

A THEORETICAL FRAMEWORK FOR DEVELOPING STATISTICAL PACKAGE COMPETENCE AS AN OUTCOME OF STATISTICAL LITERACY

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ABSTRACT

Developing students' competence with statistical packages, such as SPSS, Minitab, R and SAS, is an important, but somewhat overlooked outcome, of statistics education. This paper proposes that statistical package competence be regarded as an outcome of statistical literacy. While the development of statistical package competence should not interfere with the development of statistical literacy, statistical reasoning and statistical thinking, it should be recognised as an important skill our students need to acquire in becoming data scientists. A theoretical framework for the development of statistical package competence will be proposed along with an overview of a promising evidence-based training strategy. Issues, considerations and much needed research related to the training and assessment of statistical package competence will also be discussed.

Keywords: *statistics education technology; statistical package skills; statistical literacy; active-exploratory training, theoretical framework*

1. INTRODUCTION

Reform of statistics education has advocated the move towards “more data and concepts, less theory and few recipes” (GAISE, 2005, p. 4) for introductory statistics courses. In response to this reform, the use of technology in statistics courses has been increasing (Garfield, Hogg, Schau, & Whittinghill, 2002). The Guidelines for Assessment and Instruction in Statistics Education (GAISE, 2005) Project report stated “To the maximum extent feasible, calculations and graphics should be automated.” (p. 4). Statistical software packages, herein referred to as simply “statistical packages”, are designed for the sole purpose of conducting statistical analysis (Chance, Ben-Zvi, Garfield, & Medina, 2007). Examples include *SPSS* (<http://www.spss.com>), *Minitab* (<http://www.minitab.com>), *R* (<http://www.r-project.org/>) and *SAS* (<http://www.sas.com/>). The use of statistical packages in statistics education encourages reform efforts by automating difficult or complex statistical formulae and by equipping instructors with the facility to demonstrate statistical concepts. An additional benefit includes providing students with practical skills for operating software commonly used in research and industry.

While the primary outcome of any statistics course should focus on developing the three major learning outcomes of statistics education, namely statistical literacy, statistical reasoning and statistical thinking, it is incumbent on instructors to consider other practical outcomes that will benefit students. It is undeniable that the ability to use statistical packages is a crucial skill students must acquire in becoming “data scientists”

or producers and consumers of quantitative data. Research and industry highly value such skills. A quick search of a popular Australian employment website found many jobs that specifically listed experience with the statistical package *SPSS* as a key criterion for selection. Job descriptions included phrases such “Experienced with *SPSS*”, “An excellent working knowledge of *SPSS*”, “Experience with *SPSS* or a similar statistical package would be highly regarded”. Furthermore, the statistical package companies have responded to this demand. For a moderate fee, *SPSS* and *SAS* websites offer training and accreditation leading to recognised credentials for employment.

Despite the importance and benefits of developing statistical package skills in students, the statistics education literature has not imparted them much attention. There are two likely reasons for this. Statistics educators are still focussed on addressing greater challenges related to the achievement and assessment of the major learning outcomes of statistics education. Instructors also caution that learning should concentrate primarily on statistical content and not on the technology itself (Chance et al., 2007). This paper does not dispute either of these valid reasons, but posits that the role of technology in statistics education continues to evolve. Recently, Gould (2010) argued that the changing nature and accessibility of data will require modern statistics courses to develop students’ technological literacy, e.g. accessing data from large databases and statistical computation. Concurrent with Gould’s vision of developing modern technologically proficient “data scientists”, the sentiment of this paper focuses on a specific example of a broader construct of technological literacy – statistical package literacy. These skills are essential for current students and should therefore be developed in tandem with the major outcomes of statistics education.

2. STATISTICAL PACKAGE COMPETENCE AS AN OUTCOME OF STATISTICAL LITERACY

The statistics education literature differentiates between three major learning outcomes of statistics education. *Statistical literacy* is an understanding of data, statistical concepts, statistical terminology, 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 summarise 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).

These outcomes are the primary focus of statistics education and should take precedence over the acquisition of statistical packages skills. However, for the reasons stated previously, students can greatly benefit from acquiring these skills and statistics courses are the ideal places to develop their competency. Well-designed training should develop statistical package skills congruent with the three major learning outcomes of statistics education. However, rather than viewing statistical packages skills as an adjunct to the major outcomes of statistics education, it would be beneficial to integrate competency in their use within one of the learning outcomes.

Statistical package competence, defined as the ability to correctly operate a statistical package in order to manage, manipulate, explore, analyse and display quantitative data, should become a desirable outcome of statistics education when incorporated within the domain of statistical literacy. A statistical package can be regarded as a tool in achieving

statistical literacy. The acquiring of skills in its use can be viewed as a fundamental ability that helps inform the higher order learning domains. On its own, statistical package competence will not enhance a student's reasoning or thinking about statistical concepts. However, it will aid in the improvement of a student's ability to complete statistical literacy tasks. An alignment of statistical package competence with statistical literacy will remind instructors that statistical package competence needs to be developed simultaneously within statistical literacy and alongside statistical reasoning and thinking. This alignment will also strengthen the reform movement's recommendation to utilise technology for the purpose of emphasising data and concepts, and less so on calculation (GAISE, 2005).

Statistical package competency can vary in proficiency, but most introductory statistics courses will only develop a basic foundation due to time constraints. Competence is typically developed through computer training labs designed to learn to operate statistical packages. The aim of training labs is to build competence through the development of training transfer. Training transfer is defined as knowledge and skills gained during training which flow on to other tasks and jobs outside of training (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, Richter, & Naumann, 2010). While statistical package training is unlikely to cover all the scenarios and procedures that students will encounter during their careers, adaptive transfer skills are more desirable as they support sustained learning beyond training (Frese et al., 1991; Keith et al., 2010). Adaptive transfer may also facilitate the transfer of acquired skills to using other statistical packages and in adapting to changes in major version updates.

Defining and assessing students' statistical package competence will require the development of competency goals and specialised assessment guidelines. Much like statistical thinking, statistical package competence is most likely demonstrated in what students do spontaneously without instruction (Chance, 2002). Competence is evident in how easily students operate the package, how efficiently they complete the required analysis, how they adapt to novel situations, how they devise shortcuts to save time and how problems are dealt with when they arise. These outcomes might not be amenable to traditional forms of assessment (e.g. quizzes) and may require the development of innovative competency assessment methods. Establishing levels of competency and devising effective methods of assessing these levels requires time and effort. However, prior to doing this, a more fundamental question must first be addressed.

3. WHICH STATISTICAL PACKAGE?

A major decision that confronts instructors is the choice of statistical package. The most important consideration for the authors' institution is the relevancy of the package to enhance employment prospects. However, it's never that simple. Students originate from diverse disciplines and employers may utilise vastly different packages. Teaching the use of multiple packages would overcome this issue, but would be difficult to implement within the time constraints of most courses. Training students in the use of large commercial packages would be a safe compromise; but not all institutions will have licences to operate these packages. Less popular packages might be more affordable, but if students are unlikely to use these packages outside of their course, there might not be much incentive to learn how to use them. Utilising open source packages, such as *R*, presents a solution to the issue of accessibility, but *R* does not have the user-friendly

interface and technical support of many commercial packages. On a positive note, the major advantage of *R* is that it can be installed on students' personal computers allowing them greater access and more opportunity to hone in their skills.

Instructors may also have their own preferences for the choice of packages a student should or should not learn. Some statistical packages are feature rich, but others might lack important capabilities needed in a course. Statistical packages that are not conducive to the learning of statistics, e.g. packages with esoteric interfaces that confuse students, should be avoided. Surveys on statistical packages utilised in industry would be very useful to aid informed decision-making on the selection of packages by instructors. Statistics instructors have a unique opportunity to work with statistical package companies to ensure that the needs of their students are being met. If commercial companies want to grow their user base they need to ensure accessibility of their packages to students and training institutions. Research on the use of open source statistical packages in introductory statistics courses is also warranted to assess the viability of their use.

Choosing an appropriate statistical package for a course is likely to generate debate. It is not the intention of this paper to endorse any particular package. Every course's situation is unique and making the appropriate choice will incorporate many factors. The authors do, however, recommend that when you make this decision, you assess the students' needs. Following this decision, the next step is deciding on a training technique.

4. A THEORETICAL FRAMEWORK

This paper will propose a theoretical framework for the development of statistical package competence that will guide the development, research and evaluation of effective training strategies. Kanfer and Ackerman's (1989) integrative model of skill acquisition is consistent with learning to use statistical packages and has been used to predict training transfer performance for learning to use general software (e.g. spreadsheets, presentations and word processing, Keith et al., 2010). According to Kanfer and Ackerman, skill acquisition is explained by four notions: *attentional resources*, *task demand*, *resource allocation* and *the effect of practice*.

All tasks (e.g. training) require a certain level of attentional resources. Some tasks demand a high level of attention, while other tasks require less. Learners internally regulate attentional resources dedicated to a task and can choose to focus attention or divide attention between competing tasks. As a learner practices a task, the required level of attentional resources allocated to that task lowers, i.e. the effect of practice. The 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 1. a). Training should begin with resource-dependent tasks which will require the commitment of attentional resources. As the trainee practices, the resource-dependency of the task changes to become more resource-insensitive. It is this shift in attentional resources (Figure 1.b) that is referred to as the *effect of practice*.

Kanfer and Ackerman (1989) proposed two major factors, distal motivation and cognitive ability, that 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 statistical packages 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 statistical packages outside of a statistics course is of no use will be less inclined to commit attentional resources to training. A lack of attentional resources dedicated to resource-dependent tasks will retard the effect of practice leading to poor training transfer.

Cognitive ability determines the capacity of a learner to allocate attentional resources to any given task. 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 (e.g. Hunter, 1986). Unfortunately, cognitive ability is not something that is amenable to change, but its effect tends to be less pronounced in tertiary populations where most students are expected to have average to high cognitive ability.

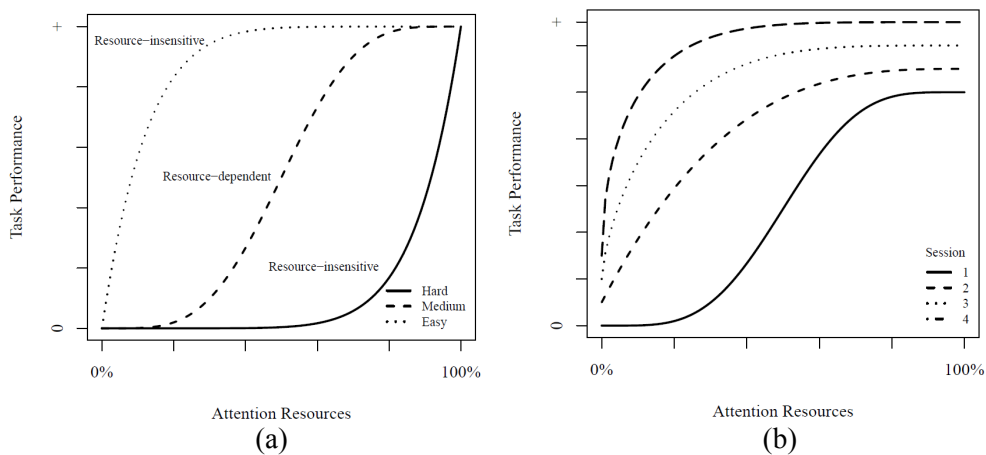


Figure 1. (a) For resource-dependent tasks, task performance is relatively proportional to the attentional resources dedicated to the task. For resource-insensitive tasks, attentional resources are relatively independent from task performance. (b) The effect of practice is to change resource-dependent tasks into resource-insensitive tasks.

In summary, Kanfer and Ackerman's theory 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 1.b). Therefore, the role of training is to transform resource-dependent tasks into resource-insensitive tasks. Kanfer and Ackerman's theory also predicts that trainees' performance early in training will be highly influenced by their motivation and cognitive ability.

Poorly motivated and academically weaker students might struggle early in statistical package training which will later lead to poor training transfer. Fortunately, Keith et al. (2010) demonstrated that active-exploratory types of training can help moderate the effect of motivation and cognitive ability on training performance.

5. IMPLICATIONS FOR TRAINING STRATEGIES

Kanfer and Ackerman's model can be used to guide the selection of effective statistical package training strategies. 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 perceived performance utility of statistical packages, it is impossible to improve student's cognitive ability for the sake of training. Effective training strategies need to minimise the impact of student motivation and cognitive ability on training transfer performance.

The most common forms of training strategies can be broadly divided into two groups - *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 2). The GT method views errors made during training as a waste of time which need to be avoided. Proficiency of the package comes through repeated practice where operational errors are avoided.

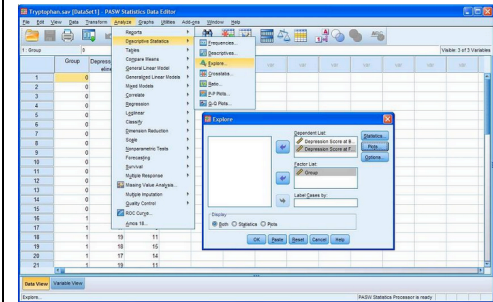
Revision - Explore

Let's run **Explore** on "Depression Score at Baseline" and "Depression Score at Follow-up" between the treatment and placebo group.

Follow these steps:

1. Click **Analyse** = **Descriptive Statistics** = **Explore**
2. Move "Depression Score at Baseline" and "Depression Score at Follow-up" into the **Dependent List** box.
3. Move "Group" into the **Factor List** box.
4. Click **OK** to explore your data.

These steps are summarised in the screen shot below.



"Don't discount your errors. Acknowledge and learn from them."

Revision - Explore

Let's run **Explore** on "Depression Score at Baseline" and "Depression Score at Baseline" between the treatment and placebo group.

Location: Analyse = Descriptive Statistics = Explore

What is the **variance** of Depression Score at Baseline for the **placebo** group?

Enter your response below:

Figure 2. 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.

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 works 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, behaviour and focus (Károlyi, 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” (Ruth Kanfer, Ackerman, & Heggestad, 1996, p. 186)

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 2). Therefore, EMT also helps develop a student’s self-regulatory skill of 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, A-ET may moderate the effect of cognitive ability and motivation by creating a large degree of overlap between A-ET and transfer tasks used to assess competence. A-ET requires trainees to develop and practice metacognitive skills to address training tasks in the absence of comprehensive instructions (see 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 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). Therefore, A-ET may moderate the relationship between training transfer performance, cognitive ability and motivation. Experimental studies support this theory (see Keith & Frese, 2005; Keith et al., 2010).

Kanfer and Ackerman’s model and the metacognitive theory of A-ET have a number of implications for the development of statistical package competence. Kanfer and Ackerman’s model predicts the moderating role of student motivation and cognitive ability on training transfer performance. A-ET strategies, such as EMT, may provide effective training strategies that minimise the potential effect of low motivation and low cognitive ability on the development of statistical package skills. However, aside from one positive study by Dormann and Frese (1994) and one inconclusive study by Baglin,

Da Costa, Ovens and Bablas (2011), the effectiveness of A-ET strategies for statistical package training requires further investigation.

Table 1. An example of metacognition promoted by AT for statistical packages

Metacognitive Activity	Example
Planning	I know how to obtain a histogram in <i>SPSS</i> , but how do I split the histogram by a grouping variable? I will need to try changing some options.
Monitoring	I will try putting the grouping variable in the panel by option and see what happens.
Evaluating	That seems to have done the trick. I will now be able to compare histograms between groups

6. RECOMMENDATIONS

The discussion thus far has raised some implications for the delivery of statistical package training within an introductory statistics course. A number of general recommendations can be made when combining these implications together with key guidelines from the statistics education reform movement. Many of these recommendations are not unique to this paper, nor do they significantly depart from common sense. Regardless, it is useful to list them here so they may act as a starting point for the effective design of statistical package training. It is also important to note that many of these recommendations are not supported by evidence specific to statistical package training. Several of these recommendations have been generalised or extrapolated from research in different contexts. Therefore, these recommendations are a starting point for future research in this area.

1. Instructors who choose to develop statistical package competence as an outcome of their course need to assess the achievement of competence. In the words of Chance (2002), instructors must “assess what you value”. Assessment is a strong incentive for students to engage in training. This type of assessment must not come at the expense of assessing the major learning outcomes of statistics. It should be formative in nature, and achievement should be based on reaching a level of competence. This might be done using an end of semester competency test that requires students to demonstrate a working knowledge of operating the statistical package. For example, a competency test might give students a real-world data file with a list of the required analysis to complete using a statistical package. By providing a list of required analyses, the competency test allows students to focus on operating the statistical package. Getting students to decide the “what” and “why” of the statistical analysis will encroach on the domains of statistical reasoning and thinking. Alternatively, the higher order outcomes may be embedded within the competency test (e.g. student must decide which statistical analysis to conduct and interpret). However, this makes it much harder to assess statistical package competency as the test is now dependent on the student’s statistical reasoning and thinking. These higher order domains might be better left to other forms of assessment. Defining levels of competence and how these levels can be effectively assessed should be a topic for future research.

2. This paper argues that statistical package competence is a desirable outcome of a statistics course. However, it is not the primary outcome and should never arise at the expense of the three major learning outcomes. Statistical package competence should originate under the domain of statistical literacy and therefore needs to be developed alongside statistical reasoning and thinking. This can be achieved by embedding

statistical package training within tutorials where exercises that develop and assess the primary learning outcomes are also given. The relative importance of statistical package competence and technological literacy in general is an issue that requires further discussion (see Gould, 2010).

3. There are many considerations for choosing the appropriate statistical package for students to train with. If an instructor has the luxury of making the choice, select a package that is accessible, user-friendly, conducive to statistics education, feature-rich and valued by students' future employers. It is unlikely that this ideal package exists, so expect to make compromises.

4. Statistical package training sessions need to be designed effectively to maximise training transfer. This paper proposes to deliver training A-ET strategies, such as EMT. A-ET methods are in line with the statistical education reform movement's aim to encourage active participation in learning activities. Also, research suggests that A-ET approaches are superior to GT for general software training (Keith & Frese, 2008). While it is still unclear whether this is true specifically for statistical package training, it is unlikely to be any less effective than GT and may prove to have other benefits including the development of students' self-regulatory skills, e.g. metacognition and emotional control.

5. Kanfer and Ackerman's skill acquisition model predicts that training performance and later training transfer can be negatively impacted by low cognitive ability and poor student motivation. A-ET strategies have been found to moderate the effect of motivation and cognitive ability on training transfer for general software training. While future research in statistical package training is needed to confirm this effect, for now, these strategies offer the greatest hope. Other approaches might include ensuring students understand statistical concepts prior to engaging in statistical training. This will help reduce the dependency of cognitive ability on training transfer as students can concentrate on operating the package instead of being confused by what they are doing.

Student motivation might be improved using more direct approaches. For example, at the beginning of the course, explain to students why they need to learn the statistical packages and how useful it will be for them in their academic and professional careers. Instructors should also provide context to training by analysing real-world data sets so that students see how statistical packages are used in real-world situations.

6. The more students engage in training the better they will be able to transfer their skills. Weekly training is ideal, but take home assignments where students must use the statistical package are also a great way to further engage students in training. However, sometimes this is difficult if expensive commercial packages are used. Student might not be able to afford licences for personal use which means they will need to use the institution's licences. Open-source packages side-step this issue, but they may require extra support from instructors when students run into difficulties outside of class.

7. As statistical package training is likely to be very brief, students will only get the opportunity to develop a basic foundation (e.g. data entry, data management, basic descriptive statistics, basic graphs and basic inferential statistics). Therefore, training should promote attitudes and dispositions that support the continued engagement with learning to operate a statistical package outside of a statistics course. This sustainable adaptation of skills developed from training is referred to adaptive transfer. A-ET strategies have been found to promote adaptive transfer above and beyond GT by proposing to develop students' self-regulatory skills, i.e. metacognition and emotional control (Keith & Frese, 2008). This may help students to continue learning statistical packages outside of training and may even assist them to learn other packages. While

further research is needed to confirm this theory in the context of statistical packages, it is yet another reason why A-ET strategies might be the preferred training strategy.

7. CONCLUSION

This paper focussed on the importance of developing statistical package competence as a desirable outcome of statistics education. Developing statistical package skills is beneficial to students and supportive of statistical educational reform efforts. It is also an example of the evolving importance that technological literacy will have on modern statistics courses (Gould, 2010). For now, the acquisition of this competency would benefit by being integrated under the learning outcome of statistical literacy. The discussion also considered issues related to the choice of statistical package, how to define and assess levels of competency, and how to effectively develop competency within a statistics course. Kanfer and Ackerman's integrative skill acquisition model was proposed as an insightful model for explaining the development of statistical package skills during training. This model makes important predictions about how students' cognitive ability and motivation can influence the effectiveness of training. Active-exploratory training strategies, such as error-management training, offer promising solutions to these issues when compared to the classical guided training techniques. Based on the integration of the paper's discussion with reform efforts in statistical education, a number of recommendations were made to steer the delivery of statistical package training. However, the underlying conclusion in this paper is the absence of a strong research base in this area of statistics education. This important but under-researched area of statistics education needs to expand.

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