruled out because the quantitative values collected were not equidistant (Sullivan & Artino, 2013) or inclusive of a true zero value (Jamieson, 2004). Moreover, since the Likert items and multiple-choice questions would be inferentially analyzed, we felt that treating such as ordinal would be appropriate (Lovelace & Brickman, 2013; Norman, 2010).

A two-phased data analysis procedure was used first to describe the data and then to test a (null) hypothesis using an inferential statistic. The research hypothesis was that students using a cloud-based service to host a web development environment would (a) spend less time installing and configuring the development environment; (b) expend less effort; (c) encounter fewer errors; (d) report a higher quality learning experience; (e) finish with higher course grades. Conversely, the null hypothesis considered in this study posited that students using a cloud-based service to host a web development environment would (a) spend the same or more time installing and configuring the development environment; (b) expend the same or more effort; (c) encounter the same or more errors; (d) report the same or a lower quality learning experience; (e) finish with equivalent or lower course grades. However, like with the research questions, we operationalized the general hypotheses into more specific, more testable statements (Table 3).

Table 3.
Summary of Operationalized Hypotheses

	Research Hypothesis Element	Null Hypothesis Element
Installing & configuring	HA_1 - Less time	$H0_1$ - Same or more time
Effort	HA_2 - Less	$H0_2$ - Same or more
Errors	HA_3- Less	$H0_3$ - Same or more
Learning experience	HA_4 - Higher quality	$H0_4$ - Same or lower quality
Grades	HA_5 - Higher	$H0_5$ - Same or lower

The Mann-Whitney U statistic was the appropriate inferential statistical to test the null hypotheses. The rationale for the decision included independence of study groups, data type (ordinal), and most importantly because the research questions required comparison of the two study groups (Huck, 2012; Salkind & Rainwater, 2003). Alternative statistical measures were not appropriate (e.g. Wilcoxon, Kruskal-Wallis) because of the number of study groups, uneven samples, and data type (McDonald, 2014).

4. RESULTS

Data were first analyzed using descriptive statistical techniques. Doing so permitted a general understanding of how participants engaged with the associated development environments. As well, the descriptive indicators facilitated quick, visual interpretation of the data. For readability, the descriptive results are organized in order of appearance on the data collection instrument.

The first question asked participants to estimate the total time spent downloading, installing, and configuring the development environment (Figure A1). The question was bounded, multiple-choice with six response options. Overall, the cloud-based group (between 554 and 1140 minutes total) described spending less time downloading, installing, and configuring the development environment compared to the local-based group (between 885 and 1260 minutes total). Further, the cloud-based group demonstrated a central tendency lower (Mdn_2 = 5 or 31-60 minutes) compared to the local-based group (Mdn_1 = 4 or 61-120 minutes). Overall, both groups demonstrated equal distribution of participants in the lowest response range (N = 4 at < 30 minutes) while the local-based group alone demonstrated more participants at the highest response ranges (N = 2 at 121 to 180 minutes; N = 1 at > 241 minutes).

The second question asked participants to gauge the level of effort or difficulty expended to download, install and configure the development environment (Figure A2). The question was bounded, multiple-choice, with three response options. Overall, the local-based study group described (Mdn_1 = 3 or Easy) the effort as easier compared to the cloud-based group (Mdn_2 = 2 or Moderate). Both groups demonstrated equal distribution at the most difficult selection option (N = 1 at Hard). However, the local-based group demonstrated a higher number of participants describing effort in the easiest selection option (N = 9 at Easy) compared to the cloud-based group (N = 4 at Easy). The inverse appeared for the middle selection option; local-based participants were few (N = 5 at Moderate) compared to cloud-based participants (N = 9 at Moderate).

The next question asked participants to select a level of agreement with the statement, my development environment contributed in a positive manner to my web development experience (Figure A3). The question was bounded and consisted of a five-element Likert scale. The two study groups differed in level of agreement by one degree according to central tendency: local-based participants agreed with the statement (Mdn_1 = 4) while the cloud-based group distributed between disagreement and neutral (Mdn_2 = 2.5). Collectively, more local-based participants gravitated towards agreement (*N* = 5 at Strongly Agree; *N* = 3 at Agree) while cloud-based participants grouped towards disagreement (*N* = 1 at Strongly Disagree; *N* = 2 at Disagree).

Next, participants offered a level of agreement with the statement; *I was able to complete my assignments without error because of my development environment* (Figure A4). The question was bounded and used a five-element Likert scale. Overall, local-based participants agreed with the statement (Mdn_1= 4) while the cloud-based group remained neutral (Mdn_2 = 3) again. Further, the two groups' responses were distributed similarly to the prior question insofar as the majority of local-based participants selected levels of agreement (*N* = 3 at Strongly Agree; *N* = 8 at Agree) compared to the cloud-based group converging towards levels of disagreement (*N* = 1 at Strongly Disagree; *N* = 4 at Disagree).

The fifth question was bounded and used a five-element Likert scale to collect participant level of agreement with the statement, my environment allowed for the efficient installation of development tools (Figure A5). The question was bounded within a five-element Likert scale. The local-based development environment study group predominantly agreed (Mdn_1= 4) while the cloud-based study group centrally distributed between neutral and agreement (Mdn_2 = 3.5). Both groups gravitated towards aggregate levels of agreement. However, cloud-based participants were more numerous across disagreement elements (*N* = 3 at Disagree; *N* = 1 at Strongly Disagree) compared to the local-based group (*N* = 1 at Disagree).

Participants selected a level of agreement with the development environment facilitating the efficient completion of coursework in the sixth question (Figure A6). The question used a five-element Likert scale and was bounded. Participants in the local-based development environment group generally agreed (Mdn_1 = 4). Moreover, more than one-third of individuals in the local-based study group (*N* = 6) described strong agreement with the statement. Comparatively, cloud-based participants were overall neutral (Mdn_2 = 3) but with equal distribution of individuals describing strong agreement (*N* = 4) as well as disagreement (*N* = 4).

The next question asked participants to select a level of agreement with the statement; I was able to rapidly build my web development environment (Figure A7). The question consisted of five agreement level options within a bounded Likert scale. Overall, the two study groups described identical levels of strong agreement (*N* = 4, each) and levels of agreement differing by one degree (Mdn_1 = 4; Mdn_2 = 3). As well, strong disagreement levels were identical between groups (*N* = 1, each). On the other hand, a proportionally large number of participants in the local-based group selected a neutral level of agreement (*N* = 6) while few (*N* = 2) cloud-based participants did so.

The eighth question posed to participants inquired if learning was effective and efficient because of the associated development environment (Figure A8). The question was bounded and measured agreement across a five-element Likert scale. Members of the local-based study group centralized upon agreement (Mdn_1 = 4) whereas cloud-based participants tended to describe a neutral position (Mdn_2 = 3). Additionally, there were zero cloud-based participants present in the Likert scalar extremes. Conversely, the local-based study group was heavily represented across both agreement elements (*N* = 5 at Strongly Agree; *N* = 6 at Agree).

The last instrument question posed to study participants inquired about the number of errors encountered during the download, installation, and configuration of the development environment (Figure A9). The question was bounded and used a five-element multiple-choice scale. Overall, both groups described encountering errors. Local-based participants indicated a lower error incidence (Mdn_1 = 5 at between zero and one errors) compared to the cloud-based study group (Mdn_2 = 4 at between one and two errors). Furthermore, participants using a local-based development environment described encountering between 9 and 24 errors in total. In contrast, cloud-based participants described encountering between 20 and 34 total errors.

Participants across both study groups performed well with respect to final course grades (Figure A10). Participants in the local-based development environment group demonstrated a higher grade tendency (Mdn_1 = 4 or A) than the cloud-based group (Mdn_2 = 3.7 or A-). Furthermore, both groups aligned the tendency of the general student sample frame in the course sections used in this study.

Inferential Analysis

Inferential data analysis was used to measure the differences between the two study groups according to the research questions and hypotheses. The inferential test results are collated below according to such groupings. Furthermore, independent variables of cloud-based development environment group (i.e., Azure) and local-based development environment group were coded as CBDE and LBDE for readability.

Installing and configuration

We first analyzed data from two questions as a comparative measure the $H0_1$ hypothesis. Descriptive testing of question one indicated that the time spent installing and configuring the development environment was lower for the CBDE group (31-60 minutes) than for the LBDE group (61-120 minutes). However, the Mann-Whitney *U* was found to be 90.5 ($p > 0.05$) and so the null hypothesis could not be rejected (Table 4). Further, the results were not statistically significant

Table 4
Time downloading, installing, and configuring the development environment between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	16.04	224.5
LBDE	15	14.03	210.5
Total	29		
Mann-Whitney U test results			
U	Z	*p-value*	*SD*
90.5	-0.611	0.542	22.91
Notes: Q1; p = 0.05 one-tailed; power at > .80			

Concurrently, we analyzed question five. Descriptive testing indicated that the LBDE and CBDE groups were close in estimating efficiency in installing development tools within associated environment. The Mann-Whitney *U* was 66 ($p > 0.05$) so the null hypothesis could not be rejected (Table 5). The results were not statistically significant.

Table 5
Efficient installation of development tools between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	12.21	171
LBDE	15	17.6	264
Total	29		
Mann-Whitney U test results			
U	Z	*p-value*	*SD*
66	1.68	0.093	22.91
Notes: Q5; p = 0.05 one-tailed; power at > .80			

Effort

Secondly, we analyzed data from two additional questions as a comparative measure of the $H0_2$ hypothesis. Descriptive analysis of question two indicated that the effort expended to install and configure the development was greater for the CBDE group (Easy) than for the LBDE (Moderate). The Mann-Whitney *U* was 74 ($p > 0.05$) so the null hypothesis could not be rejected (Table 6). Moreover, the results of the test were not statistically significant.

Table 6
Effort expended to install and configure development environments between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	12.79	179
LBDE	15	17.07	256
Total	29		
Mann-Whitney U test results			
U	Z	*p-value*	*SD*
74	1.331	0.184	22.91
Notes: Q2; p = 0.05 one-tailed; power at > .80			

In tandem, descriptive analysis of data from question seven, revealed similar information as question two. What is more, the Mann-Whitney *U* was 105 ($p > 0.05$). Such indicated that the null hypothesis, again, could not be rejected (Table 7). The results were not statistically significant though.

Table 7
Rapidity of building the development environment between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	15	210
LBDE	15	15	225
Total	29		
Mann-Whitney U test results			
U	Z	*p*-value	*SD*
105	0.022	0.984	22.91
Notes: Q7; p = 0.05 one-tailed; power at > .80			

Errors
Next, we analyzed data from questions four and nine as a comparative measure of the $H0_3$ hypothesis. Question four revealed that the LBDE group agreed that group participants were able to complete assignments without error due to the local-based development environment while the CBDE group remained neutrally aligned. The Mann-Whitney *U* was 59 ($p < 0.05$) and would support rejection of the null hypothesis. The results (Table 8) were statistically significant.

Table 8
Completion of assignments without errors between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	11.71	164
LBDE	15	18.07	271
Total	29		
Mann-Whitney U test results			
U	Z	*p*-value	*SD*
59	1.99	0.047	22.91
Notes: Q4; p = 0.05 one-tailed; power at > .80			

Analysis of question nine demonstrated a competing view of the comparison between study groups however. Descriptively, the LBDE study group reported fewer errors compared to the CBDE group. Yet, the Mann-Whitney *U* was 76.5 ($p > 0.05$) and would not support rejection of the null hypothesis (Table 9). Moreover, the results were statistically significant.

Table 9
Estimated number of errors during installation, configuration and use of development environments between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	12.96	181.5
LBDE	15	16.9	253.5
Total	29		
Mann-Whitney U test results			
U	Z	*p*-value	*SD*
76.5	1.222	0.111	22.91
Notes: Q9; p = 0.05 one-tailed; power at > .80			

Learning experience
Penultimate hypothesis ($H0_4$) testing drew upon data from three questions. Question three descriptively indicated the LBDE group agreed that the environment contributed in a positive manner to the learning experience while CBDE participants vacillated between disagreement and neutrality. The Mann-Whitney *U* was 59 ($p < 0.05$) and data suggested that the null hypothesis could be rejected (Table 10). Furthermore, the results were statistically significant.

Table 10
Contribution of development environment to positive learning experience between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	18.07	271
LBDE	15	11.71	164
Total	29		
Mann-Whitney U test results			
U	Z	*p*-value	*SD*
59	1.99	0.047	22.91
Notes: Q3; p = 0.05 one-tailed; power at > .80			

Next, we analyzed data from question six. Descriptive analysis demonstrated that the LBDE agreed that the development environment facilitated the efficient completion of coursework while the CBDE group trended between neutral and agreement. The Mann-Whitney *U* was 73.5 ($p > 0.05$). The null hypothesis could not be rejected based on these data. As well, the results (Table 11) were not statistically significant.

Table 11
Facilitation of coursework completion within development environments between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	12.75	178.5
LBDE	15	17.1	256.5
Total	29		
Mann-Whitney U test results			
U	Z	*p*-value	*SD*
73.5	1.35	0.089	22.91
Notes: Q6; p = 0.05 one-tailed; power at > .80			

Lastly, descriptive testing of question eight found LBDE group members agreed that the learning experience was efficient and effective within the development environment whereas the CBDE was neutral. The Mann-Whitney *U* was 105 ($p > 0.05$). The null hypothesis could not be rejected. The results of the test were not statistically significant (Table 12).

Table 12
Efficiency and effectiveness of learning experience between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	15	210
LBDE	15	15	225
Total	29		
Mann-Whitney U test results			
U	Z	*p*-value	*SD*
105	0.022	*0.984*	*22.91*
Notes: Q8; p = 0.05 one-tailed; power at > .80			

Grades
Final grades were collected directly from the course learning management system portals. Descriptively, data revealed that the LBDE group earned higher marks (A or 4.0) than for the CBDE group (A- or 3.7). The Mann-Whitney *U* was 53 ($p < 0.05$) and thus the null hypothesis could be rejected (Table 13). As well, the results were statistically significant.

Table 13
Earned grades between groups

Ranks			
Group	*N*	Mean Rank	Sum of Ranks
CBDE	14	11.29	158
LBDE	15	18.47	277
Total	29		
Mann-Whitney U test results			
U	Z	*p*-value	*SD*
53	2.247	0.024	22.91
Notes: p = 0.05 one-tailed; power at > .80			

5. CONCLUSIONS

This project was limited by the fact that students were able to choose between stand-alone computers and a cloud solution. As a result, the cloud solution did not take advantage of connecting to other Internet resources. Students completed the same web project whether or not they used the cloud or a personal computer. Future studies need to explore a rich connectivity environment in which students connect their website to other systems via the Internet.

Furthermore, student performance with the CBDE environment (Azure) demonstrated that students encountered greater difficulties than anticipated in gaining proficiency with the technology. If students had been given an introductory exposure to Azure, the outcome of this study may have changed dramatically. Just the fact that students knew they were in a metered environment seemed to cause students to be less playful with the system, which perhaps hindered students' learning processes. It will be important to determine whether the introductory exposure to the cloud should be in a prerequisite course, or an introduction to cloud computing within the web course.

Installation and configuration
The inability to reject the null hypothesis and the lack of statistical significance between the CBDE and LBDE participants revealed in question 1 was a surprise. Likewise, the greater efficiency of working on local machines was not expected.

Students in the class have been working with personal computers for years, however, for most in the CBDE group, this was their first experience with a cloud computing environment. Students' lack of familiarity with the environment may have led to inefficiencies.

It is reasonable to surmise that students with less capable personal computers, opted for the cloud computing environment and may, in fact, have had a better experience than would have been the case using their personal computers.

A discussion amongst faculty who teach the web course reveals that there are often between three and eight students who dedicate more than 240 minutes to installing and configuring their development environments in a given section of this class. So the outcome in this study is viewed as positive despite the inability of the results to discern variance between the CBDE and LBDE installation groups.

Future studies may need to include sections of the course in which students do not have the cloud option available and sections where the cloud service is the only option available to tease out the impact on students' time. Alternatively, perhaps a within-subjects design in which each student completes both scenarios will more fully assess the impact of differences in time consumption.

Effort
Question 2 reveals that the LBDE group met with less difficulty downloading, installing and configuring the development environment. The agreement in question 7 demonstrating that students in the LBDE group built their environments more rapidly was therefore not a surprise. Students familiarity with personal computers allows them to work effectively in this environment. Also, students in the CBDE group experienced connectivity difficulties at several points during the academic term that grew increasingly exasperating as deadlines drew near. Future studies will need to measure or control for connectivity issues to assess their impact.

This outcome raises the question if experience and time spent in cloud computing environments will allow students to gain a measure of effectiveness using the cloud that rivals current personal computer use. More effective training for students on the utilization of the cloud, coupled with increased time on tasks in the cloud, appear to be needed.

Errors
Questions 4 and 9 reveal that students in the LBDE group perceived they were better able to complete assignments without error and also reported fewer errors. This outcome was a surprise as the cloud operator specifically supported the IDE in use, and the environment was well suited to the IDE's installation.

One plausible explanation for the discrepancy lies with the connectivity issues that students experienced in the cloud group. Students' lack of familiarity with the system, coupled with erratic connectivity, may have caused students to believe their input did not register and the command to be repeated with undesirable outcomes.

Learning Experience
Question 3 results were significant and reveal that the LBDE group believed their learning environment better contributed to their learning experience. The results of questions 6 and 8, while not statistically significant, suggest the LBDE group also viewed their environment as better supporting the efficient completion of assignments and more effective and efficient learning experiences.

Learning experience results are perhaps the most troubling. Student confidence in the efficacy of their learning environment is of the utmost importance. A positive learning experience is critical to enhancing the utility of the cloud computing option to gain broad acceptance from students.

Grades
While the LBDE group earned significantly higher grades, it is also true that the class overall scored higher than normal and the distribution of scores was more consistent than typical sections of the course. The cloud environment is believed to be at least partly responsible for the higher and more consistent grades as students who may otherwise have struggled with an ill-equipped computer used the cloud instead. There also seemed to be a novelty factor that enamored students and may have led to increased time on task and therefore better grades.

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Appendix A

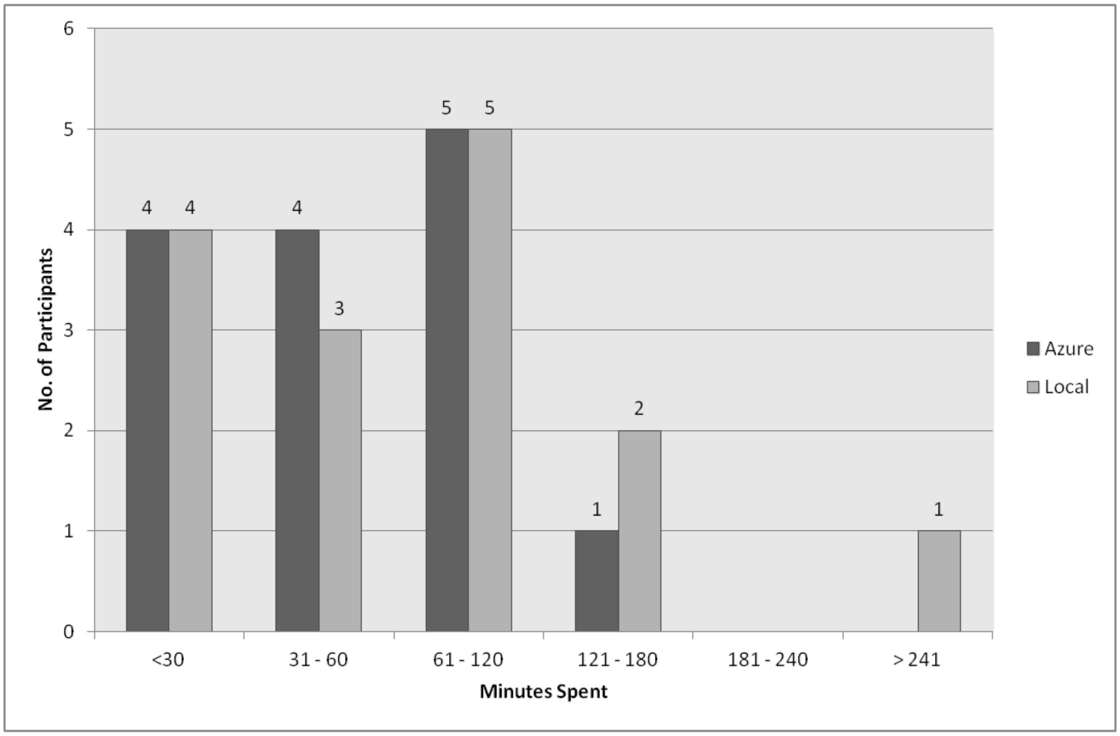

Figure 1. Minutes spent downloading, installing, and configuring development environments.

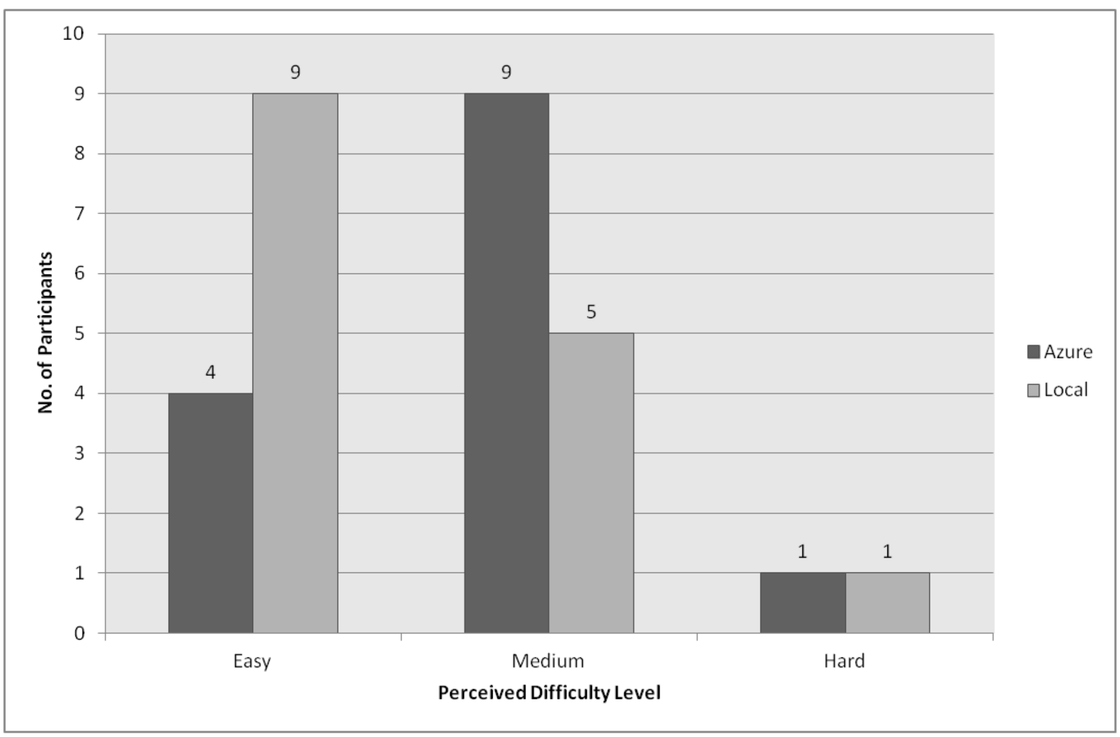

Figure 2. The perceived level of effort or difficulty downloading, installing, and configuring the development environment.

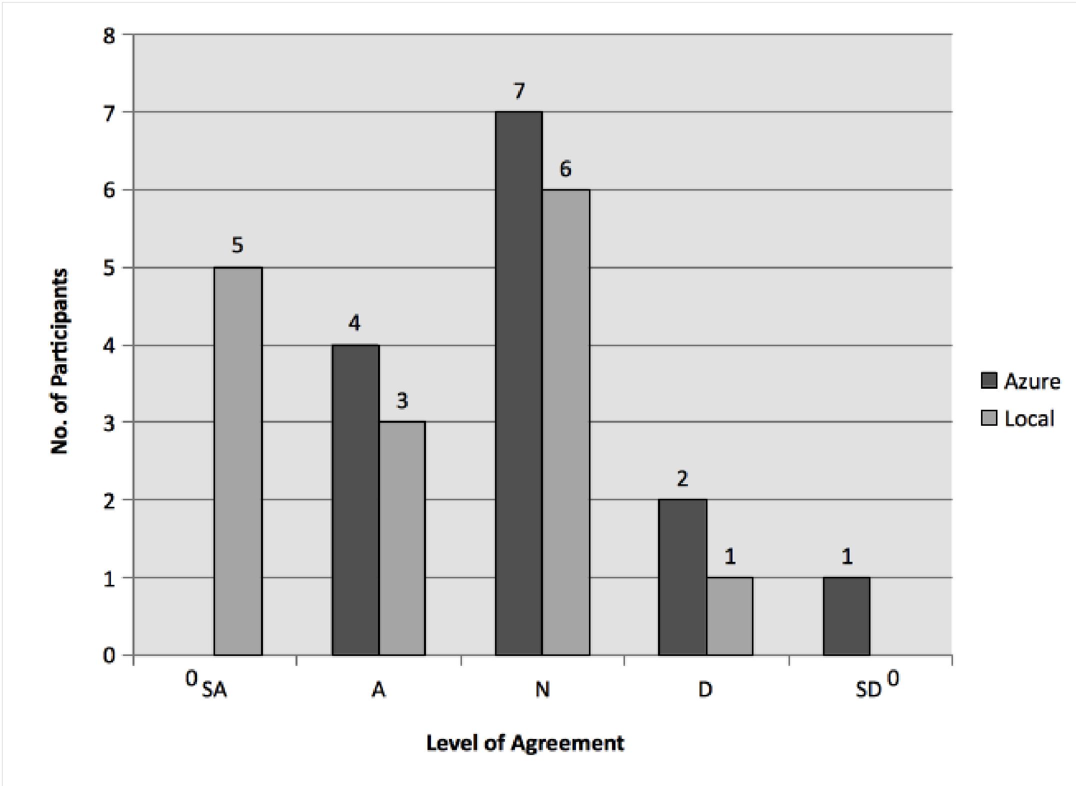

Figure 3. Participant level of agreement with the notion that the development environment contributed positively to the learning experience.

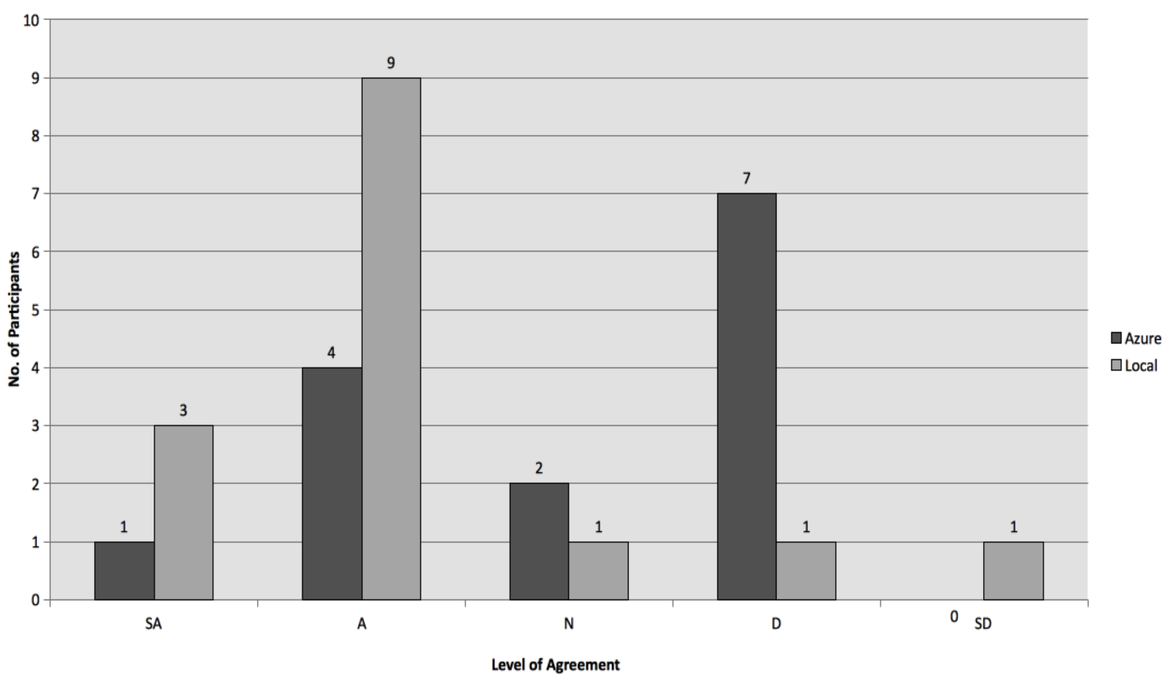

Figure 4. Participant agreement levels associated with the ability to complete assignments without error due to the development environment.

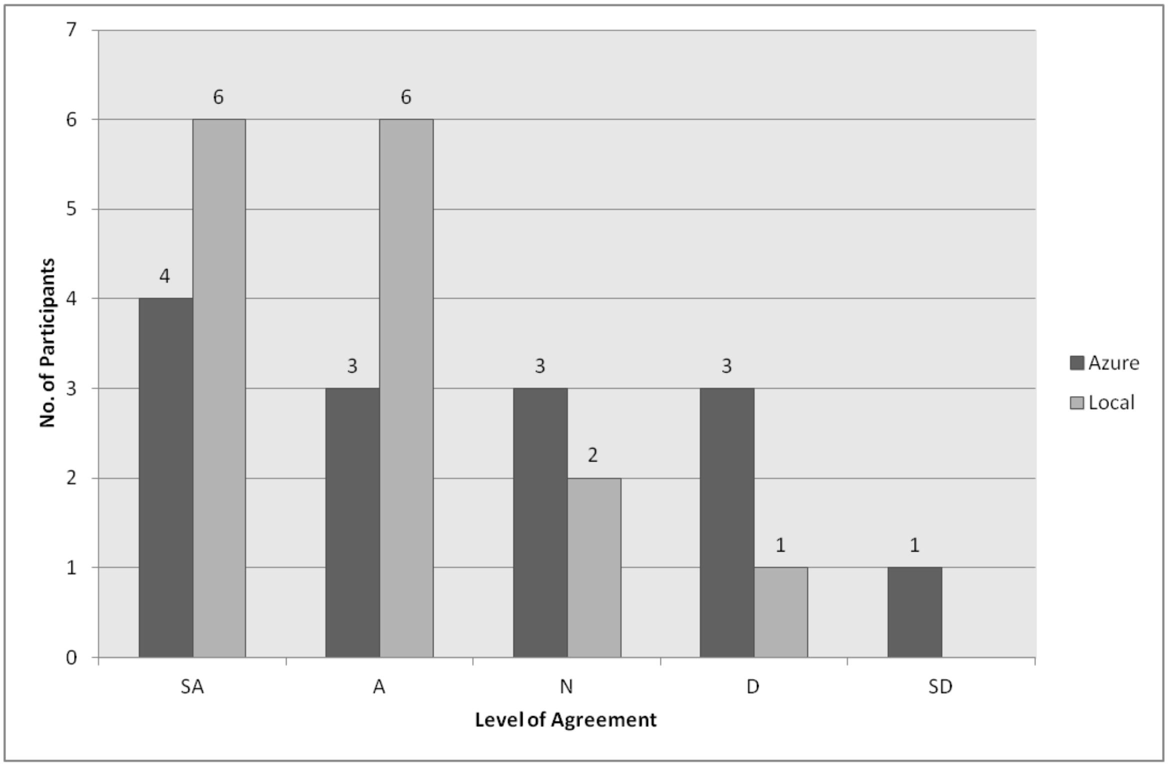

Figure 5. Participant level of agreement with level of efficiency in installing development tools within the associated group environment.

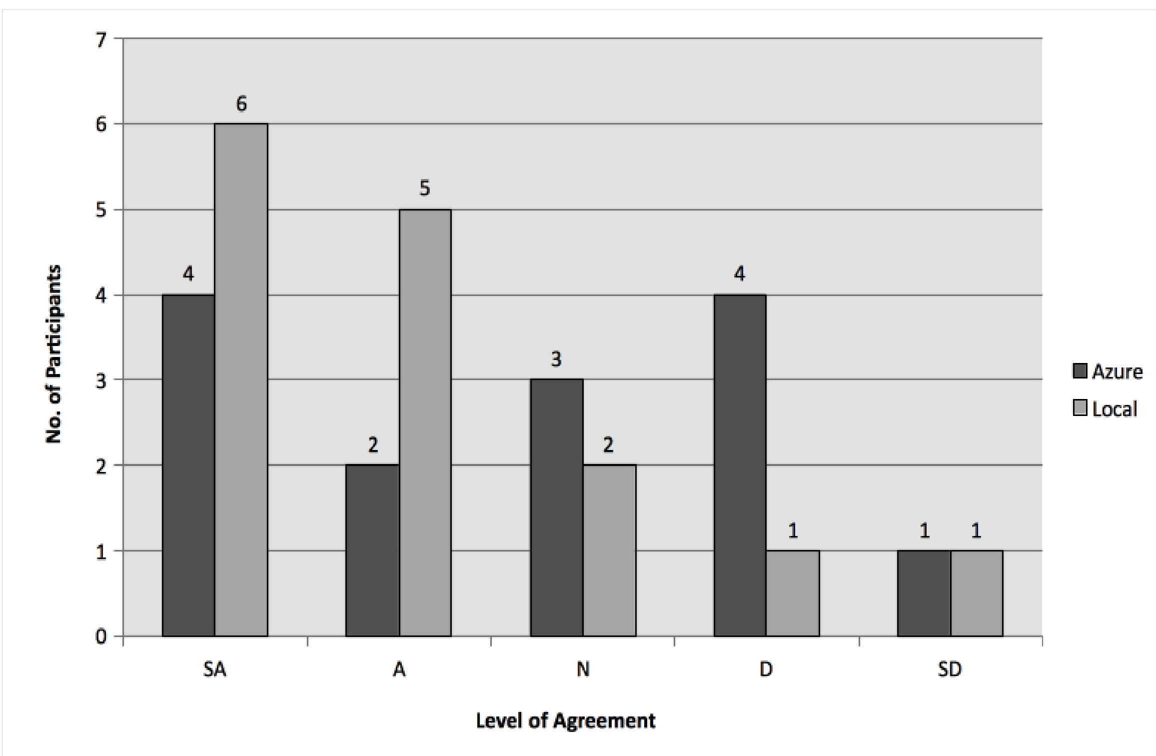

Figure 6. Distribution of participant levels of agreement with the development environment facilitating efficient completion of assignments.

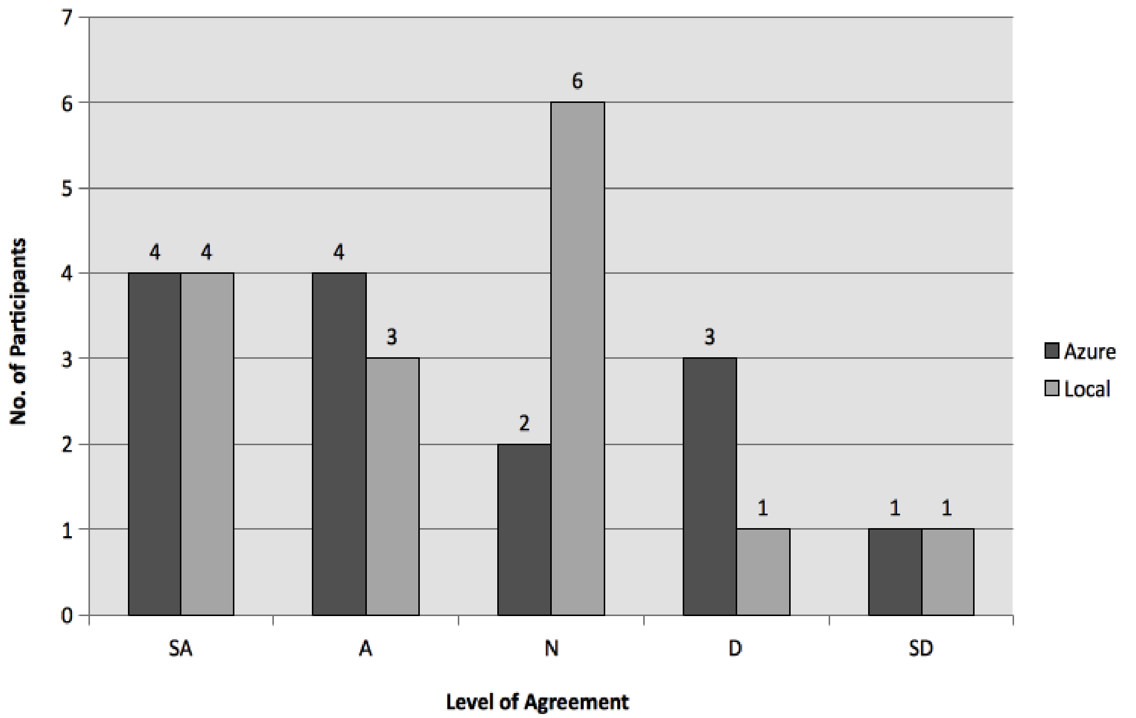

Figure 7. Participant levels of agreement with the notion that the associated development environment was built with rapidity.

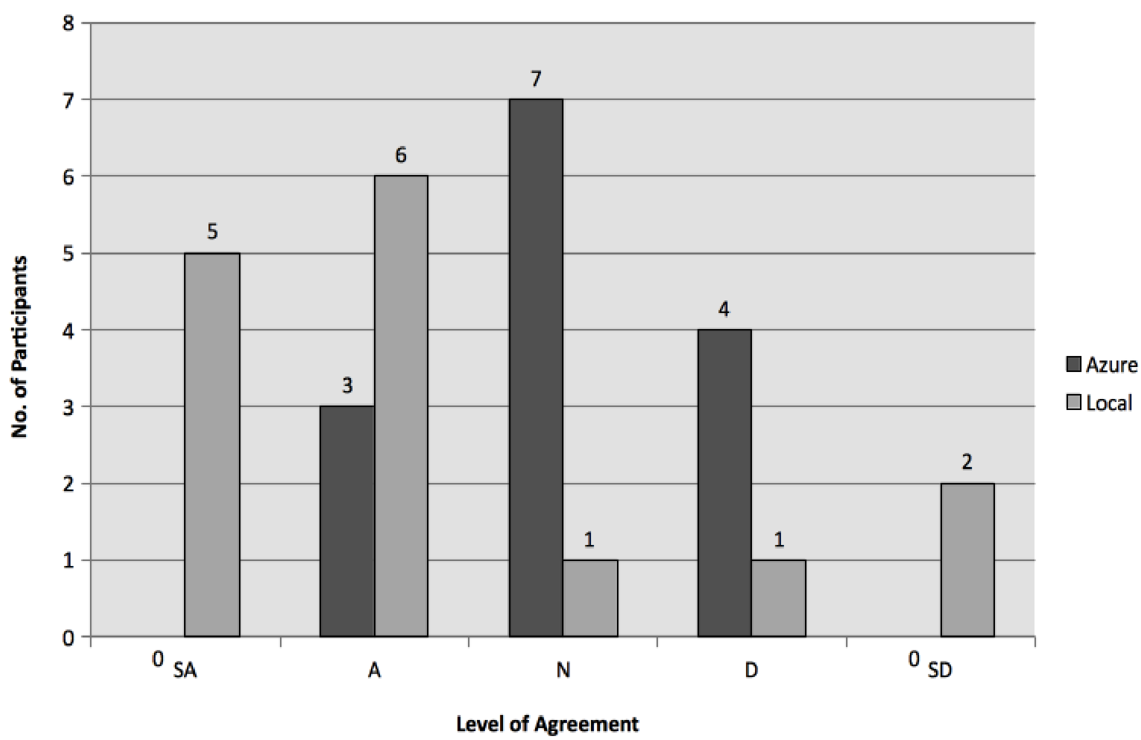

Figure 8. Participants' level of agreement relative to the development environment leading towards effective and efficient learning experiences.

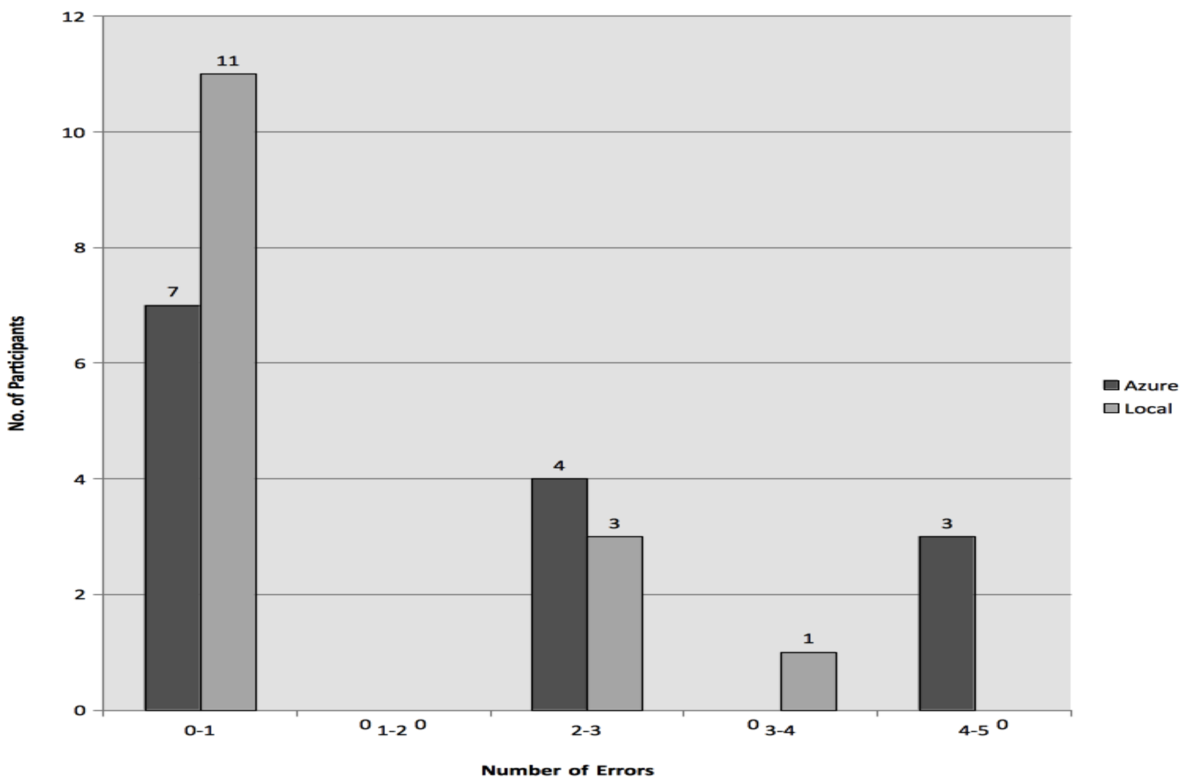

Figure 9. The number of errors encountered by participants during downloading, installation, and configuration of the development environment.

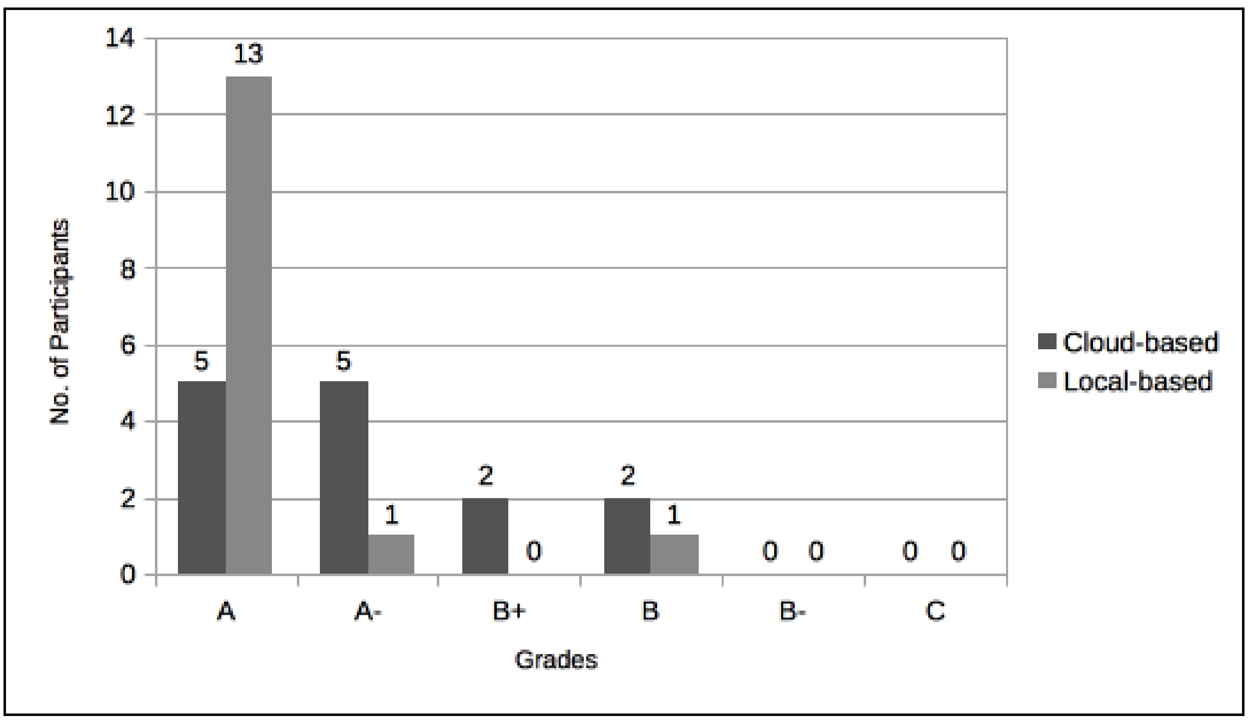

Figure 10. Distribution of final grades earned by participants using local-based development environments compared to cloud-based development environments.

The Personality of a Computing Major: It Makes a Difference

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Abstract

For the past several years, there has been an increase in the number of job opportunities in the computing field. As a result, many schools and universities are facing a significant increase in the number of students seeking to major in one of several computing disciplines. This increase in the numbers and variety of majors in the computing field poses challenges for higher education institutions in the areas of advising, retention, scheduling, and enrollment management. This paper builds upon prior research documenting the association of personality type and affinity for a computing career, and proposes using personality testing early in a student's university experience by including it as one factor in the advising process. This study employs the Myers-Briggs Type Indicator (MBTI) as a tool to help students select an appropriate computing major better suited for their given personality. This initial exploratory study shows that there is a significant difference in personalities among computing majors, specifically in the area of introversion versus extroversion, and intuition versus sensing. Testing students early, before starting a specific major, allows institutions to provide better advising to students as they choose their major, with the goal of increasing retention, degree satisfaction and completion of the degree.

Keywords: Advising, Retention, Myers Briggs Type Indicator, MBTI, Computing, Enrollments

1. INTRODUCTION

Many schools, colleges, and universities offer a variety of majors within the computing field. These majors typically fall into one of the computing disciplines: Computer Science (CS), Information Systems (IS), or Information Technology (IT). If an institution offers more than one computing major, then students are faced with the challenge of deciding which major is best suited for them.

The increase in the number of advertised computing jobs that has been occurring over the last few years has fueled the increase in the number of students wanting a degree in computing (Lazowska, Roberts, & Kurose, 2014). Unfortunately, this phenomenon attracts students to the computing field and increases the pressure to decide on a major simply by the title of the major, whether or not the student is well suited for that particular major.

The problem is further complicated by the often limited number of common courses between the different majors, forcing students to select their desired major early in the process rather than later. If a student makes a poor choice, and then attempts to switch to a different computing major, the time and cost of taking additional courses can be significant.

The challenges of increasing enrollments include: managing the limited seats in course offerings, the subsequent scheduling of additional sections, and then finding faculty to teach those additional classes. Even if space is made, it does not guarantee that the student will succeed in that course and when a student fails a course, then one of two things happens. Either the student retakes the course, placing an additional burden on an already overloaded system; or, the student leaves the computing field, reducing the number of graduates available to fill the increasing number of job opportunities.

Today, advising has become a key component in enrollment management (Brown, DeMonbrun, Lonn, Aguilar, & Teasley, (2016). Advising students early in the process, before a major is selected, has many potential benefits, but primarily trying to ensure students start in a suitable major. Successfully placing a student in a major in which they can be successful benefits the student, the institution, and the computing industry.

2. BACKGROUND

The Myers-Briggs Type Indicator (MBTI) has been a source of research since its creation in 1944. Since then, researchers have tried to predict aspects of a person's life based on that person's MBTI type. It has a long history of being used to predict college majors; first by Goldschmid, (1967) and continuing through to Pulver & Kelley (2008). Soon after, McCaulley (1976) began using the MBTI to examine psychological types specifically in engineering disciplines followed by two collaborative studies by McCaulley, Godleski, Yokomoto, Harrisberger, & Sloan (1983) and McCaulley, Macdaid, & Walsh (1987). Rosati (1993) showed that successful engineering students are largely INTJ, and that female retention could be improved by including tasks and activities geared towards ESFP types. Scott, Parsons, & Seat (2002) showed that ISTJ, ESTJ, INTJ, ENTJ are the primary types for engineering students, confirming McCaulley's (1976) earlier observation of the commonality of "TJ" types. One recent paper used correlations between MBTI type and interest in sustainability to hypothesize ways to attract "atypical engineering types and females into civil engineering" (Braxton & Nossoni, 2015).

Naturally, investigating correlations of the MBTI to the computing disciplines started much later. An early paper by Jones and Wall (1985) looked at the MBTI as it relates to anxiety about using computers. One pioneering paper tried to use the MBTI (among other factors) to predict student performance in a beginning class. Although Werth (1986) noted "no relationship between grade and the personality type", she did discover marked differences in the personalities of CS students and the general population. Werth (1986) found that "[c]omputer science students were found to be far more introverted, intuitive and thinking than the population as a whole, though they were about the same on the perceiving/judging index." Similarly, Bishop-Clark & Wheeler (1994) found that "personality type influenced achievement in programming performance, but did not influence achievement on exams or overall average." Rountree, Rountree, Robins, & Hannah (2004) also looked at the MBTI as a possible factor of success in CS1 courses. Greathead (2008) looked at code comprehension specifically and found that "[i]ndividuals who had a leaning towards Introversion on the Extroversion/Introversion preference were significantly better at the code comprehension task".

Looking more broadly at computing as a field, Teague (1998) performed an extensive literature review and found that "[t]wo types, ISTJ and INTJ, appear in the list of the three most commonly occurring personality types in all studies. ISTJ was the most common personality type in four of the studies, with INTJ second in each case," mirroring the findings reported by McCaulley (1976) for engineers nearly twenty years earlier. This was somewhat confirmed by Benest, Carter, & Chandler (2003) who reported that "[a]pproximately 50% of the [computer science] students fall into either the ISTJ or ISFJ category," and that "more than a quarter of the computer science students have an ISTJ personality." Recently, Cruz, da Silva, & Capretz (2015) conducted a review of forty years of the literature on how personality preferences relate to programming and software engineering. Not surprisingly "the most frequent MBTI personality types found among them are the ISTJ, INTJ, and INTP." Kruck, Sendall, Ceccucci, Peslak, & Hunsinger (2014) also discovered the dominance of thinkers and judgers: "Thinking type students performed better than Feeling types, and Judgers performed better than Perceivers."

Most of the previous literature has been concerned with either engineering or CS, with the exception of a longitudinal study at one institution. Sendall, Peslak, Ceccucci, & Kruck (2015) showed that extroverts and judgers in CIS have increased since 2001 and that "there was a significant difference in course performance based on whether a student self-classified as Perceiving versus Judging. This factor is a significant influence in performance in our CIS course and has not changed over the last 10 years."

Within IS, (McPherson & Mensch, 2007) looked specifically at business information systems, computer information systems, and management information systems. Between all three, ISTJ and ESTJ were the two dominant personality types. The top three personality types for each major were BIS: ESTJ, ESTP, ESFJ; MIS: ISTJ, ESTJ, ESFJ; CIS: ISTJ, INTJ, ISTP. They concluded that the predominant personality types for BIS students were extrovert/sensing; MIS students were largely sensing/judging; and CIS students were introvert/thinking.

Unfortunately, little work has been done to see if there are any differences between the various disciplines of computing: information systems, information technology, or computer science. Further, the literature to date focuses on the sixteen different combinations of preferences rather than the individual preferences themselves.

3. THE PROBLEM

Currently, typical advising uses several tools to help assist students select a major such as the student's ACT (or SAT) scores, high school GPA, interview with the student, etc. The difficult task of advising of students would benefit from having an additional tool that would help a student be more successful in their selection of a major. This paper shows the results of a study conducted at GVSU that shows potential benefits of using the MBTI survey in the advising process.

This study seeks to answer the question: Are there significant patterns in the personality preferences, as measured by the Myers-Briggs Type Indicator (MBTI), of CS and IS majors enrolled in their respective capstone course at [institution to be inserted]? The MBTI was chosen as an additional component in the advising process because of its documented validity noted earlier, and it is the "most widely used professional personality test" as well as that it fundamentally measures cognitive processes, rather than behavior, as shown in Figure 1 (Kim & Han, 2014).

Personality type	Basic definition and the preference	Personality type
Extraversion	Where they prefer to focus their attention	Introversion
Sensing	The way they prefer to take in information	Intuitition
Thinking	The way they prefer to make decisions	Feeling
Judging	How they orient themselves to the external world	Perceiving

Figure 1. The Four MBTI Preferences

4. HYPOTHESIS AND RESULTS

As noted in section 2, there has been little work in the area of describing and distinguishing the personality preferences of different majors within computing disciplines.

The purpose of this study is to evaluate the personality preferences of successful students in ABET accredited computing majors in both CS and IS. In this context, successful is being defined as completing the capstone course in the respective majors. The data for this pilot study were collected from students in the capstone course of each major in 2015.

Between the two majors, the personality profiles were compared on the individual MBTI preferences.

1) Is there a difference of E/I between majors?
H_1: Information Systems majors will have a different percentage of students who are E compared with Computer Science.

2) Is there a difference of S/N between majors?
H_2: Information Systems majors will have a different percentage of S compared with Computer Science.

3) Is there a difference of T/F between majors?

H_3: Information Systems majors will have a different percentage of T compared with Computer Science.

4) Is there a difference of J/P between majors?
H_4: Information Systems majors will have a different percentage of J compared with Computer Science.

Statistical Methodology
For each of the four hypotheses, the null hypothesis will be accepted or rejected using the significance level of .05. To compare two independent groups based on binary variables, most statistics guidelines suggest using the chi-square test of independence as long as the sample sizes are large enough. Sauro & Lewis (2008) contend, however, that the "latest research suggests that a slight adjustment to the standard chi-square test, and equivalently to the two-proportion test, generates the best results for almost all sample sizes."

To determine whether a sample size is adequate for the chi-square test, calculate the expected cell counts in the 2x2 table to determine if they are greater than 5. When the values in this study met this test, the chi-square test results were used. When the values of one or the other of the subgroups did not meet this test, the N-1 chi-square test was used. The formula for the N-1 chi-square test (Sauro & Lewis, 2008) is shown in the next equation using the standard terminology from the 2x2 table:

$$\chi^2 = \frac{(ad - bc)^2(N-1)}{mnrs}$$

Test Results
Hypotheses are supported when the null hypothesis is rejected. In this study, the null hypothesis is rejected when there is a statistically significant difference between the proportions represented by $p<.05$. Accordingly, the first hypothesis (H_1) is supported since there is a significant difference between the 82% of E who are IS majors and the 32% of E who are CS majors. The second hypothesis (H_2) is also supported since there is a significant difference between the 91% of S who are IS majors and the 53% of S who are CS majors. Both majors had a majority of students who were T, and while IS had a higher percentage, both the third hypothesis (H_3) the fourth hypothesis (H_4) are rejected since there is no significant difference.

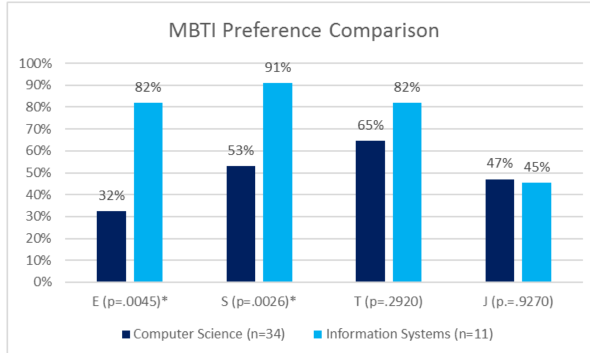

Chart 1.0 – MBTI Preference Results

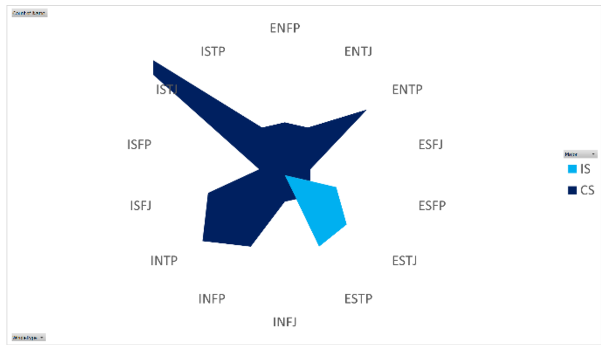

Chart 2.0 MBTI Personality Types

Since most prior literature focused on comparisons using the complete MBTI profile, Chart 2.0 is a Pivot Chart that was generated to show the clustering of majors by whole personality type.

While the sample size in this pilot study was too small to statistically compare all 16 combinations of personality preferences, the Pivot Chart does confirm the overall results of previous studies, that is, for IS majors EST is the predominate combination. The data are less clear for CS majors. While I and N and T are predominant, the Pivot Chart shows they are sometimes combined with other less predominate preferences in this sample.

5. DISCUSSION AND CONCLUSIONS

This research expands the current state of knowledge of how personality preferences correlate with specific majors. The data show that IS majors and CS majors have different preferences that are common to a significant majority of students in the respective major. Further, the results of this study match and confirm the findings of McPherson & Mensch (2007). In that study, there were clear differences between extroversion vs. introversion and sensing vs. intuition types. While they compared different types of information systems majors, that study found significant differences between "business/management" and "computer" information systems majors. The conclusion that can be drawn from this is that students who had the choice of a major focused more on the computing part of information systems, would most likely be more aligned with students choosing CS over IS.

As with the McPherson & Mensch (2007) results, the most significant differences found were that successful IS students tend to identify with extroversion and CS majors identify with introversion. Also significant, IS majors identified much more with sensing then did CS majors. The following algorithmic format illustrates these results in more specific advising choice terms:

IF "E" THEN choose Information Systems
ELSE choose Computer Science.

IF "S" THEN choose "Information Systems
ELSE choose Computer Science"

Anecdotally, the pattern of the overall data is that IS majors are strongly EST, while CS majors are more mixed (INT, IST, ENT) when combining attributes. This advice could be very helpful to new undergraduates trying to determine which major to choose if they have an interest in a career in the computing field.

6. FUTURE WORK

Since the pilot study provided additional insight into the differences between specific computing majors; IS and CS, the GVSU has decided to implement personality profile assessment beginning in the fall 2016 for the capstone courses in each major. Data gathered in future semesters will be used to refine advice given to incoming majors.

While this study has confirmed prior research, and provided insight for academic advisors, further study would be helpful to provide more confidence in this advice. Expanding this study to include (1) students from different institutions that provide a different alignment of majors across academic units, and (2) additional majors, such as information technology, in addition to IS and CS. It is the intent of the authors to seek collaboration to expand and broaden this study.

7. ACKNOWLEDGEMENTS

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Role-Playing and Problem-Based Learning: The Use of Cross-Functional Student Teams in Business Application Development

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Abstract

To create a learning experience which replicates the process by which consultants, systems developers and business end users collaborate to design and implement a business application, a cross-functional student team project was developed and is described. The overall learning experience was distinguished by specific components and characteristics of the project, including: 1) a problem-based learning approach which presented students with an accounting auditing problem requiring the design and development of computer-based application from scratch; 2) the formation of cross-functional teams comprised of students across multiple sections of two different courses (the capstone courses for both Accounting and Information Systems); and 3) the contributions of individual students based on their respective backgrounds and roles in the project. The roles included domain/content experts (accounting students) as well as consultants, business analysts and developers (information systems students). The intentional use of cross-functional teams and assigned roles distinguishes this approach from other problem-based approaches. Further, the teams had additional extrinsic motivation as the business applications they developed could be submitted to a contest hosted by a professional organization. Pre- and post-assessment data indicate that students learned, through iteration and trial-and-error, new interpersonal, analytical and technical skills through client-consultant interactions, problem definition and formulation, requirements analysis, business process and data modeling and application development.

Keywords: information systems pedagogy, problem-based learning, business application development, cross-functional teams, capstone

1. INTRODUCTION

Given the increasing market demand for business students who possess skills in areas such as communication, collaboration, critical thinking, problem-solving and self-learning, educators are under increasing pressure to re-think traditional approaches that rely primarily on information delivery. Whether the information is delivered via lectures, chapter readings, or online videos, these methods can be perceived as one-way communication and inhibit students from learning how to think, analyze, and move towards a problem solution in an unstructured, team-based environment – the very skills many professional jobs demand. Further, many companies are looking to newly minted graduates to take a highly active role in existing teams within the organization, and thus students need to have practice working effectively in a collaborative environment.

As an alternative, problem-based learning methods, which focus students on the knowledge and skills required to solve a particular problem, can be effective in instilling many of the self-learning skills required of business graduates (Smith, 2005). Certain business disciplines in turn are highly conducive to the use of problem-based learning because they naturally incorporate many of its elements. The analysis, design and development of a business application, for example, is an inherently collaborative, complex and unstructured task requiring the interaction of many different types of skills and knowledge that no one person is likely to possess. It requires progressive understanding of business requirements through iterative communication with content experts, the design of a data and process model that aligns with and addresses the requirements, and the development of a technical solution that implements the model and solves the business problem. Thus, successful completion of this complex and multifaceted task is possible only through a cross-functional team in which the various members contribute their own specialized knowledge. This last point is critical, and the course project described below focuses on implementing this very concept. The course project, which required the development of an auditing web-based business application, could not have been easily implemented, if at all, within a single class. The Accounting students had the auditing knowledge but not the skills to develop the application. Conversely, the Information Systems (IS) students, who could develop a web-based business application, did not have knowledge of the auditing domain or the decision support requirements. Thus the only feasible solution was to combine students from both disciplines and encourage them to determine what they needed to know and to learn from each other and, secondarily, from their professors.

In this paper, we describe prior research on problem-based learning and its implementation in business education. Following this, we describe the context, motivation, and approach taken during implementation of the cross-functional course project. Lastly, we discuss learning outcomes and lessons learned to set expectations regarding the success of the course project as well as provide guidance if others are considering such an implementation.

2. LITERATURE REVIEW

Broadly defined, problem-based learning (PBL) focuses on the student, who in turn is tasked with conducting a detailed and iterative process of exploration, information gathering and analysis (Barrows, 1986). As such, and as Hmelo-Silver notes, problem-based learning involves students working together, in groups, in order to "learn what they need to know in order to solve a problem" (Hmelo-Silver, 2004).

On a deeper level, there are elements inherent to PBL that distinguish it from other problem-solving approaches and make it particularly relevant as the foundation for this student project. Those elements can be characterized as follows:

- **Unstructured nature of the task and problem**: Problem-based learning is most effective when the task facing the students is ill-structured. (Stinson & Milter, 1996; Walker & Leary, 2009) Hmelo-Silver and Barrows define an ill-structured problem as one that is not solved algorithmically, but rather presents students with the possibility of multiple 'correct' answers as well as various alternative paths to reach one or more of those solutions. As such, students are required not only to 'solve' the problem but also to defend the approach they took in finding their solution (Hmelo-Silver & Barrows, 2006).

- **Holistic learning outcomes**: Much of the benefit derived from PBL lies in its ability to integrate the various facets of a complex problem. PBL began in the field of medical education, which required educators to pursue a learning approach that could combine acquired medical knowledge as well as the patient-related and social factors required for medical diagnosis (Barrows 86). This integrative characteristic of PBL that makes it useful for medical education also makes it suitable for other disciplines requiring the integration of multiple perspectives (Savery, 2006; Stinson & Milter, 1996).

- **Consultative role of the teacher**: In PBL teachers shift away from their traditional role as lecturers, and toward a less directive and more consultative, facilitative role (Walker & Leary, 2009). As such, the onus for solving the problem, and thus learning what is necessary in order to solve the problem, is placed squarely on the student.

- **Active role of the student**: As Walker and Leary explain, students must understand and formulate the problem, ascertain what they need to know in order to solve the problem, and then proceed to acquire that knowledge (Walker & Leary, 2009). Kay notes that broad complex problems require students to take a strategic approach in planning their learning strategy and communicating among group members (Kay et al., 2000; Savery, 2006).

- **Collaboration and interaction among students and teachers**: Somewhat related to the preceding two elements, the relationship between and among students and teachers is inherently collaborative. Hmelo-Silver and Barrows note that teachers using PBL are facilitators, but more specifically they are facilitators of "collaborative knowledge construction." (Hmelo-Silver & Barrows, 2006) Cockrell et al state that collaboration is "a central, organizing premise of PBL", in that it helps to link "theoretical knowledge" to "practical application". (Cockrell, Hughes Caplow, & Donaldson, 2000) They cite Vygotsky in arguing that because learning is "the social construction of knowledge," collaboration is an essential component of learning (Cockrell et al., 2000).

- **Focus on real-world and cross-disciplinary problems**: Scholars agree that problems investigated by students must have some type of relevance to the real-world, which allows students to combine theory with practice (Savery, 2006). Barrows and later Stinson and Milter defined a real-world problem as lying fundamentally within the context of professional practice (Barrows, 1986; Stinson & Milter, 1996) a context which Walker and Leary suggest is "inherently cross-disciplinary" (Walker & Leary, 2009).

PBL has been applied across a number of domains over the past 30 years, including the business and computer science disciplines that are closely related to this project. PBL is particularly applicable to business education largely because of the characteristics discussed above: It is multi-disciplinary, encourages collaboration and builds interpersonal skills, focuses on practice, and because of its relevance tends to motivate and excite students (Smith, 2005). It is in this sense that business education has been overly narrow, compartmentalized and lacking in real-world relevance, and thus has motivated a growing adoption of PBL in business education (Smith, 2005; Stinson & Milter, 1996).

Adoption in business education has occurred within two domains. The first is individual business disciplines such as accounting (Hansen, 2006; Johnstone & Biggs, 1998; Stanley & Marsden, 2012), marketing (Wee, Kek, & Kelley, 2003), organizational behavior (Miller, 2004), production/operations management (Kanet & Barut, 2003) and project management (Kloppenborg & Baucus, 2004). The second is graduate management education, which includes the creation and implementation of complex projects incorporating issues across various business disciplines. Stinson and Milter for example describe the use of PBL across the curriculum of the MBA program at Ohio University (Stinson & Milter, 1996). Brownell and Jameson describe a problem-based team project that they explain "has been the centerpiece of the Master of Management in Hospitality (MMH) curriculum" in the School of Hotel Administration at Cornell University (Brownell & Jameson, 2004). Sroufe and Ramos describe a 'thematic' approach to problem-based learning in the specialized MBA program in Sustainability at Duquesne University (Sroufe & Ramos, 2015). In each case the intent is to develop in graduate business students the real-world problem-solving, collaboration and leadership skills sought in the marketplace.

We should note that the project-orientation and technical component of our student project, which involved the design and development of a computer-based application, has also been addressed in the PBL literature. The fields of interest within this perspective are engineering and computer science which, like business, also require their graduates to develop solutions to complex problems (Kay et al., 2000; Mills &

Treagust, 2003; O'Grady, 2012) Similar to application development, Mills and Treagust explain the phased project approach, process orientation and design focus of many engineering projects (Mills & Treagust, 2003). Kay et al in turn cite analogous examples from computer science such as 'maintaining information about Olympic events and athletes and answering arbitrarily complex database queries" (Kay et al., 2000). These are very similar to the types of information management and reporting activities conducted by our student teams as part of the project.

3. CONTEXT AND MOTIVATION FOR THE CROSS-FUNCTIONAL TEAMS

The context for the course project included two capstone courses at a mid-size private university in the eastern United States. All of the students were undergraduate students nearing graduation and were either enrolled in the School of Business Administration or a program affiliated with the school. The four instructors cooperated to incorporate the course project into two capstone courses – the Accounting capstone and the Information Systems capstone. Prior work has examined the combination of capstone courses within more similar disciplines related to IS (Schwieger & Surendran, 2010) and integration of content from a major into a capstone (Reinicke, Janicki, & Gebauer, 2013).

Each instructor taught one section of a course, and two sections of each course were involved. No other sections of either course were offered during that semester. The course project was introduced towards the beginning of the semester in both courses and was included on the syllabus as a graded requirement of the course.

In addition to the grade-related motivation, students also had extrinsic motivation for completing the course project. The Pennsylvania Institute of Certified Public Accountants (PICPA) hosted a business application development contest for students, and the faculty emphasized the potential for students to submit their work. The deadline was conveniently aligned with the end of the academic semester. The PICPA invited college students in the Commonwealth of Pennsylvania to develop a web-based application that could provide automated decision support in the area of accounting, financial reporting and/or auditing. Completed applications could be submitted to the PICPA for review by their panel of experts, who in turn would award the first, second and third place winners from around the state and associated cash prizes.

Although the contest ostensibly was targeted to accounting students, it was clear from the start that while the senior accounting students had appropriate knowledge of the accounting/auditing domain, they did not have the knowledge or skills required to develop a web application. Thus, composing teams of students from both the capstone accounting course and the capstone IS course and developing a joint project where these cross-functional teams would develop applications for submission was formulated. The faculty believed that cross-functional teams would not only address the 'skills' issue, but also would inherently facilitate PBL by implicitly incorporating most if not all of the components of PBL. Note the following definition of a cross-functional team from the Institute of Management Accountants (emphasis added):

> "A cross-functional team is a small ***group of individuals*** that ***cross formal departmental boundaries*** and levels of hierarchy. The group is committed to a ***common purpose or goal*** of improvement; it acts and works as a unit — ***communicating*** frequently, cooperating and providing mutual support, ***coordinating*** activities, drawing upon and ***exploiting the skills and capabilities of the team*** while considering the needs of individual members." (IMA, 1994)

While the initial motivation for a joint project was almost purely practical – i.e., to assemble the resources required for students to submit a web application to the PICPA contest and to continue to satisfy the learning outcomes for the capstone courses, the faculty team quickly came to the conclusion that this project could be much more than that. The students could play a role in a project that would reflect what they could expect when they enter their professions. The accounting students would be the end users; i.e., the professional accountants in need of a decision support system. As such they would have to communicate their needs as well as the nuances and complexities of the decision task to the development team. The IS students, in turn, would be the development team; i.e., the consultants, business analysts and application developers who would have to glean the application requirements from the accountants, and iteratively develop and deliver an application to the accountants' satisfaction. Furthermore, the students would encounter many of the 'real world' issues and frustrations inherent in a systems development project. Students on both sides – accounting and IS – would discover that they did not possess all of the knowledge and information required to deliver a working application. Therefore they would have to acquire that knowledge by questioning their professors, by sifting through white papers and technical documents, by engaging in internet searches, and through trial and error.

Given the relatively short period of time provided to build a business application from scratch – i.e., less than three months – the faculty team did not expect the students to produce production-quality applications immediately ready for use by professionals, but rather a prototype. The main intent was for students to engage in the entire process of developing the application, with the development process essentially becoming a proxy for the learning process and all of its elements, both technical and interpersonal. And while the faculty team expected, or at least anticipated, these outcomes, the project produced other outcomes, both positive and negative, that were not expected. We discuss this further in the conclusion.

4. DESIGN AND IMPLEMENTATION OF THE CROSS-FUNCTIONAL COURSE PROJECT

The cross-functional course-project was implemented in the spring of 2015 with the following PBL elements, shown in Table 1.

PBL Element	Implementation
Unstructured nature of the task and problem	Students were required to drive their own projects – everything from picking the topic to communication strategies to design of deliverables (e.g., modeling notation). A basic timeline for the semester with a few deliverables was outlined to keep students on track, but otherwise the teams needed to define, organize, and complete the project and solve the problem at hand utilizing their own strategies and working as a team.
Holistic learning outcomes	Students were challenged with the presence of individuals with various roles, different expectations, and diverse backgrounds all on one team. In addition to completing the project, they were tasked with bringing a diverse group together to complete a goal, which presented many obstacles to their success. Students were permitted to provide input on team formation, but final team formation was conducted by the faculty team.
Consultative role of the teacher	Faculty were available to answer questions for any student from any student involved, and the faculty coordinated amongst themselves to assure they were acting as consultants and monitor the extent to which teams reached out.
Active role of the student	With multiple sources of motivation, students were driven to take an active role in the completion of the course project. Further, students were given an opportunity to provide feedback on each of their team members at specific points during the semester. This was utilized to discourage inactive or loafing team members.
Collaboration and interaction among students and teachers	Students were placed in cross-functional teams, and the task was simply too large for any one person to complete on his or her own. Further, specific roles for the accounting and IS students were discussed with the students so that they would feel confident in their ability to contribute to the team and interact with others. Student-teacher interaction was extensive as time was dedicated to meeting during class sessions, in office hours, and on-demand.
Focus on real-world and cross-disciplinary problems	While a list of potential topics was provided, the list was largely developed by a member of the faculty team with extensive industry experience and the PICPA was only willing to accept submissions of business applications that solved real-world problems.

Table 1. Illustration of PBL Components of the Course Project

The professors teaching the capstone courses in accounting and IS met prior to the start of the semester to structure and scope the student projects. In a single organizing /project launch during the first week of classes, 150 accounting and IS students (5 were double majors) were distributed into 28 teams of approximately five students each. To make this more manageable, one IS instructor was paired with one accounting instructor, and this pair formed 14 groups across their two classes. This method of forming the teams was selected so that the instructor pairs could visit each other's classes if needed, rather than requiring all four instructors to go to four classes.

Each team was charged with creating a web application that focused on an accounting, financial reporting or auditing topic. The teams were cross-functional, consisting principally of two to three accounting students and equal number of IS students. Student teams had the opportunity to choose a topic from a suggested list of topics or develop their own related topic. Most of the topics chosen for the projects focused on the following areas in auditing: segregation of duties; determination of auditor independence; inventory obsolescence; establishment of lower of cost or market for inventory; calculation of ratios and analysis to identify "red flags" in an audit of financial statements; and determination of whether to consolidate or use the equity method for financial statement consolidation. The student groups who chose their own topics focused on areas of audit efficiency and accuracy.

To evaluate the teamwork, the instructors utilize the CATME Smarter Teamwork system to periodically check in to see how the teams were working together (Ohland et al., 2012). This system can generate flags to mark certain types of behavior that might be occurring in a group based on the students' responses. Students can also view their peer feedback, compare it to their self-evaluation, and then attempt to improve their teamwork skills.

For classroom purposes, the task presented to the students was structured similar to a consulting project. The accounting students served as both the client and the content experts, identifying a particular accounting or auditing need and proposing that an app could address the particular need. The accounting students also supplied the detailed technical knowledge of the focus area and provided feedback regarding the final design and finished product. The IS students gained an understanding of the client's need by interviewing the accounting students and asking questions about the topic area and the requirements of the application. The IS students then proposed a design to the client, developed the app to the specified design, and prepared the applicable documentation.

Specifically, development of the application required the following analysis, design, development and implementation activities:

- Documentation of current state vs. future state processes in standard modeling notation

- Design of interfaces with a focus on the end user

- Modeling and implementing databases to support the app

- Development of web-based applications in ASP.NET with Visual Basic, using Microsoft Visual Studio as the development environment

- Publishing the app to Microsoft Azure, a cloud-based platform that hosted the app and database

Final testing of the app was conducted by all members of the team to ensure the overall objectives were achieved. At the end of the semester, each team was required to make a formal presentation to a panel of faculty members and external judges, as well as a peer teams. The teams were evaluated on the functionality of the app, its usability, overall design, and accuracy. Throughout the semester, teams had the opportunity to interact with teams examining a similar app topic during class, which created a natural audience for ideas and feedback generation.

Overall, the IS courses, given the nature of their task, dedicated a larger portion of the course to completing the course project. On the other hand, the accounting courses dedicated a smaller portion given their role in formulating the problem for the IS students. In retrospect, this was one of the weaknesses of the project design as the students very quickly noticed the inequity, which created tension on some teams. However, this is also representative of real work project teams as different team members can have different priority levels for the project at hand. To attempt to alleviate tension, instructors made themselves available to any students from either section so that issues could be discussed and addressed.

5. IMPACT ON STUDENT LEARNING

The learning outcomes, and therefore the impact on student learning, were significantly dependent on the students' role in the project. For the accounting students, application development and performing the role of a client were new areas, and thus the primary assessment question focused on the extent to which their role helped to reinforce and augment their accounting knowledge. To answer that question, pre- and post-project quizzes were administered to the accounting students to determine their base level of knowledge prior to starting the project, and then to assess their level of knowledge after the project was complete. The quizzes included questions about apps in general as well as auditing and business topics. The results of the post-quiz showed an 18% increase when compared to the pre-quiz, with significant improvements in areas such as inventory valuation (64% increase), audit quality (57% increase) and identifying red flags during an audit (36%). Other factors that could have impacted the students' learning, such as assignments in the mentioned or other classes, were not controlled. While we are unable to conclude that the increase in learning was directly attributable to the completion of the app project, it certainly was a contributing factor.

Grading Rubric Items (measured on 5-point scale)
• Document client's webapp requirements • Document client's data requirements • Document as-is or current state processes in diagrams (e.g. DFDs, use case) • Document to-be or future state processes in diagrams (e.g. DFDs, use case) • Design appropriate database based on requirements • Design appropriate screens, forms, and reports based on requirements • Document/explain how the design is fulfilling the specified webapp requirements • Create database in MS SQL Server in Azure • Develop screens, forms, and reports based on design • Demonstrate and explain the application to the client • Completion of project

Table 2. Grading Rubric

For the IS students, the learning outcomes and impact were directly attributable to the accuracy of the process and data models, the quality and usability of the applications developed, and the extent to which the applications addressed the accounting need. A grading rubric (see Table 2) was utilized by the faculty members, external judges and the student peers to ensure consistency in evaluating the applications developed. Of the 28 teams, 26 teams completed business applications that earned an average of satisfactory or above (3 out of 5) on the rubric. The two teams that did not achieve this metric either did not finish core functionality or the functional incorporated lacked basic usability.

On an affirmative note, the apps were submitted to the PICPA for the independent evaluating and judging. Our student teams placed first, second and third, with the first place team having designed an app to assist with understanding segregation of duties.

6. CONCLUSIONS

Based on the learning assessments, problem-based learning was effective in promoting student learning. The students themselves generally agreed with this assessment, in that their feedback on the project was generally positive. Notably, students indicated that they were able to see the connection between classroom learning and actual implementation, which was a key learning objective of the capstone courses. This made the experience more relevant to the students, and as such they were more motivated to participate actively in their own learning. Overall, utilizing this approach was an innovative way for students to apply knowledge from their previous courses as well as integrate newly learned concepts.

With regard to lessons learned and a 'word to the wise' to others who might wish to use this approach, we should note that significant time was required of faculty members for the project, especially in the early stages and for the IS faculty during the app coding stage. In a problem-based learning approach, the model of faculty as facilitators/mentors is in many ways more challenging than a more 'traditional' approach. The students themselves were surprised at the time required to bring everyone on a team to at least a similar level of knowledge in order to begin the project.

Finally, and in a broader sense, the learning was about more than the technical knowledge of information systems and accounting gained from the experience. Students also learned valuable 'soft skills', including communication, overcoming the challenges of working in cross-functional teams, and time management in the context of a complex project with multiple deliverables, uncompromising time deadlines, and a real-world client who is expecting a solution to a real problem, as other studies have suggested (Russell, Russell, & Tastle, 2005).

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