Title
Applying a Theoretical Model for Explaining the Development of Technological Skills in Statistics Education

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Author
Baglin, James

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1. INTRODUCTION

The Guidelines for Assessment and Instruction in Statistics Education Project College report states that, "Technology has changed the way statisticians work and should change what and how we teach" (Aliaga et. al, 2005, p.4). In response to this reform, the use of technology in statistics courses has been on the rise (Garfield, Hogg, Schau, & Whittinghill, 2002; Hassad, 2012). The prevailing attitude towards the use of technology in statistics education has been to focus "on the content and not the tool" (Chance, Ben-Zvi, Garfield, & Medina, 2007, p. 4). This sentiment was epitomized by Moore (1997) who argued that the most effective teaching occurs when content, pedagogy and technology align. Statistics instructors have focused their use of technology on enhancing the teaching and learning of the major outcomes of statistics education, namely statistical literacy, reasoning and thinking (Ben-Zvi & Garfield, 2005). These outcomes deal with students' knowledge and understanding of statistical methods and concepts.

While there is no universal agreement on the distinction between the three major learning outcomes of statistics education (Ben-Zvi & Garfield, 2005), the following brief definitions serve as a guide. *Statistical literacy* is an understanding of data, statistical concepts, statistical terminology, and methods of data collection, computation of descriptive statistics, basic interpretation skills, and communication skills in basic statistics (Rumsey, 2002). *Statistical reasoning* impinges on the thought processes people employ to understand statistical inference and is the product of a conceptual understanding of the important statistical ideas of distributions, central tendency, variation, association, uncertainty, randomness, and sampling (Garfield & Gal, 1999). *Statistical thinking* involves the ability to summarize data, answer research questions, problem solve, understand the reasoning underlying a procedure and make appropriate inferences from statistical analysis within a research context (Chance, 2002). So how does technology impact these outcomes?

The use of technology in statistics education can be broadly categorized as serving two major roles, technology for *understanding* statistics and technology for *doing* statistics. Technology for *understanding* statistics aims to improve students' statistical knowledge. The technology is a tool that when coupled with sound pedagogical practice assists in developing students' statistical knowledge, i.e. literacy, reasoning and thinking. Examples include applets (e.g. Statistics Online Computational Resource, http://www.socr.ucla.edu/SOCR.html), multimedia material (e.g. Harraway, 2012, http://www.maths.otago.ac.nz/videos/statistics/) and educational software (e.g. *Tinkerplots*, http://www.keycurriculum.com/products/tinkerplots). On the other hand, technology for *doing* statistics assists students to engage in the practice of statistics. The skill for using the technology takes a more central role and assumes that a student has the necessary knowledge to understand its use. The most pervasive example is the use of a statistical package such as *SPSS, Minitab, R,* or *SAS.* Statistical packages are software tools designed for the sole purpose of conducting statistical analysis (Chance et al., 2007).

Statistical packages allow students to spend less time in so called "computational drudgery" (Smith, 2003, p. 276) and more time on data exploration and interpretation. In fact many modern types of statistical methods are inaccessible without the ability to use a statistical package, for example, fitting multivariate models, bootstrapping confidence intervals, and visualizing complex representations of large data.

While these categories may appear dichotomous, in reality the role of many technologies can fall somewhere in between and be adapted to suit the purposes of an instructor. For example, *Minitab* (http://www.minitab.com/en-US/default.aspx) is an example of technology that can have a strong focus on helping students to both understand and do statistics. *Minitab's* intuitive user interface makes exploring and visualizing data easy and its macro capabilities have been used extensively to design dynamic learning activities (e.g. Butler, Rothery, & Roy, 2003). On the other hand, some types of technology are almost purely for doing. For example, Nolan and Temple Lang (2010) provides a comprehensive overview of topics that underlie technological knowledge and skills as they relate to statistical computing. Topics include fundamentals of statistical computing, visualization, web technologies, information technologies, integrated development environments and advanced computing. These technological topics all relate to real world skills where the focus is purely on using technology to access, manage, manipulate, compute and visualize data in real world practice.

Both roles of technology are a means for learning statistics. Figure 1 distinguishes between the two major roles of technology and hypothesizes how technology for doing statistics leads to improved statistical knowledge. The model begins with the first role of technology being used to develop students' basic knowledge (literacy, reasoning and thinking). For example, students may watch video demonstrations, use computer applets and run simulations to explore statistical concepts. This basic knowledge is then used to learn different types of technology for engaging in statistical practice. For example, the student may learn how to manage, explore and analyze data using a statistical package. Engaging in statistical practice increases students' experience with statistics which motivates further understanding and prompts further learning when current knowledge reaches its limits. The cycle continues when new knowledge leads to the development of new technological skills, further engagement in statistical practice and continued accumulation of knowledge. As such, teaching technology for doing statistics is equally important as the use of technology for understanding statistics. The remainder of this paper addresses the somewhat overlooked skills that are necessary for using technology for doing statistics. From here, technological skills will be the term used to refer to the ability to operate statistical technology for the purposes of statistical practice, i.e. "doing statistics".

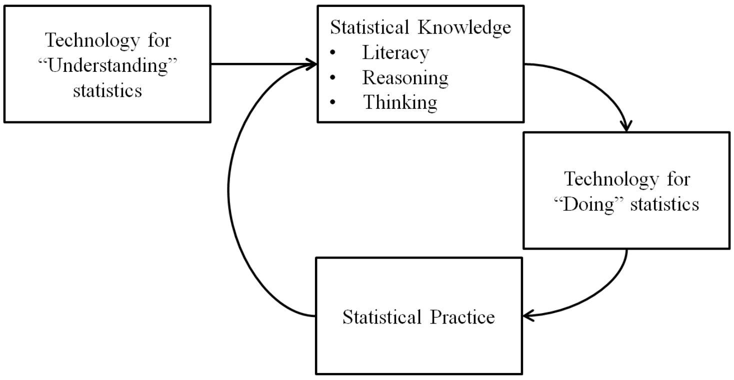

Figure 1: A flowchart showing the proposed distinction between the two major roles of technology used in statistics education and how both are hypothesized to promote student learning.

The development of technological skills for doing statistics warrants some much needed attention, especially if their development is likely to impact on student learning outcomes and the preparation of students for engaging in statistical practice. With the focus of the field of statistics education having been mostly on the use of technology for understanding statistics, some instructors have begun to shift their attention to technological skills. Spurred on by Peck and Chance's (2007) advice, Nolan and Temple Lang (2010) challenged other instructors to think about the outcomes of their courses in preparing students for the real-world. Are our courses preparing students to use technology for modern statistical practice and are we doing it in way that builds their confidence to tackle unfamiliar problems and continue to develop new skills? As Gould (2010) observes, instructors need to stop assuming that students develop these skills on their own. Gould argues that it is time to teach technology. Instructors need a better understanding of how these important skills are developed. By understanding the factors that are likely to explain student variation in the acquisition of these skills, instructors will be better prepared to help foster these skills. This paper uses Kanfer and Ackerman's integrative model of skill acquisition for this purpose. The model is described in the following sections along with its implications as they pertain to the context of technological skill development in statistics courses. Future directions and challenges facing this area of research are also examined.

2. A THEORETICAL MODEL

Kanfer and Ackerman's (1989) integrative model of skill acquisition is consistent with learning to use statistics technology and has been used to predict skill acquisition for general software (e.g. spreadsheets, presentations and word processing, Keith, Richter, & Naumann, 2010). According to Kanfer and Ackerman, skill acquisition is explained by four notions. All tasks require a level of *attentional resources* and each person has a finite amount of resources that they are able to dedicate to a task. The nature of the *task demand* varies with the required amount of attentional resources needed to complete a task. Some tasks have low attentional demand, i.e. easy tasks, and other tasks have high attentional demand, i.e. difficult tasks. People control their *resource allocation* by choosing to dedicate more or less resources to a task. Finally, over time *the effect of practice* decreases the required amount of attentional resources required for a task. Kanfer and Ackerman's model assumes that there is a relationship between resource allocation and task performance, i.e. the more resources allocated to a task, the better the performance. However, this relationship is moderated by the nature of the task, motivation and cognitive ability.

Tasks can be divided into being either *resource-dependent* or *resource-insensitive*. Resource-dependent tasks are those tasks where an increase in attentional resources corresponds with a large performance gain. These tasks are generally those which are moderately difficult. On the other hand, resource-insensitive tasks are those where a change in attentional resources is associated with minimal changes in performance. Easy and difficult tasks are resource-insensitive as in both cases performance is relatively independent from attentional focus (Figure 2. a). Training should begin with resource-dependent tasks. Tasks which are resource-insensitive may lead to boredom or frustration. As the trainee practices, the resource-dependency of the task changes to become more resource-insensitive. It is this change in required attentional resources (Figure 2.b) that is referred to as the *effect of practice*.

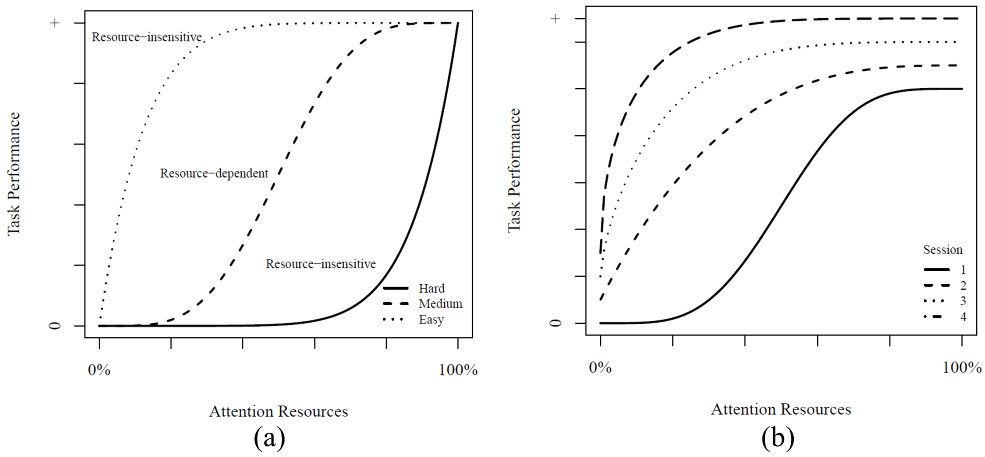

Figure 2: (a) For resource-dependent tasks, task performance is relatively proportional to the attentional resources dedicated to the task. For resource-insensitive tasks, attentional resources are relatively independent from task performance. (b) The effect of practice is to change resource-dependent tasks into resource-insensitive tasks.

Kanfer and Ackerman (1989) proposed two major factors, distal motivation and cognitive ability, which regulate attentional resources allocated during training. Distal motivation determines the level of attentional resources allocated early on in training. Keith et al. (2010) discusses the distal motivation of *perceived performance utility*. Perceived performance utility relates to level of belief that a task will be important to an individual. For example, a trainee with high perceived performance utility regarding statistics technology will view training as being beneficial to their career. Thus, they will more likely allocate a high level of attentional resources when tasks are resource-dependent. Those with low perceived performance utility will be less inclined to dedicate the required attentional resources to training. For example, a trainee who believes knowledge of statistics technology outside of a statistics course is of no use will be less inclined to commit attentional resources to training. In other words, if a student doesn't value the intended outcome of training, they will not engage in training tasks.

Cognitive ability, i.e. intelligence, determines an individual's attention capacity. In other words, an individual's attention is a finite resource. High cognitive ability trainees have more attentional resources to offer, while those with low cognitive ability have less to offer. Because of this relationship between attention allocation and cognitive ability, task performance can largely become a function of cognitive ability. This relationship has been established in a large body of literature showing a strong relationship between job performance and cognitive ability (Hunter, 1986). Regardless, the inclusion of motivation in Kanfer and Ackerman's model includes an interaction where poor motivation can bring the performance of low and high cognitive ability trainees largely on par. This interaction also suggests a pronounced performance gain when motivation and ability are high (Figure 3).

In summary, Kanfer and Ackerman's model predicts that motivation and cognitive ability interact with early training performance when tasks are resource-dependent. As the trainee practices, tasks begin to become more resource-insensitive (Figure 2.b). Therefore, the role of training is to transform resource-dependent tasks into resource-insensitive tasks. Individual differences in motivation and cognitive ability are likely to impact on students' skills acquisition. Kanfer and Ackerman's model predicts that poorly motivated and cognitively weaker students might struggle early on in training when tasks are resource-dependent which will negatively impact on technological skill development. The model also suggests that cognitive ability alone will not guarantee high task performance. Motivation also matters. We will now consider the implications of this model on the selection of training strategies for technological skills. The following sections will focus on the use of statistical packages as these types of technology are the most relevant to the majority of statistics instructors and their students. However, other forms of technology should be kept in mind, e.g. programming languages, web technologies, spreadsheets and databases.

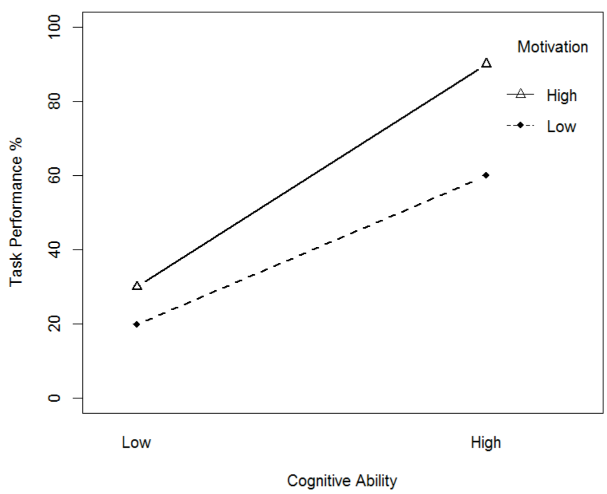

Figure 3: While cognitive ability is important, Kanfer and Ackerman's model predicts that high motivation can help compensate for low cognitive ability.

3. IMPLICATIONS FOR TRAINING STRATEGIES

Introductory statistics courses which incorporate technology will include some level and method of training for students to use that technology. For example, students may learn to use statistical packages in dedicated computer laboratory sessions, through in-class demonstrations, take-home assignments or self-guided tutorials. The intended outcome of all forms of training is the transfer of knowledge and skills. Training *transfer* is demonstrated when knowledge and skills gained during training are enacted outside of the training environment (Hesketh, 1997). There are two major forms of transfer. *Analogical transfer* refers to the ability to complete tasks that are similar to what was covered during training while *adaptive transfer* tasks are distinct from training tasks and require the learner to adapt their knowledge to confront novel situations (Keith et al., 2010). While technological training is unlikely to cover all the scenarios and procedures that students will encounter during their careers, adaptive transfer skills are more desirable as it supports sustained learning beyond training (Frese et al., 1991; Keith et al., 2010). Adaptive transfer may also help facilitate the learning of new technologies.

Kanfer and Ackerman's model can be used to guide the selection of effective technological training strategies. Training strategies are approaches used to inform the design and delivery of training material and activities. According to Kanfer and Ackerman's model, training transfer performance is likely to be influenced by a student's motivation and cognitive ability. While it might be possible to improve student's motivation to learn a technology, it is impossible to improve student's cognitive ability for the sake of training. Therefore, effective training strategies should aim to minimize the impact of initial differences in student motivation and cognitive ability on training transfer outcomes.

The most common forms of training strategies can be broadly divided into two schools - *guided training* and *active-exploratory training*. Guided training (GT) is based on the programmed learning method developed by Skinner (1968). The learner is assumed to be a passive participant during training which uses step-by-step, comprehensive and explicit instructions to teach the features and procedures of a statistical package (Keith et al., 2010, Figure 4). The GT method views errors made during training as a waste of time which need to be avoided. Technological proficiency arises through repeated practice where operational errors are avoided.

Active-exploratory training (A-ET), on the other hand, views trainees as active participants during training (Bell & Kozlowski, 2008). Minimal instruction is given to trainees to engage them in actively exploring the task domain instead of relying on comprehensive instructions. This approach will inevitably lead to trial and error. According to Keith (2010), A-ET is designed to work by developing trainees' self-regulatory skills. Self-regulatory skills, e.g. metacognition and emotional control (Keith & Frese, 2005), refer to an individual's ability to "guide his or her goal directed activities'' by controlling cognition, mood, behavior and focus (Karoly, 1993, p. 25). Metacognition can be defined as the ability to exert "control over his or her cognitions" (Ford, Smith, Weissbein, Gully, & Salas, 1998, p. 220) and involves three basic processes - planning, monitoring, and evaluating (Brown, Bransford, Ferrara, & Campione, 1983). Emotional control refers to "the use of self-regulatory processes to keep performance anxiety and other negative emotional reactions (e.g. worry) at bay during task engagement" (Kanfer, Ackerman, & Heggestad, 1996, p. 186).

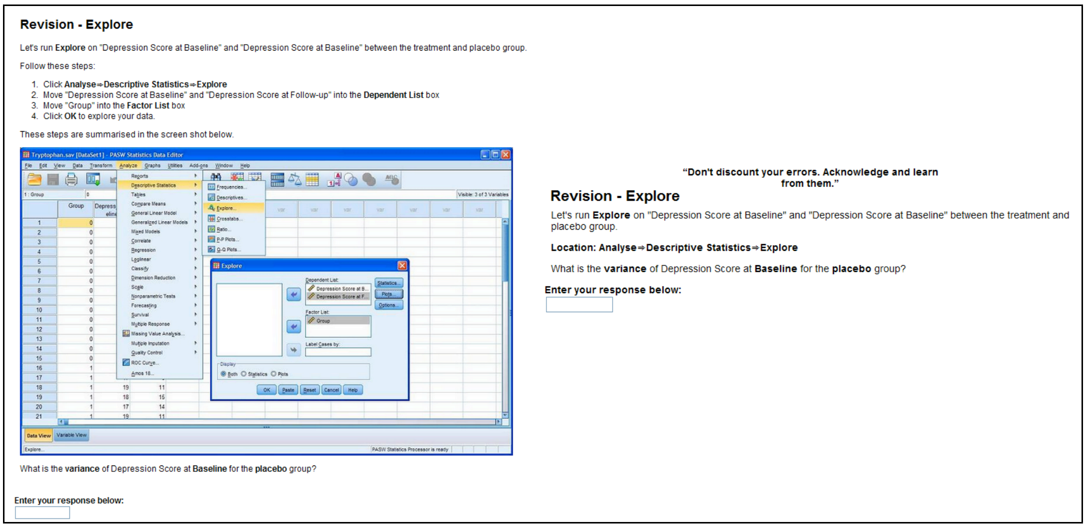

Figure 4: On the left is an example of GT instructions for SPSS. On the right is an example of error-management training instructions. Note the error-framing heuristic and use of minimal information.

Research suggests that A-ET methods, such as Error-management training (EMT), are superior to GT in terms of training transfer performance (Keith & Frese, 2008). EMT is a special type of A-ET with a specific focus on errors made during training. According to EMT, errors are argued to be beneficial to training as they promote exploration, help develop the know-how to avoid errors and the know-how to overcome errors once they have been committed (Frese et al., 1991). EMT frames errors in a positive light by presenting heuristics to trainees during training, such as "Errors are a natural part of learning. They point out what you can still learn!" (Dormann & Frese, 1994, p. 368, Figure 4). Therefore, EMT also helps develop a student's emotional control (Keith & Frese, 2005). Keith and Frese (2008) conducted a meta-analysis of 24 studies comparing EMT to GT on training transfer performance across a wide range of different software (e.g. word processors, spreadsheets, presentations and email) and found that EMT was slightly better for analogical transfer and moderately better for adaptive transfer.

Keith et al. (2010) also found that A-ET might moderate the role of motivation and cognitive ability on training transfer performance predicted by Kanfer and Ackerman's model. Keith et al. explains that the effects of motivation and cognitive ability depend on the degree of overlap between training tasks and transfer tasks. When training tasks overlap transfer tasks, i.e. analogical transfer tasks, the influence of cognitive ability and motivation on transfer performance is minimal. On the other hand, when there is little overlap between training and transfer tasks, i.e. adaptive transfer tasks, cognitive ability and motivation have a noticeable impact. When dealing with difficult or novel situations, trainees will activate their self-regulatory skills, i.e. emotional control and metacognition – planning, monitoring, and evaluating (Kanfer & Ackerman, 1989).

Assuming that A-ET works through the development of self-regulatory processes, it may moderate the effect of cognitive ability and motivation by creating a large degree of overlap between training and transfer tasks. AE-T requires trainees to develop and practice metacognitive skills to address training tasks in the absence of comprehensive instructions (Table 1). In contrast, trainees in GT do not practice self-regulatory skills during training. As these skills have not been developed during GT, the trainees' ability to self-regulate becomes more sensitive to their level of cognitive ability and motivation. The trainees in A-ET are better off because they have been fine tuning these skills throughout training and the effect of cognitive ability and motivation becomes less pronounced (Keith et al., 2010). Consequently, A-ET may moderate the relationship between training transfer performance, cognitive ability and motivation. Experimental studies examining general software training support this theory (see Keith & Frese, 2005; Keith et al., 2010). However, studies assessing statistical package skills, arguably the most pervasive technological skills in statistics education have so far been inconclusive.

Table 1: An example of metacognition promoted by A-ET for statistical packages

Metacognitive Activity	Example
Planning	I know how to obtain a histogram in *SPSS*, but how do I split the histogram by a grouping variable? I will need to try changing some histogram options.
Monitoring	The options don't make sense. I don't know which options to change. Thinking about it any longer won't help. Better I just try something.
Evaluating	Those options didn't quite work, but I think I was close. Let's try again.

Nearly two decades ago, Dormann and Frese (1994) conducted an educational experiment on thirty psychology students who learnt to use the statistical package SPSS in a two hour training session. Students were randomly allocated to receive EMT or GT. Immediately following this session, each student was assessed on easy, moderate and difficult training transfer tasks. The researchers found that students who were trained using an EMT approach scored significantly higher on measures of moderate and difficult training transfer. There was no difference on easy transfer tasks. While the study had limitations related to a small sample size, training brevity and immediate assessment of training transfer, Dormann and Frese concluded that EMT was superior to GT for training transfer of statistical package skills.

Recently, an experiment reported by Baglin et al. (2011) and Baglin and Da Costa (2012a) failed to replicate Dormann and Frese's original findings. Baglin and Da Costa randomly allocated 100 psychology students to EMT and GT for learning to use the statistical package SPSS in an introductory statistics course. After four one-hour fortnightly training sessions, performance on self-assessment tasks assessing analogical and adaptive training transfer found no significant difference between strategies. The tasks required students to conduct statistical analysis using a statistical package to answer randomly generated sets of quiz questions. Baglin and Da Costa found that the strongest predictor of training transfer was students' performance on end of semester exams. The researchers believed that this relationship was due to the nature of the self-assessment tasks used to measure training transfer. Baglin and Da Costa argued that they may have unintentionally measured the students' knowledge of statistics and not their actual technological skill because the quiz questions required students to make judgments about the statistical analysis to perform. Other limitations of the study included time constraints which may have invalided the EMT condition, short training duration, student non-compliance and poor student engagement during the self-assessment exercises.

Baglin and Da Costa (2013) performed a follow-up study to address the limitations to the internal validly of Baglin and Da Costa's (2012a) study. The authors designed a quasi-experiment that allocated EMT or GT for computer laboratory training sessions in two different campuses of the same introductory statistics course. The sample included 115 students enrolled in a psychology program. The study focused on improving the validity of EMT by minimizing time constraints, increasing the number of training sessions to ten across the semester and using a more valid measure of training transfer that minimized dependency on statistical knowledge. The study considered only adaptive transfer as this was deemed the most desirable outcome. At the end of the study, there was no significant difference between campuses allocated to EMT or GT on measures of adaptive transfer, even after controlling for statistical knowledge, personal access, training progress and gender. While this study was limited by its quasi-experimental nature, the authors concluded that factors other than training strategies must be at play in explaining variation in the early development of technological skills.

The evidence supporting the use of AE-T methods for technology use in statistics education is lacking and it's interesting to hypothesize why. Understanding how learning to use statistics technology differs from general technology must be considered. Baglin and Da Costa (2013) suggest that the strong dependency between statistical package skills and knowledge of statistics might be moderating the effect of AE-T for technological skills. This does make sense as the overall consensus on the effectiveness of AE-T is based on general software skills (e.g. word processors, presentation software, spreadsheets etc., Keith & Frese, 2008) which do not require a specialized body of knowledge. This is in fact one major difference between the studies of Dormann and Frese and Baglin and Da Costa. Dormann and Frese used students who had already completed an introductory statistics course while Baglin and Da Costa (2013, 2012a) used students currently completing their first introductory statistics course. Dormann and Frese's participants would have had the specialized knowledge prior to training, while Baglin and Da Costa's participants were concurrently developing this knowledge.

Baglin and Da Costa (2013) predict that the level of prior statistical knowledge moderates the effectiveness of AE-T for developing adaptive transfer, which brings it on par with GT when prior knowledge is low. Whereas, when prior statistical knowledge is high, AE-T would be predicted to be more effective for promoting adaptive transfer compared to GT. This hypothesis is consistent with Kanfer and Ackerman's model. Learning to use statistical technology in addition to the early development of statistical knowledge would likely place a high demand on the attentional resources of students during skill acquisition. Students would need to alternate between their developing knowledge and technological skills as they try to make sense of the task at hand and the execution of the skills required to complete the task. Training transfer would be slowed and any difference between training strategies would be small and difficult to detect. However, mastery of the required knowledge would free up students' attentional resources which can then be dedicated to the development of self-regulatory skills. An analogy to illustrate this point would be someone trying to learn to use a word processor while also learning to read and write in a given language. This analogy is even more relevant given that learning statistics has been likened to learning a second language (Lalonde & Gardner, 1993). This hypothesis is conjecture at this stage, but an interesting issue to address in future research.

Training transfer is not the only outcome of technological skills training that is likely to be of concern to statistics instructors. There are concerns that AE-T may be perceived as more difficult than GT which may lead to higher anxiety, lower self-efficacy and lower overall training satisfaction. Both the Baglin and Da Costa (2012a) and Baglin and Da Costa (2013) studies surveyed student's self-reported perceptions of training difficulty, satisfaction, anxiety and statistical package self-efficacy following training. While Baglin and Da Costa (2012a) found no statistically significant difference in average student ratings between training strategies, Baglin and Da Costa (2013) found that EMT was associated with higher training difficulty and lower satisfaction. These findings do suggest potential trade-offs between using different training approaches. Students' perceptions of technological skill development in statistics courses require further examination. Fortunately, studies are beginning to emerge (e.g. Baglin & Da Costa, 2012b).

4. CHALLENGES AND FUTURE DIRECTIONS

Thus far we have applied a theoretical model for understanding the development of technological skills in statistics education and discussed the implications of this model on the training strategies that we employ. However, there are many other challenges and future directions for research facing this area of statistics education. In the following sections these challenges will be outlined and suggestions for future research will be proposed.

4.1 What Do We Teach?

There are many technologies that students of statistics may require. We have proposed statistical package skills as being fundamental, but even within this skill there are many decisions to make about what is taught. A simple question to begin with is which statistical package? Do you use commercial or open-source? Do you teach one package or multiple packages? Many courses will only have time to cover one statistical package, but students are most likely to encounter other packages throughout their careers. Do you teach students about command line/syntax/programming, graphical user interfaces, or a combination of the two? How do skills in one statistical package transfer to another? Does knowledge of command lines, syntax and programming make learning other packages easier? How do we foster dispositions towards technology in our students that will enable them to build upon their skills in the future? Theoretically, AE-T types which propose to promote adaptive transfer may prove to be one solution, but empirical findings are inconclusive.

What level of technological skill do we require? Selber (2004) provides a useful framework of computer literacy which might act as a model. Selber's model of multiliteracies includes three categories, functional, critical, and rhetorical literacy. Each category aims to describe a different type or level of literacy. *Functional* literacy refers to the use of technology as tools. This literacy would be the outcome of most introductory statistics courses where students are viewed as users of technology. The next level, *critical* literacy refers to technology as a cultural artifact. This might be the outcome of an entire program of statistics where students learn to question and critique different types of technology and understand its strengths and weaknesses. *Rhetorical* literacy refers students as being producers of technology. This might be evident in advanced courses

(e.g. Honors, Masters or PhD) where students are required to produce technologies to address problems. Gould (2010) argues that we need to teach more critical literacy and even some level of rhetorical literacy.
The next major challenge is fitting it all in to a course or degree program. We do not want to be teaching these skills at the cost of students' understanding of statistical concepts. While teaching technological skills are predicted to ultimately lead to improved learning, the major focus of all courses should remain on the development of statistical literacy, reasoning and thinking. A pedagogical framework for getting the best of both worlds, i.e. statistical knowledge and technological skills, should be a focus of future research.

4.2 Developing Technological Skills

Statistics courses must develop relevant technological skills and dispositions that will enable a student to meaningfully engage in statistical practice. In order to understand the best way to achieve this, we must begin to carefully understand how these skills are developed. By explicitly examining these skills we can also learn how these skills relate to other outcomes and their impact on our courses. The knowledge required to implement effective approaches to developing technological skills in statistics education will be attained with this knowledge. This is important because, as instructors, we have the ability to improve these skills. We can change attitudes towards the use of technology, implement effective technology training, drive skill development using appropriate assessment and acculturate our students to modern statistical practice. We believe Moore (1997) is as correct today as he was over a decade ago when he stated that effective teaching will come when content, pedagogy and technology complement each other. The challenge will be to achieve technology proficiency while still emphasizing the primary learning outcomes of statistics education.

A theoretical model explaining the development of technological skills is an important starting point. Kanfer and Ackerman's model of skill acquisition proposes a detailed explanation of skill development that has implications on the training that instructors use to develop technological skills. Studies in general software training have suggested that active-exploratory training approaches might be more effective than conventional GT approaches for the development of adaptive training transfer. Interestingly, studies attempting to replicate these findings in a statistics education context have been contradictory. Consistent with Kanfer and Ackerman's model, the high attentional demands placed on students with low prior statistical knowledge as they learn to use statistics technology may be moderating this effect. The effectiveness of active-exploratory training approaches in populations with prior statistical knowledge remains to be seen. Other research has also begun to explore the overall student experience of technology training in order to gain further insight into factors that might affect skill development (see Baglin & Da Costa, 2012b). This initial research is a positive step forward but much more is needed.

4.3 Assessment and Outcome

Assess what you value because students value what you assess (Chance, 2002). Effective assessment drives student learning. If we are to promote technological skill in statistics education, how can we use assessment to drive its development? There are two possible approaches, implicitly and explicitly. Implicitly assessing technological skills would require students to utilize technology in order to assess primary learning outcomes of a course. For example, a take-home project requiring the statistical analysis of a large data set. The use of technology is not directly assessed, but is indirectly assessed as completion of the assessment requires the student to employ their technological skills. Most modern statistical courses are likely to take this approach. The drawback though is that we gain little insight into the student's level of technological proficiency. In other words, we just assume that they have picked up the skill. If they fail the assessment, we are likely to accredit it to the students' lack of knowledge. However, what if they failed because they couldn't use the technology? A better, but perhaps slightly more provocative, approach would be to examine these outcomes explicitly.

Explicitly assessing technological skills would mean setting dedicated assessment aimed at evaluating a student's level of proficiency with a technology. The benefit of this approach is that technological skills deficiencies could be identified and corrective action could be taken. It would also send a clear message about the value of these skills. A simple approach might be to include an assessment task for technological skills at the end of the semester, for example, a computer laboratory activity that requires students to demonstrate their ability to use key features of a technology. The challenge of this approach is to disentangle technological skills from statistical knowledge. For example, effective use of a statistical package requires good statistical knowledge. Innovative assessment methods which target technological skills are needed. Competency-based assessment (CBA) might be an effective approach. Technological competency can be defined as the ability to transfer skills and knowledge to a required standard (Rutherford, 1995). A competency standard is a defined explanation of what a student should be able to do (Rutherford, 1995). Rutherford provides a detailed account of how CBA could be implemented. The benefit of a CBA approach is that students get direct feedback regarding their skill proficiency. The potential disadvantages are the extra time and resources required and the potential for students to compartmentalize technological skills as being a separate outcome of the course. Further research is needed to understand how instructors can utilize the power of assessment to drive the development of technological skills.

Assessment also raises the question of exactly what to assess. For example, CBA would assess students to a standard such as correctly performing a simple linear regression using a statistical package. Standards are convenient places to start, but earlier, we proposed that adaptive training transfer outcomes should be the goal of technology training. Adaptive training transfer is evident in students who can successfully adapt their existing skills to confront novel tasks. Adaptive outcomes are important because they promote sustainable and continued learning outside the brief training afforded by most courses. Adaptive training outcomes are likely to be more difficult to assess from a CBA framework as evidence of this outcome is likely to be manifested in how students approach novel tasks outside of formal assessment. Regardless, Baglin and Da Costa (2013) proposed that exercises requiring students to replicate difficult and novel statistical output generated by a statistical package might be one approach. However, research examining innovative assessment methods for acquiring technological skills would be welcome.

4.4 Teaching a Culture of Technology

Gould (2010) and Nolan and Temple Lang (2010) urge statistic educators to consider the skills our students will require to meaningfully participate in current and future statistical practice. They propose teaching students more technology and statistical computing practices which will be necessary to deal with the ever increasing digital world and the unprecedented level of access to data. While the kinds of technological skills required will vary between statistics majors and non-majors, the message is clear that the development of technological skills for doing statistics has never been more important. Instructors need to instil a culture of technology in statistics courses that will lead to this goal, but little is known about what motivates and sustains the adoption of technology in statistics education. Gould proposes that technology needs to be taught explicitly alongside the fundamental concepts, while Nolan and Temple Lang propose that instructor training for technology is a crucial factor. Survey studies on attitudes towards the use of technology in statistics education have arrived at similar recommendations (Hassad, 2012). Indeed, a broader theoretical framework guiding the development of such a culture that promotes technology use at all levels (students, faculty, and institution) is needed. Not only will such a framework assist in the integration of technology in statistics education, but it will also assist in understanding the factors that influence students' motivation to engage in technological training, which Kanfer and Ackerman's model predicts will impact skill acquisition. Teaching a culture of technology may be the biggest challenge facing statistics instructors in promoting technological skills.

The Technology Acceptance Model (TAM, Bagoozi, Davis, & Warshaw, 1992; Davis, 1989) and its later extensions, the Technology Acceptance Model 2 (TAM 2,Venkatesh & Davis, 2000; Venkatesh, 2000) and the Unified Theory of Acceptance and Use of Technology (UTAUT,Venkatesh, Morris, Davis, & Davis, 2003), may provide a starting place to develop such a framework. These models were born from the Theory of Reasoned Action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) and, its extension, the Theory of Planned Behavior (Ajzen, 1991). All models deal with explaining the factors that influence behavioral intentions, which can ultimately be used to predict technology adoption. These models have been used widely in different educational settings (e.g. predicting teachers adoption of computer games for formal learning, De Grove, Bourgonjon, & Van Looy, 2012; and students use of learning technology, Lai, Wang, & Lei, 2012; Marchewka, Liu, & Kostiwa, 2007) including statistics education. A study by Hsu, Wang and Chiu (2009) incorporated components of the TAM, computer attitudes, statistics software self-efficacy and statistics anxiety to predict 207 U.S. masters of business administration students' intentions to use the statistical package SPSS. The authors found that students' intended use of SPSS was significantly negatively predicted by statistics anxiety and significantly positively predicted by students' perceptions of perceived usefulness and ease of use. In addition, both SPSS self-efficacy and attitudes towards computers were positive predictors of perceived usefulness. The technology acceptance models have great potential for explaining the uptake of technology in statistics education, but further research is needed to further validate the use of these models in diverse educational settings and across different user levels. Teaching a culture of technology will entail understanding technology use as it pertains to students, faculty and institutions.

5. CONCLUSION

In conclusion, the ability to use technology is an important skill for modern statistics students, which inevitably leads to improved student learning. In addition, without technological skills for doing statistics, our students would not be able to meaningful engage in modern statistical practice. Statistics instructors must capitalize on the benefit of developing these skills and find effective methods of fostering them in students. Kanfer and Ackerman's integrative model of skill acquisition provides insight into how these skills are developed and the major factors that are likely to impact acquisition. Active-exploratory training approaches, such as error-management training, may provide viable approaches for prompting sustaining skill transfer from technological training efforts. However, research findings suggest that this effect is moderated by the early development of students' statistical knowledge. Many challenges and questions face future research and it is hoped that this paper will guide future efforts. Reflecting back on the earlier quote from the GAISE (Aliaga et. al., 2005) college report which stated, "Technology has changed the way statisticians work and should change what and how we teach" (p. 12) the overall message of this paper becomes quite clear. Technology has mostly impacted on "how" we teach, but it's time we take another look at "what" we teach. Technological skills are an important component of statistical literacy.

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