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# **The Above-Average Effect in an End-User Computing Context**

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A Thesis  
submitted in partial fulfilment  
of the requirements for the Degree of  
Doctor of Philosophy

at

Lincoln University

by

Shirley F. Gibbs

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Lincoln University

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# **ABSTRACT**

Abstract of a thesis submitted in partial fulfilment of the requirements for  
the Degree of Doctor of Philosophy

## **The Above-Average Effect in an End-User Computing Context**

by

Shirley F. Gibbs

This thesis investigates how the above-average effect presents in the ubiquitous, fast-changing domain of end-user computing (EUC). EUC is mandatory in many workplaces but can be performed with different levels of skill. The above-average effect has been the subject of many studies in many different domains, as has end-user computing. This study brings these two areas together using an original approach to understand how processes, such as the above-average effect, interact with personal factors to influence perceptions of EUC skill level in self and others.

The Above-Average Effect is a social bias found in many domains considered routine, or vaguely defined. This bias involves making an unwarranted, positive assessment of the difference between one's abilities and knowledge and those of an 'average person'. Explanations for this effect include self-enhancement, focalism, ego-centrism and the Dunning-Kruger Effect. The focus of this study was on the relationship of personal factors, such as age, sex, expertise and personality, with the occurrence of the Above-Average Effect in the context of end-user computing. This context has several characteristics that should make it an ideal setting for the occurrence and investigation of the Above-Average Effect. First, there are few opportunities for end-users to observe directly the ability of others, which contrasts with settings such as driving in which near-continuous observation of others' skill level is possible. Second, end-user computing has undergone continuous change that many users may not notice if they perform routine tasks. Third, end-user computing roles and jobs cover a range of skill levels, the full extent of which may not be clear to many users.

Measures of personal factors, demonstrated skill, self-perceptions of end-user computing skill and perceptions of the average end-user's skill were taken from a sample of employed computer end-users. Both objective and subjective measures were used to compare self-reports with demonstrated skill and to test eight hypotheses addressing the Above-Average Effect and the Dunning-Kruger Effect. A results based testing system was developed and validated specifically for assessing end-user skill typical of workplace computing. Measurement of perceptions was undertaken using a visual analogue scale.

Findings confirmed expectations that the Above-Average Effect is present in the end-user computing domain. In this domain, users often are unaware of the extent of the domain, their own skill level within it or the skill level of other end-users. Unexpectedly, however, it was found that variables that previous studies had found to be associated with the Above-Average Effect in this study were not significantly associated with the Above-Average Effect when analysed in combination. This suggests the presence of previously unidentified interactions between these variables that lessen the strength of the Above-Average Effect, specific to the domain of end-user computing.

Evidence to support the operation of the Dunning-Kruger Effect as an explanation for the occurrences of the Above-Average Effect was mixed. Findings revealed a significant relationship between self-assessment and estimations of the breadth of the domain. However, there was no support for an association between a person's estimation of the breadth of the domain and the above-average effect. Likewise, there was no support for an association between a combination of personal and expertise factors and the Dunning-Kruger Effect. As for the Above-Average Effect, this raises questions as to the types of interactions that lead to reduced evidence of the Dunning-Kruger Effect.

It was concluded that (1) the Above-Average Effect is present in end-user computing; (2) interactions between variables individually associated with the Above-Average Effect may moderate the effect; (3) interactions between variables individually associated with the Dunning-Kruger Effect may moderate the effect, and (4) the domain of EUC has differences that make it stand out from other domains the AAE typically occurs in. Possible explanations for and implications of these findings for theoretical development of the Above-Average Effect and Dunning-Kruger Effect are considered, especially in domains that are commonplace, constantly changing, and that incorporate a wide range of levels of expertise. Implications for skill development and training in end-user computing are also discussed. Based on the findings, further work is recommended to explore the Above-Average Effect

and its relationship to other variables, especially in ubiquitous, fast changing domains such as end-user computing.

End-user computing is a vast and fast changing domain that, due to its wide use, is often misunderstood in terms of complexity and range of use. This study contributes to understanding the AAE in an area not otherwise investigated for this bias. This bias leads to overestimation of skill and knowledge which can present potential problems for accuracy and efficiency of use. This is significant because these skills are critical to modern workplaces. A further contribution extends to the instrumentation developed. This study has proved the worth of such instruments for use in social settings and shows the VAS provides a more accurate measure of perceptions than do discrete scales.

**Key Words:** Above-average effect, Dunning-Kruger effect, End-user computing, self-assessment, workplace computing, computing experience, individual differences, measures of perception, personality, demonstrated computing skill.

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## Glossary and abbreviations

A number of terms that are used continually throughout this chapter have been abbreviated. These terms are explained below.

|                    |   |
|--------------------|---|
| AAE                | Above Average Effect  |
| AEU                | Average computer end-user   |
| Association        | In statistical terms, an association refers to any relationship between variables that renders them statistically dependent |
| BFI                | Big Five Inventory  |
| DKE                | Dunning Kruger Effect   |
| ECDL               | European Computer Drivers Licence*  |
| EoD <sub>EUC</sub> | Extent of Domain  |
| EUC                | End-user computing  |
| FFM                | Five Factor Model   |
| ICDL               | International Computer Drivers Licence*   |
| IITP               | Institute of Information Technology Professionals   |
| IT                 | Information Technology  |
| MOS                | Microsoft Office Specialist   |
| SA                 | Self-Assessment   |
| SAM                | Skill Assessment Manager  |

|     |   |
|-----|---|
| TAM | Technology Acceptance Model                                     |
| VAS | Visual analogue scale   |
| *   | Same system marketed as ECDL in Europe and ICDL outside Europe. |

# Chapter 1 Introduction

## 1.1 Background

Bob, who works in a marketing role, is known in his workplace as a spreadsheet expert. This reputation was gained through self-promotion, as Bob truly believes that his spreadsheet skills are at an advanced level. One morning Bob's boss asks him to review a spreadsheet and to update the analysis sheet to include a pivot table. He looks at the spreadsheet but does not know how to create a pivot table; in fact, Bob is not even sure what a pivot table is. This surprises Bob as he had thought there was not much more to know about spreadsheets than he already knew, which he believes is more than anyone else does.

This scenario is likely to be familiar to more and more workers in modern economies. In fact, it may be familiar to most people in many areas of their lives as computers, and their use, become increasingly common. One side effect of the ubiquity of this type of technology is the general expectation that most people in the workforce will be able to operate it effectively. Relatedly, the expectation by many people who use computers regularly may be that, relative to others, they are skilled users.

Extensive research on social and self-evaluative biases in social psychology, however, suggests that, often, such self-assessment is overly optimistic, with a person's demonstrated ability being lower than they perceive it to be. This point is illustrated by the fictitious example of Bob, used above – but its implications are far reaching in today's world.

The purpose of this study is to investigate relationships between social biases in self-perception and the individual differences of personality and expertise in the context of end-user computing in the workplace. The context of end-user computing (EUC) has been chosen because this type of computing is an integral part of many jobs, with employers expecting employees to have these skills when employed.

In order to achieve the purpose of this study it is necessary to understand why social perceptions are affected by social biases and how these biases are affected by individual differences such as experience or personality. In the sections that follow an overview of these areas will be provided, as will an outline of how this thesis is structured. The first subject of discussion will be that of social perception, as this type of perception and the biases that may affect perceptions, is at the core of this study.

### **1.1.1 Social perceptions and social biases**

"Whenever two people meet, there are really six people present. There is each man as he sees himself, each man as the other person sees him, and each man as he really is."

William James

Social perceptions are the perceptions people have about themselves, the social situations they are in and the other people involved in those situations (Hogg & Vaughan, 2008; Markus & Wurf, 1987). They are formed by a number of cognitive and motivational processes and are based on individual differences (Markus & Wurf, 1987; Sedikides & Strube, 1997).

When people evaluate themselves in social settings they are often subject to cognitive biases (Sedikides & Strube, 1997). A cognitive bias can be described as an error of judgment and is often seen in competitive judgment situations (Haselton, Nettle & Andrews, 2005). Social biases, one type of cognitive bias, can result in inaccurate judgements being made about oneself, or what is believed about others, are often motivated by a desire to be seen in the best possible light (Sedikides & Strube, 1997). This type of self-report can result in a social bias known as the above-average effect.

The above-average effect is a well-researched social comparative bias found in situations where self-evaluations are required (Brown, 2012; Dunning, Meyerowitz, & Holzberg, 1989; Kruger & Dunning, 2009, 1999). It is present in situations of either direct or indirect comparison resulting in people believing, not always accurately, that their knowledge, skill, or ability is better than that of an average person (Dunning, et al., 1989). Direct comparisons require people to explicitly compare two things or themselves with others (Moore, 2007), whereas indirect comparisons ask for the target and the referent (to which the target is being compared) to be compared independently (Moore, 2007). In direct comparison situations the above-average effect is stronger where the self has central

focus (focalism or egocentrism) and in situations where the subject area being evaluated is something considered to be easy or has been loosely defined (Krizan & Suls, 2008; Moore, 2007). Several cognitive and motivational processes are thought to influence occurrences of this bias, including a lack of information about the domain that is the context of an evaluation (Kruger & Dunning, 1999, 2009; Moore, 2007). In an indirect comparison situation, a lack of information about, or expertise in a subject, can mean that a person does not have enough information on which to base accurate estimations of their ability or knowledge (Kruger & Dunning, 1999, 2009; Moore, 2007). Occurrences of overly optimistic self-evaluations in situations where the person making an evaluation has little information about the domain, and is unaware of their lack of knowledge in the domain, are examples of what has become known as the Dunning-Kruger effect (Kruger & Dunning, 1999, 2009). In addition to, and alongside the cognitive and motivational explanations for the above-average effect, are the individual differences of personality and expertise.

“Personality” refers to the differences in characteristics and behaviours that make people different from each other (Markus & Wurf, 1987). After many years of debate over the composition of personality, including the number and types of traits involved, consensus was reached in the 1980’s with the adoption, by many, of the Five-Factor Model of personality (Barrick & Mount, 1991; McCrae & John, 1992). The five-factor model proposes five main traits of personality, each with positive and negative sub traits (Barrick & Mount, 1991; McCrae & John, 1992). The traits which make up the five-factor model - openness, conscientiousness, extraversion, agreeableness and neuroticism - each have some influence over how people act in, and react to, different situations (Markus & Wurf, 1987).

People who have high scores in conscientiousness are driven toward self-improvement and studies show that this trait relates positively to job performance (George & Zhou, 2001). Openness to experiences means that people will embrace new situations and probably excel in situations where creativity is welcomed (George & Zhou, 2001). The trait of agreeableness, also known as friendliness or likeability, has been found to be associated with being good-natured, courteous, trusting and tolerant people (Barrick & Mount, 1991). Overconfidence has been found to be present in people with high scores for extraversion and not for those with low scores on this trait, whereas those with high scores in neuroticism may suffer more negatively in life than others (Barrick & Mount, 1991; George & Zhou, 2001). Personality tests are often routinely completed by job seekers as part of the recruitment processes to give employers further information about the suitability of applications for a particular role (George & Zhou, 2001). Given that personality traits can affect situations where self-reports are involved (Schaefer, Williams, Goodie & Campbell, 2004), it is unclear if this is taken into

account in employment situations. Similarly, a person's expertise or experience in a given domain is also thought to influence a self-report (Kruger & Dunning, 2009, 1999).

Expertise is defined as having superior skills and knowledge in a particular subject or domain (Herling & Provo, 2000). There has been a great of work done on understanding manifestations of expertise and expert knowledge with several different viewpoints proposed (Anderson, 2013; Chi, Glaser & Reese, 1981, Herling & Provo, 2000). A person, known to be an expert in their domain, will have more knowledge and greater problem solving ability than those with less expertise, even those considered competent in that domain (Herling & Provo, 2000). Experts not only know their domain well, but they can also recognise and solve problems that those with less expertise either miss, or do not have the skill to solve (Herling & Provo, 2000). People considered to have expertise in a domain are thought to be able to make more accurate self-assessments than those with less knowledge (Kruger & Dunning, 1999, 2009). In the context of the above-average effect it is fair to say that expertise is operationalised as experience in a domain ( Kruger & Dunning, 1999, 2009; Larrick, Burson & Soll, 2007). It has been found that those with little knowledge or experience in a domain and are unaware of their lack of knowledge will not recognise the knowledge that others have (Kruger & Dunning, 1999, 2009).

Social comparisons, specifically situations which require some type of self-report, have been found in a wide range of situations and social settings from driving (Sundstrom, 2008) to academic achievement (Larrick et al., 2007). Inaccurate self-assessments are thought to be more likely in domains that are either poorly defined, or in situations which are considered commonplace and, perceived as easy (Dunning, et al., 1989). Self-evaluations of driving ability, an area in which this bias is routinely found (Sundstrom, 2008), indicate that this ability is considered easy as driving is something that many people do routinely. Similarly, end-user computing is increasingly commonplace and may be seen, at least by some, as therefore being easy.

### **1.1.2 Workplace end-user computing**

Computers and computer technology have become ubiquitous (Hotzman & Kraft, 2010). People have access to technology at home, in educational settings and in the workplace (Hotzman & Kraft, 2010). Most types of employment now have some type of computing requirement included in them (Hotzman & Kraft, 2010). However, a mismatch can occur when the end-user computing skill level of employees is not at the level necessary for productive, accurate and effective use of the software required for a job (Gibbs, Steel & Kuiper, 2010; Murray & Perez, 2014; Murray, Sherburn & Perez, 2007). This disparity may occur because employers expect that employees will have the requisite

skill level without formally assessing it (Gibbs & McKinnon, 2009; Gibbs, Steel & Kuiper, 2010). This can and does occur, because, as computers and associated technology have become more common, there is an expectation that most people have experience using them (Gibbs et al., 2010). This expectation has included the use of software commonly found in the workplace and has meant that computer skills have made their way into the list of soft skills required for many different jobs in many different workplaces (Hotzman & Kraft, 2010).

Businesses invest large sums of money in information technology and information systems and many employees require end user computing skills to carry out their daily work (Yoon, 2009). However, there is confusion as to how to rate and assess the end-user computer skills required of those working in a business situation (Yoon, 2009). Gibbs and McKinnon (2009) found that employers, while realizing the need for well-developed computing skills, often did not know how to articulate their computing requirements or how to test for the required skills.

A report commissioned by the New Zealand Computer Society (now IITP) stated that New Zealand businesses could potentially increase productivity by \$1.7 billion by increasing the computer literacy of the workforce in general (Bunker, 2010). This report noted that, while computers and associated technology were part of most businesses, those running organisations were often unaware of how to promote efficient use of technology in the workplace. Partly, this problem could be attributed to the commonly held belief that all people, especially those newly entering the workforce, are competent end-users (Murray et al., 2007). Frequently employers assumed that new employees, especially young people, would have the computing skills required (Gibbs et al., 2010; Murray et al., 2007). This is further exacerbated by job seekers self-assessing their own computer ability at a greater level than warranted (Gravill, Compeau & Marcolin, 2001, 2006). Inaccurate self-assessments are not helped by the use of ambiguous labels such as advanced skill or average skill. What is average to one person will be some-one else's advanced (Gravill et al., 2006). This ambiguity is partly due to the lack of a mechanism by which people can benchmark their own skill level (Bunker, 2010). Other issues include ever-changing technology. Some people find it difficult to keep up-to date or to maintain their level of knowledge and skill when software and hardware changes frequently (Gravill et al., 2006).

## 1.2 Thesis statement and aims

The aims of this research are to determine if the above-average effect is (a) evident in people's beliefs about their end-user computing knowledge, (b) evident in their estimations of the skill level

of the average computer end-user and, (c) if this effect is moderated by factors such as dominant personality traits or expertise in the domain.

By addressing these aims this research potentially adds to theoretical knowledge of occurrences of social biases such as the above-average effect. It should also help to inform and aid both employers and employees to support and enhance the increasingly fundamental area of computing skills necessary to succeed in a workplace.

Further, with its focus on inaccurate self-reporting in workplace computing, this research highlights an issue for many organisations that has been under-researched. In the early days of personal computing much was written about the need for digital or computer literacy; more recently, however, that emphasis has decreased (Leahy & Dolan, 2010; Murray & Perez, 2014). This may be due to the prevalence of computer technology and a general perception that most people have sufficient digital skills to survive in the world and, specifically, the workplace (Gibbs et al., 2010; Murray & Perez, 2014).

The specific research question that informs the focus of this study is:

*What individual differences, if any, are critical in instances of the above-average effect in the context of end-user computing?*

This question was chosen for three reasons: (a) to confirm the occurrences of the AAE in the context of end-user computing. (b) To determine if this effect, in this context, is moderated by the influences of a combination of individual factors. (c) To understand more about the domain of end-user computing, and differences between this domain and other domains in which this effect is routinely found. The answer to this question will help in understanding more about occurrences of the AAE, the type of contexts in which is evident and if it is influenced by a combination of individual factors, which have previously been found to individually influence this effect in other contexts.

To address this question two sets of hypotheses are proposed. The first set ( $H_1$  to  $H_4$ ) is intended to test occurrences and explanations for the above-average effect. A focus of this group of hypotheses is the identification of the affect that individual difference have on occurrences of the above average effect. The second group of hypotheses ( $H_5$  –  $H_8$ ) tests occurrences of the Dunning-Kruger Effect as an explanation for the above-average effect.



All hypotheses were developed to be non-directional. That is, the positive or negative nature of associations between the independent and dependent variables was deliberately not specified in the hypotheses. Previous studies have found that individual differences effect the AAE both positively and negatively. For example, Schaefer, William, Goodie & Campbell (2004) found conscientiousness was negatively associated with over-confidence; they also identified a positive relationship between over-confidence and extraversion. Likewise, Dunning & Kruger say that experience in a domain is more likely to produce a negative relationship with the AAE than lack of domain experience will.

**H<sub>1</sub> A person who uses end-user software as part of their employment will believe their computing skills to be better than the average computer end-user.**

**H<sub>2</sub> A combination of age, sex, experience, extraversion and conscientiousness is associated<sup>1</sup> with a person's self-rating of their own EUC ability in comparison with their ratings of the average computer end-user.**

**H<sub>3</sub> Self-perceived computing knowledge will be greater than demonstrated computing ability.**

**H<sub>4</sub> A combination of age, sex, experience, extraversion and conscientiousness are associated with estimations of the computing ability of the average computer end-user.**

The following four hypotheses, directly associated with the Dunning-Kruger Effect are:

**H<sub>5</sub> A person's self-assessment of end-user computing skill will be associated with their awareness of the breadth of the domain of EUC.**

**H<sub>6</sub> The difference between people's self-reported EUC knowledge and their estimation of the knowledge of an average computer-end-user is associated with awareness of the breadth of EUC**

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<sup>1</sup> Associated, in statistical terms, refers to any relationship between measured quantities that renders them statistically dependent (Hair et al., 1995),

**H<sub>7</sub> Perceptions regarding the estimated breadth of the EUC domain are associated with a person's demonstrated computing ability.**

**H<sub>8</sub> Perceptions regarding the estimated breadth of the EUC domain are associated with a person's computing ability combined with demographic and expertise factors and levels of extraversion and conscientiousness.**

### 1.3 Research description

As outlined in the previous section, the main aim of this research is to determine if social biases, such as the above-average effect, are evident in the context of end-user computing and if this effect is moderated by individual factors such as sex, age, dominant personality traits or expertise in a domain. Although there is an extensive body of literature examining the notion of expertise and manifestations of expertise (Anderson, 2013; Chi et al., 1981; Herling & Provo, 2000), for the purposes of this study, and in keeping with work on the Dunning-Kruger Effect (Brown, 2012; Kruger & Dunning, 1999; 2009; Larrick et al., 2007), 'expertise' is used in relation to indications or measures of the awareness a person has of a particular skill or knowledge domain.

This study takes several approaches to data gathering: collection of demographic and expertise data using a simple questionnaire, self-perception measurement; personality inventory; and a practical skills assessment exercise.

Included in this study are three measures of perception. These measures include a measure of the estimation of the extent to which end-user computing contributes to the field of knowledge about all areas of computing, for this study labelled as Extent of Domain (EoD<sub>EUC</sub>). The remaining two are a measure of self-assessment of end-user computing knowledge and a measure of the estimation of the end-user computing knowledge of the 'average computer end-user' (AEU).

The third approach is to measure the personality traits for each participant. The BFI (Big Five Inventory) personality inventory was used to collect personality data for this study (see Chapter 2 for a more detailed discussion of personality traits, their measurement and selection for this study). This instrument is a forty-four item Five Factor Model (FFM) inventory that has been shown to provide reliable results in studies where time is important and personality is not the focus of the study (Gosling et al., 2003).

The final approach to collecting data was the skill assessment exercise. This was undertaken using two automated instruments to test spreadsheet and word-processing skill. The tasks assessed using these instruments were tailored for the purpose after extensive pilot testing which included input from panels of subject matter experts (see Appendix 4).

Data from each of these sources were brought together with the aim of highlighting factors that will affect a person's perception of their computing skill and that of others. Each of these instruments will be described in detail in Chapter 3, the methods chapter.

## **1.4 Thesis Outline**

This thesis is organised into six chapters, including this introductory chapter, plus a number of appendices. Each of the remaining chapters and the appendices are described in detail in the sections that follow.

### **1.4.1 Chapter 2 –Literature review**

This chapter is a comprehensive review of literature presented in two main sections relevant to this study. Section one reviews literature from social science and, specifically, social psychology focussed on biases in self-evaluations and the motivations and cognitive processes that affect or moderate these. Included is a review of the social comparative judgment bias known as the above-average effect. This well-researched effect, identified in many common domains, is often explained by a number of motivational or cognitive processes and has been found to be affected by individual differences such as expertise and personality, and has been found in many different social settings. This section of the literature review also reviews literature from the domains of expertise and personality. These areas are included in this study as individual differences that combine in each individual.

Section two of this review focusses on the social setting of workplace end-user computing in which the above average effect may be present in a domain that is becoming increasingly common and even dominant in many workplaces. Literature outlining end-user computing, computing end-user types and methods of evaluating end-user competence are reviewed.

### 1.4.2 Chapter 3 – Research methods

This chapter presents comprehensive outlines of the methods used for data collection including the extensive process of instrument development and participant recruitment. Also included is an outline of the analytic methods used in testing each of the eight proposed hypotheses.

In this study, four separate approaches are taken to collecting data.

The first type of data collected were demographic data. All of the variables were used to test the effect of a 'combination' of individual differences on the AAE.

Information for this study included:

- age
- sex
- occupation
- average weekly time spent using a computer
- number of software applications used as part of a job
- approaches taken to learn/expand computing knowledge

The second approach was the creation of three measures of self-perception: the measure of self-assessment of EUC knowledge; the estimation of the extent of the domain of EUC ( $EoD_{EUC}$ ); and the estimated knowledge of the average computer end-user (AEU). Each of these measures uses an adapted visual analogue scale. A visual analogue scale is presented as a line with marked end-points on to which a participant places a mark to indicate their estimation of skill or knowledge. For this study, the scales have been modified to incorporate the analogy of a 1000 page book, with participants making estimations based on a number of pages in the book. This process is described in full in Section 3.5.

The third approach to the data was the use of a widely used measure of the FFM for personality. As previously noted, the Big Five Inventory (BFI) was used. This is a 44-item personality inventory, which is a short version of the 240-item Neo-PI-R. This inventory was chosen, as it is a widely used instrument with proven levels of internal validity. Because personality is only one factor for this study and time for participants is important, it was considered that this shorter version would give adequate information for the purpose of this study.

The final data collection method was that of demonstrated computing ability. This was assessed using two end-user computing instruments created with common workplace spreadsheet and word-processing tasks. The development and validation of the skill assessment instruments is described in detail in Section 3.8.

Chapter 3 concludes with a description of the statistical methods used to analyse the data.

### **1.4.3 Chapter 4 – Results and data analysis**

This chapter, organised into five sections, presents the results from each of the data collection methods outlined in the previous chapter. Results and statistical tests for each are presented and described in this chapter, with full discussion of the implications of these presented in Chapter 5.

Chapter 4 begins with an introduction of the statistical methods used to analyse the data and then provides an overview of how the results are presented. Section 2 reports participant characteristics. This includes demographic features, workplace expertise measures, and personality trait results for extraversion and conscientiousness. In section 3 of this chapter, the results from the skill assessments are outlined in detail. In the fourth section, the above-average effect and the Dunning-Kruger effect are explored in relation to the demographic, expertise and personality variables as related to the hypotheses. In this section, results from the multiple regression analysis investigating predictors for above-average effects evident in self-assessments are presented. Results from each approach to the data are displayed individually in table and chart format with the final section of this chapter providing a summary of all results.

### **1.4.4 Chapter 5 – Discussion**

The findings from this study presented in the previous chapter (Chapter 4) are discussed in detail with key findings expanded.

Chapter 5 is organised into five sections. Section 1 introduces the discussion. Section 2 discusses the results as they relate to the above-average effect. Section 3 discusses the results as they relate to the Dunning-Kruger effect. Section 4 provides a discussion of the findings as they relate to the domain of end-user computing. The final section in this chapter provides a summary of the discussion.

#### **1.4.5 Chapter 6 - Conclusion, Implications, Recommendations and Future research**

The thesis concludes with a summary of the contributions of this study, outlines theoretical and methodological implications of this study, makes recommendations for employers and computer users and includes suggestions for future research.

#### **1.4.6 Appendices**

Supplementary material has been included in six appendices.

- Appendix 1 includes participant recruitment information including the invitation to participate, the study consent form and the study information sheet.
- Appendix 2 contains the combined demographic, personality and self-perception measure instruments in full.
- Appendix 3 has results, in raw data form, from the skill assessments.
- Appendix 4 contains the design and implementation approach used in the formation of the skill assessment instruments. This includes a summary of the pilot studies used to test effectiveness of the instrument.
- Appendix 5 contains the design and implementation approach taken to create the measures of self-perception. Also included in this appendix are results and discussions from each of the three pilot studies undertaken in the development of these instruments.
- Appendix 6 contains all bootstrap information for the significant regression analysis. Bootstrap information for the non-significant associations are included in the results for the appropriate hypothesis.

## Chapter 2 Literature Review

If I don't know I don't know

I think I know

If I don't know I know

I think I don't know

RD Laing (1927 - 1989)

Social scientists have long had an interest in the perceptions that people hold about themselves and how those perceptions influence their views of others and the world around them. Considerable research has been undertaken in the area of self-perceptions and the biases that influence these.

Biases, which affect self-perceptions have been found in different social situations and may influence how a person performs, or is perceived, by others. It is believed that such perceptions and subsequent errors in judgments are influenced by individual differences including personality and a person's expertise in the domain or area for which a self-assessment is being made.

This chapter is presented in three sections. Section 1 presents a review of literature from social psychology on self-perception, personality and expertise. This section of the chapter is presented in four main parts that consist of a general discussion of the self-concept and how we as individuals evaluate ourselves, the motivations that influence self-evaluation, the social comparative biases of the above-average effect, which has been found to influence self-evaluations and, finally, the individual differences brought about by personality and expertise. Section 2 of this chapter explores the practical domain of work-place end-user computing where perceptions and biases may affect workplace productivity and self-awareness of skills that are considered necessary in the current working environment. The third section concludes the literature review with a summary of the main points.

## 2.1 Section one - Perceptions of self-ability from a social perspective

For any study involving people and the perceptions they have, it is necessary to have some understanding of how people process information about themselves and others in different social settings (Hogg & Vaughan, 2008). In social psychology, the dominant approach to understanding social behaviour is social cognition, which comprises the various ways people process, use and store information about themselves and others in social situations (Hogg & Vaughan, 2008). Part of the work on social cognition focuses on cognitions people have about themselves. These include beliefs that constitute the 'self-concept', a concept that forms in the social context (Hogg & Vaughan, 2008; Markus & Wurf, 1987).

### 2.1.1 Self-Concept

The self-concept is a dynamic collection of beliefs one has about oneself and includes perceptions about abilities, expectations, personality traits and motivations (Hogg & Vaughan, 2008; Markus & Wurf, 1987). Although the concept of self is used to explain an individual's behaviour, other factors that work together, can influence how a person may act in different situations (Markus & Wurf, 1987). While behaviour is not solely controlled by how the self is represented, representations of how people feel about themselves or what they think they know about themselves are strong self-regulators in many different behaviours (Markus & Wurf, 1987).

Greenwald (1980) explains the concept of self as being the organisation of knowledge that is characterised by three cognitive biases: egocentricity, beneffectance and cognitive conservatism. Egocentricity essentially explains how we, as individuals, organise our memories by how we remember our involvement in things or where we were at the time an event occurred. In other words, we organise our sense of self from our own point of view rather than in an objective manner. Beneffectance, a term coined by Greenwald (1980), is a combination of beneficence (achieving desirable outcomes) and effectance (motivation to act) that describes how individuals selectively accept responsibility for good outcomes but not for bad ones. For example, students who do well in an exam are willing to take credit whereas those who do poorly are more likely to place blame on the exam being a poor measure of their knowledge (Greenwald, 1980). The third facet is that of cognitive conservatism that Greenwald (1980) describes as a resistance to cognitive change. What Greenwald (1980) is saying is that people accept what fits their current beliefs even to the extent of trying to justify things that make no sense, whereas they are inclined to ignore those things that do not fit their current beliefs.



The self-regulatory process of the self-concept affects how a person thinks, feels and acts in different situations (Markus & Wurf, 1987). This process includes self-monitoring of behaviour followed by self-judgments of how the person executes a particular behaviour against a set of self-defined criteria (Markus & Wurf, 1987). Markus & Wurf (1987) argue that the growth of the self-concept is driven by information one gains about oneself through self-perception, reflection and social comparison and by one's ability to process this information. A well-developed self-concept is influenced by self-knowledge (Hogg & Vaughan, 2008; Sedikides & Strube, 1997). As the self-concept grows so does the need for self-knowledge, which is influenced by self-evaluation through our comparisons with others based on what we believe we know about ourselves (Hogg & Vaughan, 2008; Sedikides & Strube, 1997).

### 2.1.2 Self-Evaluation

Self-evaluation, "the process by which the self-concept is socially negotiated and modified" (Sedikides & Strube, 1997, p. 209) is considered to have four motivations: self-assessment; self-verification; self-improvement and self-enhancement. Each of these motivations is concerned with a person's desire to enhance, improve, verify or assess information about himself or herself (Hogg & Vaughan, 2008; Markus & Wurf, 1987; Scholer, Ozaki & Higgins, 2014; Sedikides & Strube, 1997).

Self-assessment motivation is concerned with people's need for favourable information about themselves (Hogg & Vaughan, 2008; Markus & Wurf, 1987; Sedikides & Strube, 1997). This motivation drives people to seek indicative information about themselves, positive or negative, that can be used to increase the certainty of self-assessment (Hogg & Vaughan, 2008; Sedikides & Strube, 1997).

The motivation of self-verification proposes that people use social interactions as a method of confirming their self-conceptions by seeking subjectively accurate feedback (Hogg & Vaughan, 2008; Sedikides & Strube, 1997; Swann & Reid, 1980). Self-verification is an interesting process, in that those seeking to enhance positive self-conceptions seek positive feedback, while those with existing self-conceptions, positive or negative, seek feedback to confirm those self-conceptions (Sedikides & Strube, 1997; Swann, Pelham & Krull, 1989). Although there is no doubt that people seek self-verification, why they do so is not as easily explained. It may be as a means of self-improvement or it may be simply that people seek verification of what they already know or believe about themselves (Swann et al., 1989).

Self-enhancement motivation is driven by people's desire to learn and confirm positive information about themselves (Alicke, 1985; Greenwald, 1980; Hogg & Vaughan, 2008; Sedikides & Strube, 1997). As a means of increasing self-esteem, people like to find new positive aspects of themselves, confirming what they already believe, while reducing the negativity of the self (Hogg & Vaughan, 2008; Sedikides & Strube, 1997; Swann et al., 1989). People seek to affirm the positive traits of who they are. This affirmation may be done publicly and could be interpreted as boasting or arrogance, or might be a more subtle process of rationalising a situation (Hogg & Vaughan, 2008; Sedikides & Strube, 1997; Swann et al., 1989). Aside from the processes explained here, other possible explanations said to account for self-enhancement include simple wishful thinking (Williams & Gilovich, 2008) or egotistic resolution to ambiguous situations (Dunning et al., 1989). It is possible that any of the processes noted here could account for the self-enhancement motivation (Williams & Gilovich, 2008).

The fourth motivation for self-evaluation is self-improvement. People are motivated to improve their skills, abilities, knowledge, well-being and traits. Somewhat different to the previous three motivations, self-improvement does not necessarily include self-concept positivity (Sedikides & Strube, 1997). Instead of focusing on the differences between old and new information about the self, this motivation is concerned with self-concept change, and is not necessarily concerned with the accuracy of self-knowledge but rather the betterment of the self-concept (Sedikides & Strube, 1997).

Of these motivations, Sedikides & Strube (1997) found that self-enhancement was the strongest motivator of self-evaluation. The motivation of self-enhancement stems from a general perception that people are self-encouraging and protective of their concept of self. Studies have found that memory can be self-enhancing, with people remembering situations in a way that their involvement is shown in the best possible light (Greenwald, 1980; Sedikides & Strube, 1997).

People, generally, have the need for accurate information about themselves but this need may, at times, be offset by the equally demanding need to maintain a positive self-concept (Alicke, 1985; Sedikides & Strube, 1997). The desire to appear in the best possible light may lead people to make overly optimistic estimations of their own skill or quality. That is, inaccurate estimations of the self are often affected by some type of cognitive bias as discussed in the next section (Haselton et al., 2005; Sedikides & Strube, 1997).

### 2.1.3 Cognitive Biases

A cognitive bias is a general term used to describe a number of processes that can influence the inclination of a person to make decisions based on cognitive factors rather than fact (Haselton et al., 2005; Hogg & Vaughan, 2008). A person may hold beliefs where logical or evidential support is insufficient (Haselton et al., 2005). Biases can affect a person's decision-making process, which in turn will lead to errors of judgment (Haselton et al., 2005; Hogg & Vaughan, 2008).

Haselton et al. (2005) identified three types of cognitive bias: heuristics (stereotypes); artefact biases (resulting from placing a person in an unnatural setting) and error management bias (positive illusions). Error management biases include biases in self-judgment that often lead to illusions of superiority (Haselton et al., 2005). Many of the decisions and judgments people make occur in social settings such as workplaces, at home or while at leisure. In these settings, the cognitive biases evident are known as social biases (Haselton et al., 2005).

#### 2.1.3.1 Social biases (in self-evaluation)

A social bias is a cognitive bias that refers to errors made when people evaluate or try to find reasons for their own and others' behaviours (Haselton et al., 2005). Included in the bias type identified by Haselton et al. (2005) as error management are biases in self-judgment. Often a self-judgment bias is evidenced through positive illusions where people hold unrealistically optimistic views of their own qualities, skill or knowledge relative to others in similar positions (Alicke, 1985; Haselton et al., 2005).

Biases occur in situations of social comparison, when a person is trying to understand their own feelings or abilities by making comparisons with others (Larrick et al., 2007; Moore, 2007). Two types of social desirability were distinguished by Paulhus (1986), impression management, and honest reporting based on a genuine belief. Impression management occurs, according to Paulhus (1986), when people make a deliberate attempt to present themselves in the best possible light, and may be in response to particular social situations such as job interviews (Paulhus & Reid, 1991; Pedregon, Farley, Davis, Wood & Clark, 2012).

One social comparison bias, concerned with inaccurate overly optimistic self-evaluations, is the above-average effect. An above-average effect is evident in situations where people incorrectly believe their knowledge or skill is better than that of an average person (Sedikides & Strube, 1997).

In some cases where the effect occurs it is not clear it is indeed a bias or that the people involved are accurate in their estimations. For example, studies have shown that people believe positive events will occur for them more than for others, but that negative events will occur more often for others than themselves (Moore, 2007). However, other studies have shown a bias where the effect has occurred in situations where measures taken show that a person's estimations of themselves are inaccurate. For example, Mattern Burrus & Shaw (2011) found that incoming college students who made the largest overestimation how they would perform in their entrance test in comparison to others sitting the same test were those whose performance was the poorest.

Williams and Gilovich (2008) said there were two possible accounts for occurrences of the above-average effect. Either participants truly believed they were above average or they were motivated by self-enhancement. It is important to understand this effect further as it has implications for people's judgments of their own abilities concerning socially significant behaviours in different social situations (Dunning et al., 1989; Larrick et al., 2007).

### 2.1.3.2 Above Average Effect (AAE)

The above average effect, variously known as 'illusory superiority' or the 'better than average effect', is a cognitive bias resulting in people unrealistically, and positively, judging themselves and their skills relative to others (Alicke, Govorun, Dunning & Kruger, 2005; ; Dunning et al., 1989; Larrick et al., 2007; Mattern, Burrus & Shaw, 2010; Matz & Hinz, 2000; Moore, 2007; Moore & Healy, 2008; Sedikides & Strube, 1997). This well-researched effect has been found to have wide-ranging application and implications for people's judgments of their own abilities in socially significant behaviours (Larrick et al., 2007; Dunning et al., 1989) and is often considered a product of self-enhancement (Chambers & Windschitl, 2004). Since it was first defined more than 25 years ago this effect has been demonstrated in a range of domains including studies of driving ability (Sundstrom, 2008), academic achievement (Larrick et al., 2007), health and well-being (Dunning et al., 1989) and social predictions (Brown, 2012).

Literature from psychology suggests that people have only small amounts of self-knowledge, which leads to inaccurate self-judgements, and inaccurate judgments made of others (Carter & Dunning, 2008). Given that self-judgments are an important aspect of life, and that self-knowledge increases as we learn more, it is interesting that self-reports are more often inaccurate than they are accurate (Carter & Dunning, 2008).

The above-average effect has been illustrated using direct and indirect comparisons (Krizan & Suls, 2008). A direct comparison situation is one where a person is asked to compare himself or herself with that of a peer using a scale such as “much happier” to “much unhappier”. An indirect comparison is one where a person makes separate ratings about themselves and their peers or an average person (Krizan & Suls, 2008). A direct comparison is said to produce stronger and more consistent occurrences of the above-average effect than an indirect comparison (Krizan & Suls, 2008). Typically, in a direct comparison situation a person will be asked to make a comparison on a single scale. For example, a person may be asked to compare their intelligence with that of an ‘average person’ using a scale with a midpoint marked as ‘average’. If self-reports are above this midpoint then an AAE is present (Zell & Alicke, 2011). This suggests that in the case of a direct comparison AAE the average refers to a median average rather than a mean average.

The above-average effect is regarded as a bias because it is statistically unlikely, although not impossible, that the majority of people would be above average in a given population (Klar & Giladi, 1997; Larrick et al., 2007). Although it is unclear if lay people, in a comparison situation, would be considering an arithmetic mean or a median, studies have found that more than 50% of respondents believe they were above the 50<sup>th</sup> percentile within a particular population (Larrick et al., 2007). Evidence shows that people are inclined to see themselves and their skills in the best possible light, especially with what they perceive as being easy or common tasks. Therefore it follows that they see their ability as better than that of others and when asked for a self-assessment people are likely to rate their ability or knowledge as being above average (Mattern et al., 2010; Matz & Hinsz, 2000). For example, Chambers and Windschitl (2004) claimed that most people have a persistent inclination to believe that negative things such as illness or academic failure are less likely to occur to them rather than to others. They argue, further, that people, who want to be seen in the best possible light, exhibit instances of the above average effect by believing that they are better drivers than other road users, or more polite than other people. In a review of literature on subjective driving skill, Sundstrom (2008) found that in studies where people were asked to rate their skill against that of the ‘average’ driver the results showed that the majority of people rated themselves as above average. However, in studies where people are asked to rate themselves against a ‘very good’ driver, the results showed that people were more conservative in their self-assessment.

Self-evaluations may be inaccurate not only because people want to be seen in the best possible light, but also because it is difficult to define expertise in some domains, especially when information about those domains may be ambiguous (Dunning et al., 1989). In situations where the domain or

trait being assessed is ambiguous or difficult to define people are likely to rate themselves optimistically based on their interpretation of that skill or trait (Dunning et al., 1989; Sundstrom, 2008). Conversely, in domains where the skill or trait to be assessed is clearly defined, people are more likely to make a more accurate assessment of their skill or knowledge. For example, when subjects in Dunning et al's., (1989) study were asked to rate themselves for loosely defined traits, such as 'sophistication' and 'sensitivity'", and for more defined traits such as being 'punctual' or 'studious', respondents rated themselves more highly than they rated an average peer for the more ambiguous (less defined) traits than they did for the less ambiguous (more precisely defined) traits.

Inaccurate self-assessments also occur when people have insufficient information about the domain in which the assessment is being made (Kruger & Dunning, 1999, 2009; Mattern et al., 2010). Therefore, while it is likely that over-estimations are made by people with lower skill than they believe they have, the inverse may also be true. Those with higher skills in a domain may also incorrectly estimate their skill or knowledge. However this group will more likely under-estimate rather than over-estimate their own skill or knowledge (Kruger & Dunning, 2009, 1999; Mattern et al., 2010). For example, in a study involving university students Mattern et al. (2010) found that only 7% of students with below average mathematics ability believed that they were below average relative to their peers. On the other hand they found almost 70% of those in the top 10% of mathematics ability believed they were average or below. In their study, Mattern et al (2010) analysed data from two sets of data collected from the Capability Project (see Bridgeman, Pollock & Burton, 2004). In this project data was collected from undergraduate students, both on how they rated their ability in subject areas such as mathematics, chemistry, and actual test scores from these areas. The data sets utilised by Mattern et al (2010) contained more than 150,000 records from more than 40 colleges. Their findings, they suggested, replicated those from previous research by confirming that those with the least ability are more likely to make the most inaccurate over-estimations of ability.

When originally defined it was thought that the above-average effect was solely motivated by the self-enhancement motivation of self-evaluation (Brown, 2012; Sedikides & Strube, 1997). This motivation drives people to assess their own ability more than that of others because it makes them feel better about themselves (Brown, 2012; Sedikides & Strube, 1997). Researchers have since offered different explanations for its occurrence including cognitive mechanisms underlying the use of a self-serving type of self-evaluation (Brown, 2012; Dunning et al., 1989; Moore, 2007). Each of

the various explanations, motivational or cognitive, for social comparative biases such as the above-average effect has applicability in different situations (Brown, 2012).

Motivational explanations for occurrences of the above average effect are relatively difficult to define because they are usually only obvious when people care about the outcome. Importantly, this effect is driven by the need for self-enhancement (Brown, 2012; Sedikides & Strube, 1997). Cognitive mechanisms explain the above-average effect as a type of comparative judgment formed by processes that remain unaffected by the comparison being made (Brown, 2012). Included in these cognitive mechanisms are focalism (focusing on the first subject of comparison), egocentrism (placing too much emphasis on yourself rather than on others) and informational differences (not knowing what you do not know) (Alicke, 1985; Brown, 2012; Carter & Dunning, 2008; Kruger & Dunning, 1999).

### 2.1.3.3 Cognitive mechanisms explaining the above-average effect

Focalism describes the tendency for people to rely on the first piece of information received, or point of focus, when making a decision while not paying any or much attention to equally applicable background information (Brown, 2012; Chambers & Windschitl, 2004; Kruger & Burrus, 2004 ). In a self-assessment situation, where a person is asked to estimate his or her own knowledge or ability compared to that of an average person, focalism says that the self is the focal point. Therefore it follows that more attention will be placed on the focal point (self) than upon the comparison (average person) (Brown, 2012; Chambers & Windschitl, 2004; Kruger & Burrus, 2004; Windschitl, Conybeare & Krizan, 2007). Simply put, focalism assumes that people are more focussed on the target of the assessment than they are on the referent entity that is likely to seem less relevant (Windschitl et al., 2007). Chambers and Windschitl (2004) note that focalism suggests that when, for example, a student is asked to compare their athletic ability with that of a classmate they will place more emphasis on their self-information not because of any relevant information they may have but just because the self was specified as the target and the classmate as the referent. Focalism, which by definition is only found in direct comparison situations, is also present in situations where a group is the focus of the evaluation (Kruger & Burrus, 2004).

When the self becomes the focal point then the above average effect increases the individual's perception of the differences between themselves and others (Brown, 2012; Chambers & Windschitl, 2004; Kruger, Windschitl, Burrus, Fessel, & Chambers, 2008). If focalism is the reason people place their own ability higher than an average peer, then it follows that the above-average

effect should be moderated if the focal point of the comparison is the average person (Brown, 2012; Chambers & Windschitl, 2004; Kruger & Burrus, 2004). Focalism is not considered a factor in situations where a comparison is not being made. Similarly in comparative situations focalism was found to be neutralised when one of the entities being compared was made the “to be judged” entity (Chambers & Windschitl, 2004; Windschitl et al., 2007). Studies where the self was the referent rather than the target have found the bias attributed to focalism to be neutralised. For example, Chambers and Windschitl (2004) cited a study that asked students a number of questions including a comparative question about performance in a future exam. When the comparative question selected the self as the target and ‘average students’ as the referent, comparative judgments were strongly biased toward the student’s performance. When the comparative question selected the ‘average student’ as the target and the self as the referent, comparative judgments were less strongly biased.

Egocentrism, defined as a special case of focalism resulting from the focus on the self (Moore, 2007), can be explained as thoughts and relevant information about one’s self having greater importance in social comparative judgments than thoughts and relevant information about others (Greenwald, 1980; Windschitl, Rose, Stalkfleet & Smith, 2008 ). Egocentrism is a self-serving bias with the tendency for an individual in a comparative situation, to place more importance on their own skill or attribute than on the target of the comparison (Brown, 2012; Moore 2007). Self-relevant information appears to be more important when it is easier for people to recall their performance rather than the performance of others in, for example, a group situation (Krizan & Suls, 2008).

Egocentrism, when referring to an above average effect, can be demonstrated in either of two ways, the differential valuation or the differential weighting approaches (Krizan & Suls, 2008). The differential valuation in self versus other assessments produces favouritism toward the self. An implication of this approach is that the self is favoured in both direct (where a direct comparison is required) and indirect comparisons (where self and referent evaluations take place separately). This is because the majority of information available concerns the self and most people have positive self-concepts. This means that there is likely to be more positive than negative self-information available (Krizan & Suls, 2008; Moore, 2007; Sundstrom, 2008). The differential weighting approach (Krizan & Suls, 2008) is apparent only in direct comparisons and means there is no difference in how self versus others are evaluated in isolation because people are likely to consider their own characteristics and behaviours before considering those of the referent (Krizan & Suls, 2008; Kruger & Dunning, 1999, 2009). Although evidence of the above-average effect is often solely attributed to



motivated self-enhancement and egocentrism, Krizan and Suls (2008) found instances where these two processes were moderated by focalism and other group mechanisms. For example, in their study settings in which the self was part of the group being judged egocentrism did not appear to contribute to comparative biases as much as it did in situations where comparisons only involved individuals.

Another explanation for the occurrence of overly optimistic self-assessments in social comparisons is a lack of information available to a person about the group or person they are making a comparison with or the amount of information available about the subject of the evaluation (Carter & Dunning, 2008; Kruger et al., 2008). Just knowing something about a domain does not necessarily mean that a person will have all the information required to make an accurate assessment of their knowledge in that domain (Carter & Dunning, 2008). In particular, while a person may have enough information to know some things about a domain they do not necessarily know what information they are missing (Carter & Dunning, 2008). Errors of omission can prevent people from evaluating themselves accurately because they are not aware of the information they are missing and may under-estimate how much information they are missing. However, if the missing information is provided it will be used appropriately (Caputo & Dunning, 2005). For example, in a study evaluating the importance of errors of omission in self-assessment, Caputo and Dunning (2005) asked participants to find grammatical errors in a text. After identifying and correcting the grammatical errors participants were asked a question about their ability with grammar and a question about their own performance for the given task. They were then told how many errors there were in the document and again asked the same questions relating to ability and performance. Once participants were made aware of the errors they had missed, they placed importance on this by lowering their self-evaluation ratings. In studies such as that undertaken by Caputo and Dunning (2005) all participants had a level of expertise in the area that was the subject of the evaluation and were therefore willing to expand their expertise by adding the missing information. This is not always the case, however, especially for people with little or no expertise in a domain (Carter & Dunning, 2008; Kruger & Dunning, 1999). When people lack expertise or competence in a domain, often they are unaware of their deficiencies in knowledge and therefore are less able to assess accurately their knowledge or level of performance (Carter & Dunning, 2008; Kruger & Dunning, 1999, 2009).

Incomplete information in a domain combined with the inability to learn from errors of omission has been labelled the 'curse of the incompetent' and become known as the Dunning-Kruger effect

(Dunning, 2011; Kruger & Dunning, 1999, 2009). Given the complexity of many computing environments and tools it is useful to examine this effect in more detail.

Kruger and Dunning (1999, 2009) argue that “incompetent” people are more likely to overestimate their own ability than those who are more competent. They also say that the incompetent are doubly “cursed” as they will fail to recognise competence in other people.

Kruger and Dunning (1999, 2009) proposed that, for a given skill, less competent people will:

1. Be inclined to overestimate their own level of skill.
2. Be unable to identify genuine skill in others.
3. Fail to identify how little they do know about a given skill.
4. Recognise and accept their own previous lack of skill, if they can be trained to improve.

Further, it is claimed that the skills necessary to succeed in a particular domain are the same skills necessary to recognise that skill level in oneself and in others (Dunning, 2011; Ehrlinger, Johnson, Banner, Dunning & Kruger, 2008; Kruger & Dunning, 1999, 2009; Schlösser, T., Dunning, D., Johnson, K. L., & Kruger, J., 2013). Those without the necessary skill in a domain, but who are unaware that their skill level is lacking, are also unlikely to benefit from feedback about this and are likely to make overly optimistic self-assessments (Carter & Dunning, 2008; Dunning, 2011; Ehrlinger et al., 2008; Kruger, 1999; Kruger & Dunning, 1999, 2009). For example, in a study of the Dunning-Kruger effect in the aviation industry by Pavel, Robertson and Harrison (2012) aviation students were given a FAA (Federal Aviation Administration) test on material that, as potential pilots and aircraft engineers, they were all expected to know. In a pre-test exercise, participants were asked for an estimate of how many questions they would get correct. They were then given the test followed by a post-test exercise that asked them to estimate their performance. The results from this study showed that those who gained lower actual scores in the aviation test had higher pre and post-test estimates of their performance than those with higher actual scores. Experiments such as that undertaken by Pavel et al. (2012) provide evidence of biases such as the Dunning-Kruger effect in different and critical domains.

Gross over-estimations of ability and performance are likely to occur with participants who lack knowledge and are unaware that they do so (Ehrlinger et al., 2008; Kruger & Dunning, 1999, 2009; Schlösser et al., 2013). The unskilled not only do not have the knowledge or skill they think they have but also do not realise what skill or knowledge they need or what skill competent people possess

(Carter & Dunning, 2008; Dunning, 2011; Ehrlinger et al., 2008; Kruger & Dunning, 1999, 2009). Conversely, those with higher levels of actual competence - or as Kruger and Dunning (1999, 2009) labelled it a 'burden of expertise' - were likely to underestimate their knowledge or skill level. The suggested explanation for this finding is that those who are more competent think that others have a similar level of competence, so do not rate themselves as being outstanding (Kruger & Dunning, 1999, 2009).

In summary, inaccurate self-assessments have been shown to be present in different domains such as driving (Sundstrom, 2008; Waylen, Horswill, Alexander & McKenna, 2004); education (Dunning, Heath & Suls, 2004; Larrick et al., 2007); health (Dunning et al., 2004, 1989); the workplace (Dunning et al., 2004) and attribute importance (where attributes included honesty, kindness, intelligence etc.) (Brown, 2012). Likewise, the Dunning-Kruger effect has been mentioned as an explanation for inaccurate self-assessment in studies in several domains such as aviation (Pavel et al., 2012); peer review (Huang, 2013); academic performance (Kruger & Dunning, 1999). Although there are both cognitive and motivational explanations as to why exaggerated self-assessment may occur in different situations, there are also differences between individuals, which potentially have an impact on these (Schaefer et al., 2004).

## 2.2 Individual personal differences

Individual differences that may affect a person's perception of their knowledge or skill in a given domain include a person's personality. Studies have found that the basic process of personality can predict over-confidence (Schaefer et al., 2004). For this reason, personality traits will be discussed in detail in the following section.

### 2.2.1 Personality

A person's beliefs, attitudes, behaviours, thoughts and perceptions can, in part, be attributed to personality (Devaraj, Easley & Crant, 2008; Hogg & Vaughan, 2008; Markus & Wurf, 1987; Svendsen, Johnsen, Almas-Sorensen & Vitterso, 2013). Personality refers to the differences between people in enduring patterns of behaviour, cognitions and emotions (Devaraj et al., 2008; McCrae & John, 1992; Svendsen et al., 2013). A person's personality is a reflection of unique facets and traits that are revealed in thoughts, attitudes and beliefs (McCrae & John, 1992; Devaraj et al., 2008; Hogg & Vaughan, 2008). Personality traits are broad dimensions of individual difference that are revealed by a particular pattern of behaviour (Barrick & Mount, 1991; Devaraj et al., 2008; McCrae, 1993).

Personality and the traits that make-up a person's personality have been the subjects of debate for many years with different claims made about the number of distinguishable traits that provide a comprehensive account of personality (Barrick & Mount, 1991; Devaraj et al., 2008; McCrae & John, 1992). In 1932 William McDougall proposed five distinguishable traits: intellect, character, temperament, disposition and temper (Barrick & Mount, 1991; Digman, 1990). About a decade after McDougall's proposal Cattell (1943) proposed that personality consisted of 16 primary factors with 8 second-order factors (Barrick & Mount, 1991; Digman, 1990). Successive attempts to re-create Cattell's 16-factor model were unsuccessful with researchers continually coming back to five dominant and distinguishable factors or traits. Although this is the same number, the actual traits chosen were not those suggested by McDougall (Barrick & Mount, 1991). This work led to the creation in the 1980's of what has become known as the Five-Factor Model (Barrick & Mount, 1991). This model was introduced as a comprehensive framework in which personality traits are classified into five central dimensions, openness, conscientiousness, extraversion, agreeableness and neuroticism that are considered to best encompass the fundamental dimensions of personality (Barrick & Mount, 1991; Devaraj et al., 2008; Gosling, Rentfrow, & Swann, 2003; McCrae & Costa, 1987; McCrae & John, 1992). Despite ongoing debate and various definitions of the model, the basis of the five-factor model has proven to provide a robust framework that is widely cited in research on both personality and organisational behaviour (Barrick & Mount, 1991; George & Zhou, 2001; McCrae & John, 1992).

Each of the five traits (openness, agreeableness, neuroticism, conscientiousness and extraversion) can be described by a number of adjectives, which express positive or negative attributes (Barrick & Mount, 1991; Devaraj et al., 2008; George & Zhou, 2001; Gosling et al., 2003; McCrae & John, 1992).

### 2.2.1.1 Openness

People whose personalities have high levels of openness are said to be imaginative, cultured, independent thinkers, tolerant of ambiguity, and open to new experiences and new ideas (Barrick & Mount, 1991; Griffin & Hesketh, 2004; McCrae, 1993). The trait of openness to experience, variously known as openness, intellect was the most difficult of the five to define (Barrick & Mount, 1991). This difficulty may be because, as a trait, it has proven difficult to define simply by using a single adjective (Griffin & Hesketh, 2004; McCrae & Costa, 1987). Another difficulty may be because openness has also been co-defined as intellect or intelligence, with some saying that individuals who score high for openness are, by definition, intelligent (Barrick & Mount, 1991; McCrae & Costa, 1987). Although openness to experience is strongly related to intelligence, the trait is broader than

just intellect and can be broken down into two aspects: openness and intellect. Both traits can be explained through the process of cognitive engagement, with intellect being engagement with semantic and abstract information by way of reasoning and openness as engagement with sensory and perceptual information (DeYoung, Quilty, Peterson & Gray, 2013).

In their study investigating the impact of openness to experience on job performance Griffin and Hesketh (2004) suggested that openness could be either external (related to the external environment), or internal (related to thoughts and feelings). Using this approach Griffin and Hesketh (2004) found that the trait of openness to experience was only positively related to job performance when taking into account external factors, suggesting that those who are aware of their external environment are likely to adapt well to changes. However, openness to internal experience (feelings and thoughts) was positively related in situations where there was evidence of tension between workers in a workplace. People with a low score for openness are inclined to be conservative in outlook and unwilling to take chances or make change (Rothmann & Coetzer, 2003). Conversely, those with high scores for openness are said to be willing to break rules or conventions and question authority (Rothmann & Coetzer, 2003).

### 2.2.1.2 Agreeableness

The trait of agreeableness can be characterised by the adjectives: kind, sympathetic, cooperative and considerate (Barrick & Mount, 1991; McCrae & Costa, 1987). Agreeableness has been found to be a significant predictor for success in occupations that require interpersonal interactions, creativity and training (Barrick, Parks, Mount, 2005). The personality construct found to be most highly related to job performance is conscientiousness (Barrick & Mount, 1991; McCrae & Costa, 1987). However, Witt, Burke, Barrick & Mount (2002) warn that the benefits of high levels of conscientiousness can be negated by low levels of agreeableness. They say that an ideal predictor of job performance are workers who scored high for conscientiousness and also for agreeableness, as these people are likely to be effective in situations where collaboration and inter-personal communication is necessary. The inverse of this is likely in situations where there is little interaction with other people. For example, Landers and Lounsbury (2006) found an inverse relationship between agreeableness and Internet usage. They explained this by arguing that less agreeable people, those who may not get along well with others, choose to spend more time on the Internet rather than in interpersonal settings. In a study on the impact of personality traits on academic performance and motivation, De Feyter, Caers, Vigna & Berings (2012) found that agreeableness was a predictor for academic performance but not

for academic motivation. They suggested this was due to more trusting students being more likely to learn in a group or team situation but were not necessarily those who would engage in diligent study.

In their study of the association between personality traits and overconfidence Schaefer et al (2004) did not find agreeableness to be a predictor of confidence, accuracy or over-confidence to any significant degree, however an example of what they called a puzzling result, was a partial positive correlation between agreeableness and over-confidence and confidence. On further investigation, they concluded that this result was likely to be a reflection of other traits such as extraversion correlated with agreeableness rather than agreeableness itself correlated with over-confidence (Schaefer et al., 2004).

### 2.2.1.3 Neuroticism

Neuroticism is the trait associated with emotional stability and can be described using adjectives such as angry, depressed, anxious, worried or insecure (Barrick & Mount, 1991). Neurotic individuals are said to suffer from more episodes that are negative during life than more positive people. This may in part be due to them selecting situations that foster negativity (Barrick & Mount, 1991; De Feyter et al., 2012; Gosling et al., 2003; Griffin & Hesketh, 2004; Judge, Heller & Mount, 2002). People with high scores for this trait may suffer from a psychiatric problem and could be prone to episodes of irrational thought and impulses (Rothmann & Coetzer, 2003). Those with low neuroticism scores are said to be emotionally stable. Such stability has been found to relate strongly to employability and job performance, as these people will usually remain calm and even-tempered even under extreme circumstances (Rothmann & Coetzer, 2003). People who are emotionally stable have been found to be more interested in using social media and other Internet media than those who exhibit negative traits associated with neuroticism (Svendsen et al., 2013).

### 2.2.1.4 Conscientiousness

People who score high for the personality trait conscientiousness are said to be efficient, organized and hard-working (Barrick & Mount, 1991; De Feyter et al., 2012; Gosling et al., 2003; Griffin & Hesketh, 2004; Judge et al., 2002). Individuals with high levels of conscientiousness, display a strong sense of purpose, are reliable, and work hard to achieve goals (Barrick & Mount, 1991; George & Zhou, 2001; Gosling et al., 2003; Griffin & Hesketh, 2004; Judge et al., 2002). For example, De Feyter et al (2012) found that conscientiousness was a strong predictor of academic motivation related to

academic achievement in undergraduate students. Conscientiousness may be governed by conscience or by a thorough and careful thought process that helps to moderate behaviour and promote efficiency and organisation (McCrae & Costa, 1987). McCrae & Costa (1987, p. 88) describe someone low on conscientiousness as being *“not so much uncontrolled as undirected, not so much impulse ridden as simply lazy”*.

The trait of conscientiousness is related to positive job performance and self-improvement so it is likely that self-assessments from people with high levels of this trait will be relatively accurate, as these people, by nature, will be inclined to seek improved knowledge and be aware of what they know already (George & Zhou, 2001). For example, in their study on the relationship between personality and Internet usage Landers & Lounsbury (2006) found conscientiousness was positively related to Internet use for academic or study purposes but negatively related for leisure purposes. However, while some aspects of this trait suggest a strong relationship to job performance there are other aspects, which may hinder this (George & Zhou, 2001). These aspects include the tendencies for people high in this trait to be controlling with conformist characteristics, which may in fact stifle creativity and lead to job dissatisfaction (George & Zhou, 2001). Schaefer et al., (2004) found that people high in conscientiousness were confident and made accurate self-assessment with no linkage between this trait and overconfidence.

### 2.2.1.5 Extraversion

People who score high for extraversion are people who like to be the centre of attention, enjoy engaging with people, are high in confidence and viewed as being energetic and positive (Barrick & Mount, 1991; Griffin & Hesketh, 2004; Gosling et al., 2003; Judge et al., 2002; Rothmann & Coetzer, 2003). De Feyter et al (2012) found that students who scored high for extraversion were motivated to perform well but this motivation did not necessarily transfer over into results, as extraverts are also strongly socially inclined. The result of this social inclination meaning that the desire to study for assessment may be outweighed by the desire for enjoyment (De Feyter et al., 2012).

Extraversion has been found to be an indicator of job success and job performance in roles that involve social interaction, such as sales, marketing, or management (Barrick & Mount, 1991; Rothmann & Coetzer, 2003). However, it has not been found to be a predictor of performance in jobs where there was little chance for social interaction such as production workers or accountants (Barrick & Mount, 1991; Rothmann & Coetzer, 2003). In their study of Internet usage, Landers and Lounsbury (2006) found an inverse relationship between Internet usage and extraversion. This can

be explained as introverted people being engaged in online activities far more than the more socially inclined extraverts are. This may be because the introverted have more free time to engage with the internet and are attracted to this type of solitary activity (Landers & Lounsbury, 2006). Extraversion has also been found to have a strong relationship with overconfidence; this relationship can be attributed to high levels of confidence combined with low levels of accuracy (Schaefer et al., 2004).

In addition to personality factors, expertise is an individual difference that has been found to affect a person's perception of their knowledge or skill in a given domain (Carter & Dunning, 2008; Kruger et al., 2008). Studies have also found that, as expertise in a domain increases, over-confidence decreases (Dunning et al., 2004; Gravill et al., 2006; Kruger & Dunning, 1999, 2009). For this reason, it is necessary to explore the area of expertise in greater depth.

### 2.2.2 Expertise

Expertise, in a general sense, can be considered as having exceptional skills and knowledge in a particular area, which distinguishes a person from others with lesser skills, and knowledge (Chi, Glasser & Rees, 1981). Expertise was defined in Chi et al. (1981, p. 7) as the *"possession of a large body of knowledge and procedural skill"*

Anderson (1983) proposed the ACT (Adaptive Character of Thought) theory as a unitary theory of the mind. ACT depicts the mind as a multifaceted set of representations and processes. The unitary part of ACT is the same set of representations and processes required for all aspects of the mind (Anderson, 1983). According to ACT, abilities as seemingly diverse as mathematical ability, ability in computer programming, linguistic or musical ability are manifestations of the same underlying processes and representations. Anderson further developed ACT into ACT-R (Adaptive Character of Thought – Rational) (Anderson, Bothell, Byrne, Douglass, Lebiere & Qin, 2004; Whitehill, 2013). ACT-R models how people recollect information from memory in pieces and how these pieces of information are further broken down to solve problems (Whitehill, 2013). The term 'rational' in the name implies that the mind works in a rational way to solve problems and to gain and develop skills and knowledge (Anderson et al., 2004; Whitehill, 2013). ACT-R uses units of declarative knowledge that undergo a series of production type rules, and that intelligence, no matter its complexity, is a result of this architecture (Anderson, 1996, 2004, Whitehall, 2013). Declarative knowledge, in an ACT-R sense, contains a series of 'chunks' or pieces of knowledge that while they are separate entities they are associated with each other in the network (Whitehill, 2013). Whereas, in an ACT-R



sense, procedural knowledge is a set of production rules used to determine how a particular goal is achieved after conditions have been met (Anderson et al., 2004; Whitehill, 2013).

In an operational or workplace sense, expertise is usually considered as the possession of superior skills or knowledge in a particular domain and having the ability to improve organisational systems (Herling & Provo, 2000). There is little to suggest that expertise is transferable between domains. That is a person, who is an expert in one area may not become an expert in others areas, although people of very high intelligence may have skills which transcend different domains (Chi et al., 1981). Competence is an attribute of expertise and a subset within a person's domain of expertise (Mott, 2000). While being competent suggests that a person has some ability to complete tasks to a satisfactory level, expertise goes one-step further and suggests knowledge, experience and problem solving ability (Herling & Provo, 2000; Shanteau, Weiss, Thomas & Pound, 2002). Experts have wide-ranging knowledge within a domain while a competent person has task specific knowledge and experience (Chi et al., 1981; Herling & Provo, 2000; Shanteau et al., 2002). Experts are said to have greater depth of perception in their domain, allowing them to see and understand meaningful patterns that may be lost on non-experts (Chi et al., 1981). Chi et al. (1982) claim that this pattern recognition reflects the manner in which some experts organise and store knowledge and may differ between domains. For example, people with expertise in computer programming may recall relatively complex sub routines whereas non-expert programmers may only be able to recall clusters of meaningful programming words (Chis et al., 1981). Another aspect of expertise is the speed at which an expert can complete a task compared with a less-competent person. This speed can be attributed to the practice an expert has had within their domain and because an expert will arrive at a solution more quickly than a less competent person would (Chi et al., 1981, Herling & Provo, 2000). Further, experts have been found to have better long and short-term memory recall than non-experts.

Two theoretical perspectives used to understand the constructs of expertise are cognitive or knowledge engineering theories (Herling & Provo, 2000). In the study of cognitive theory expert characteristics are central to understanding expertise, where experts know more, recognise and solve problems more quickly than non-experts and approach tasks in a different way than non-experts do (Chi, Glasser & Farr, 2014; Chi et al., 1981; Herling & Provo, 2000 ). Experts in a domain are likely to have fast and accurate recall of facts in that domain and will have strong self-monitoring skills and spend time analysing problems in order to provide suitable solutions (Ericcson & Smith, 1991). While cognitive theories are an attempt to find what actually make an expert, knowledge

engineering theories focus on the thinking process and make distinctions between domain and task knowledge, with expertise being defined as a competency for achieving a task (Herling & Provo, 2000). Expertise can be defined by different categories of expert such as expert judge, expert witness, expert instructor, etc. (Weiss & Shanteau, 2003). In each of these areas, the expert must have sufficient cognitive ability to be able to evaluate problems, make judgements and perform well (Weiss & Shanteau, 2003, 2014).

Although expertise is important in an organisational environment there are problems associated with accurately assessing what expertise is (Paloniemi, 2006). Knowledge on its own is not enough to suggest expertise in a domain. Expertise also requires the motivation to increase knowledge (Weiss & Shanteau, 2003, 2014). A person who may know a great deal about a domain may still not be able to make competent decisions in that area, whereas someone with expertise is able to evaluate a situation and make an expert judgment based on their evaluation (Shanteau et al., 2002; Weiss & Shanteau, 2003, 2014).

Expertise has proven difficult to define with judgments of superior expertise being based on what may be subjective and therefore ambiguous criteria such as education, certification, job title or experience (Shanteau et al., 2002; Herling & Provo, 2000; Weiss & Shanteau, 2003, 2014). Although in education having passed a qualification or received certification may mean a certain standard has been reached it does not guarantee the breadth of knowledge necessary to have expertise in a domain (Herling & Provo, 2000; Shanteau, 2003, 2014; Shanteau et al., 2002; Weiss & Shanteau, 2003, 2014). Several approaches have been developed to explain and characterise expertise (Anderson, 2013; Dreyfus, 2004; Ericsson & Charness, 1994; Mott, 2000; Shanteau et al., 2002; Weiss & Shanteau, 2003, 2014). These approaches include the previously mentioned ACT-R (Anderson, 2013). Other approaches include the skill acquisition approach, expert performance, the CWS (Cochran-Weiss-Shanteau) ratio (Shanteau et al., 2002; Weiss & Shanteau, 2003, 2014), the mental schema approach (Dreyfus, 2004; Ericsson, 2014; Ericsson & Charness, 1994; Mott, 2000; Weiss & Shanteau, 2003, 2014) and the knowledge engineering approach (Herling, 2000; Herling & Provo, 2000).

The skills acquisition approach attempts to show that basic information processing and abilities remain intact as new skills are being developed and that expert performance is a result of small and incremental increases in skill because of the extended effects of experience (Dreyfus, 2004; Ericsson, 2014; Ericsson & Charness, 1994; Mott, 2000). Other approaches focus on individual

differences in exceptional performers brought about by a link between individual intelligence and the demands of a particular domain (Ericsson, 2014; Ericsson & Charness, 1994).

The expert performance approach, put forward by Ericsson and Charness (1994), focuses on domains where objective measures of expertise are available rather than using poorly specified judgment factors. This approach suggests that experts have had long-term experience or practice in their particular domain and this experience can be demonstrated through reproduced superior performance (Ericsson, 2014; Ericsson & Charness, 1994; Weiss & Shanteau, 2003, 2014).

The CWS ratio approach proposed by Shanteau et al., (2002) combines two of what they determined to be the most important factors from other methods: discrimination and consistency. Shanteau et al. (2002) argue that for a person to be deemed an expert they must show high levels of discrimination. That is, they must be able to distinguish the subtle details that a non-expert may miss. They also say that for a person to be an expert their assessments of situations should be consistent in similar cases. Under this approach, an expert is someone who has consistently high levels of discrimination. By contrast, a non-expert has lower - or not consistently as high - levels of discrimination. Shanteau et al. (2002) point out that while they focussed on discrimination and consistency as the key determinants of expertise they were not sure if these could be learned or were skills that were inherent to individuals.

Knowledge engineers categorised expertise into five types of model: heuristic, deep, implicit, competence and distributed (Herling, 2000). The heuristic model broadly explains expertise as having knowledge in a domain, including heuristic knowledge. The Deep Model explains expertise as having the skill and knowledge to solve complex problems in a domain. The implicit model was introduced in an attempt to differentiate between implicit and explicit knowledge where explicit knowledge is said to include domain facts while implicit knowledge was experienced based knowledge. Competence models distinguish between static knowledge and task knowledge and define expertise as being competence based. Each of these knowledge engineering models recognise experts as having a depth of domain knowledge who know how to solve problems, and that task knowledge is practice based (Herling, 2000).

One aspect these approaches have in common is the premise that expertise is related to experience in a domain (Ericsson, 2014; Ericsson & Charness, 1994; Herling & Provo, 2000; Weiss & Shanteau, 2003, 2014). The acquisition of knowledge and experience in a domain has various stages ranging from novice or beginner through to expert (Dreyfus, 2004; Mott, 2000). A novice has no experience

and requires guidelines to complete tasks, whereas an expert can solve problems without the requirement of guidelines, and has an intuitive feel for the domain (Dreyfus, 2004). In the middle of this range is the stage of competence, where a person has developed an awareness of a domain and can devise plans and routines to identify important factors (Dreyfus, 2004). This stage suggests that a person has the ability and knowledge in a domain to complete tasks to a reasonable level and, given more experience, is likely to progress through stages closer to expertise (Dreyfus, 2004; Herling & Provo, 2000; Shanteau et al., 2002).

Perhaps the most important commonality between each of the approaches outlined is the premise that an expert not only has experience, which they can use to solve problems, but also they have the foresight to recognise situations where problems may occur before they do (Ericsson, 2014; Ericsson & Charness, 1994; Herling & Provo, 2000; Mott, 2000; Weiss & Shanteau, 2003, 2014).

In the context of the above-average effect, and in an operational sense, it is fair to say that expertise manifests as experience in a domain ( Kruger & Dunning, 1999, 2009; Larrick, Burson & Soll, 2007). It has been found that those possessing the least amount of knowledge or skill within a particular domain are likely to be unaware of their lack of knowledge and will not have the skills necessary to recognise the knowledge that others have (Kruger & Dunning, 1999, 2009).

## **Summary of section one**

Section 1 of this review explored the areas of self-perception and the biases that can affect this. The impact of a social bias is influenced not only by motivations and cognitive process but also by individual differences such as personality and expertise (Kruger & Dunning, 1999, 2009; Schaefer et al., 2004). The literature has shown that as expertise increases overly optimistic self-evaluations decrease (Kruger & Dunning, 1999,2009) and the literature has also shown that overconfidence is more likely to be found in people with higher levels of some personality traits, such as extraversion, than others (Schaefer et al, 2004). Also noted in the literature is the argument that ill-defined competence is associated with instances of social biases such as the AAE (Dunning et al., 2008).To explore these effects further in the context of a significant social setting the following section of this literature review will give an overview of the domain of end-user computing. More specifically, it will consider the type of end-user computing found in most workplaces (Eschenbrenner & Nah, 2014; Govindarajulu & Arinze, 2008). As explained in Chapter 1, this domain has been chosen as it has become a relatively common domain and one that relies quite heavily on self-evaluation of skills by

those who are required to have these skills for their jobs (Gravill et al., 2006; Murray & Perez, 2014; Murray et al., 2007).

## 2.3 Section two – End-user computing

As computers and computing technology have advanced and become more available to a greater number of people, the field of computing has expanded to include many different aspects. End-user computing is just one of these aspects (Birch, 2007; Eschenbrenner & Nah, 2014; Govindarajulu & Arinze, 2008). The ACM (Association for Computing Machinery) computing curricula ([www.acm.org](http://www.acm.org), 2005) defined computing as being

"Any goal or activity requiring or benefitting from or creating computers. Thus, computing includes designing and building hardware and software systems for a wide range of purposes; processing, structuring, and managing various kinds of information; doing scientific studies using computers; making computer systems behave intelligently; creating and using communications and entertainment media; finding and gathering information relevant to any particular purpose, and so on. The list is virtually endless, and the possibilities are vast." (p9)

The definition of computing from ACM clearly shows that computing is a broad domain with many different facets, with end-user computing being just one component. End-user computing is the type of computing that non-computing professionals do more and more of in workplaces and at home (Birch, 2007; Eschenbrenner & Nah, 2014; Govindarajulu & Arinze, 2008; Leahy & Dolan, 2010; Panko, 1989, 2013; Torkzadeh & Lee, 2003).

Computers, and the associated computing technology, have changed the face of workplaces radically over the past three decades (Murray et al., 2007). In the early days of computers in the workplace, only a few people used them, but in recent times, it is more usual for people to be responsible for their own computing. This responsibility has meant that people entering the workforce and those already in employment need to have the computing skills required to use common office type software effectively (Gibbs et al., 2010; Murray et al., 2007).

In an organisational sense, end-user computing can be defined as the interaction with, and the development of, software applications and systems in order to make business decisions but not involving system design (Davis, 1985; Govindarajulu & Arinze, 2008). End-user computing is a requirement for securing many different roles within many workplaces (Walton, Putnam, Johnson & Kolko, 2009) and has become a research domain that combines the theory and practice of organisations, information technology and human resources (Govindarajulu, 2014; Govindarajulu & Arinze, 2008; Walton et al., 2009). Users of end-user applications can be separated into groups ranging from lower level users, who use computer applications for general clerical tasks such as letter writing or data entry, to those who extend existing applications using common programming languages (Barker & Fielder, 2010; Costabile, Mussio, Provenza, & Piccinno, 2008; Govindarajulu & Arinze, 2008). Since organisational end-user computing became relevant in the late 1970's several different user classifications are available, notably those put forward by Rockart & Flannery (1983) and Cotterman & Kumar (1989). Both of these classifications still have value, with the former identifying characteristics based on end-user computing knowledge and the latter identifying characteristics more akin to an end-user developer (Govindarajulu, 2014). The Rockart & Flannery (1983) classification highlights six different end-user types from the non-programmers to data-processing programmers (Govindarajulu & Arinze, 2008). The latter group of end-users are often referred to as end-user developers (Barker & Fielder, 2010; Govindarajulu & Arinze, 2008). These are, generally, non-computing professionals with the skills to extend current applications and to create their own applications (Govindarajulu & Arinze, 2008). These users or end-user developers are also sometimes referred to as power users. Often they are the 'go-to' people in an organisation when other users require assistance with computing problems (Costabile et al., 2008). An example of power users are those identified by Costabile et al. (2008) as domain experts. These people are specialists in their own field who use software to solve domain related problems. Costabile et al. (2008) likened the way that these users manipulated software to achieve solutions for their problems as being similar to the way that children might modify their toys for different purposes. They say that these domain experts are likely to work in teams to change and use the software applications to fit their needs better. While some of these people may develop software for their own use, they are not software developers and may have no real interest in being so.

### 2.3.1 Workplace computing requirements

Most jobs in modern workplaces require employees to be responsible for their own computing. In fact this requirement is often taken for granted, along with a number of other soft skills expected for

employment such as an ability to work in a team, ability to communicate well, etc. (Kyng, Tickle & Wood, 2013; Hansen & Hansen, 2010; Holtzman & Kraft, 2010; Leahy & Dolan, 2010; Murray & Perez, 2014; Rosenberg, Heimler & Morote, 2012). The assumption that people entering the workforce have suitable skills often is misguided as many - even those graduating from tertiary education - do not have adequate workplace computing knowledge and experience (Murray & Perez, 2014; Perez & Murray, 2010).

Workplace computing may include low-level tasks such as data entry or sending and responding to emails. It could extend to letter or report writing or other types of word-processing or it may involve developing quite complex spreadsheet or other data models (Baker, Powell, Lawson, & Foster-Johnson, 2008; Hansen & Hansen, 2010; Holtzman & Kraft, 2010; Panko, 2013). The two most common types of skill required are those associated with the use of word-processing software and spreadsheet software (Barker & Fielder, 2010; Gupta & Anson, 2014; Hansen & Hansen, 2010; Holtzman & Kraft, 2010; Murray et al., 2007; Stoner, 2009). The type of computing an employee undertakes depends on the organisation, the computer systems in use and the skill level of the user (Barker & Fielder, 2010; Hansen & Hansen, 2010; Holtzman & Kraft, 2010; Murray et al., 2007; Stoner, 2009). Spreadsheets are one of the two most commonly used end-user applications and the most common research end-user application. While these tools include the functionality required for reasonably sophisticated data analysis, use ranges from simple data entry to creating complex automated models (Baker et al., 2008; Panko, 2013; Powell, Baker & Lawson, 2008). Differences in use are likely to be relative to the experience of the user, relative to the context in which the spreadsheet is used, and relative to the size and complexity of the spreadsheet and the role of the user in the organisation (Eschenbrenner & Nah, 2014; Lawson, Baker, Powell & Foster-Johnson, 2009; Panko, 2013). One reason why the use of spreadsheets dominates use in many application categories is that people may often choose to use spreadsheets over industry or domain specific software (Panko, 2013, Singh, Bhadauria, Jain & Gurung, 2013). This occurs because spreadsheets are seen as easy to learn, are capable of quite complicated data manipulation and analysis, and because bespoke software packages can be expensive and difficult to modify (Panko, 2013; Singh et al., 2013). While it may be a common belief that spreadsheets are only used to develop small applications as one-off solutions, the opposite is more correct. Spreadsheets are often developed to create both small models and very complex models containing large amounts of data and calculations (Baker et al., 2008; Lawson et al., 2009; Panko, 2013). Although the use of spreadsheets may be expected in industries such as accounting, finance, insurance, etc., these tools are regularly used by employees in other industries (Eschenbrenner & Nah, 2014; Lawson et al., 2009; Panko,

2013). For example, Cox, Edgar, Munise and Johnson (2011) argue that graduates from undergraduate agricultural courses will not prosper in the workplace with under-developed EUC skills. Results from their study showed that the majority of graduates from agricultural courses had not reached a level of spreadsheet, database and word-processing skill to be considered proficient with these applications. In their study, it was reported that a significant discrepancy existed between the self-perceived level of computing ability and actual ability. These researchers were concerned that, given the importance of information technology in every facet of society, some educational institutions were failing their students by not providing them with workplace ready computing skills. In another example, this one from the hospitality sector, Berezina, Bilgihan, Cobanoglu and Okumus (2011) found a significant gap between the end-user computing skills employers expected and those of new graduates. They state that, as well as ability with industry specific software applications, there is also a need for general end-user computing skills. Spreadsheet software was listed as the number one requirement in their list of the top five general software skills required. The only computing skill in their study where participants' scores were higher than those expected by the Hospitality Industry experts was that of online shopping. Their study highlighted the need for new employees to be better equipped at using spreadsheets and word-processing software than their results indicated was the case. Their results concerning online shopping also highlighted that people, who use computers for social reasons (networking, shopping etc.), may be mistaking this use for having general computing skills.

Along with the increase of workplace technology use that has and is changing the face of the modern workplace, another factor that is having an impact on modern workplaces is an increasingly ageing population (Meyer, 2011; Rizzuto, 2011). Life expectancy has increased and birth rates and the labour force participation by those in the 15- 24 age group have decreased, particularly since the beginning of this century (Frosch, 2011; Meyer, 2011, Rizzuto, 2011). These demographic changes, coupled with the increase in the use of technology in the workplace, may have implications for some workers who are required to adopt new and ever-changing technology to complete tasks that were once fully manual (Elias, Smith & Barney, 2012; Meyer, 2011; Morris & Venkatesh, 2000; Rizzuto, 2011). For example, Rizzuto (2011) investigated the interactions and reactions between the use and adoption of technology in the workplace and the different age groups using this technology. Findings suggest that, contrary to studies they reviewed, the older people in their study reacted more favourably in some situations to the use of new technology for their work than did their younger colleagues. According to Rizzuto (2011), older workers in departments where the mean age was low, were more enthusiastic about trying new systems and learning new skills than were their younger



colleagues. In work-groups where the mean age was higher, younger people, who were not as represented, showed greater levels of confidence with the new technology than did their older colleagues. One interpretation of these results is that older people, in workplaces with a lower mean age, have more opportunity of mentoring from their younger, more technology confident, work colleagues, than those working in groups with a higher mean age. Rizzuto (2011) concluded that, while a great deal of expense and time are involved in implementing new workplace technology, not nearly enough time, training and mentoring is given to those who will be using the technology.

Given the mixture of ages in most large workplaces there are different issues that need to be taken into account and different training and mentoring is required for people of different ages. Employers need to be aware of the implications of an ageing workforce and the affect that a fast rate of change in the technology environment has on the positive engagement of a workforce and not just assume that all workers will respond well to change (Elias et al., 2012; Meyer, 2011; Rizzuto, 2011, Venkatesh & Morris, 2000).

End-user activities, over different roles and in different organisations, can cover a range of tasks and make use of a wide range of end-user type software tools (Birch, 2007). Primarily technology is used to provide an organisation with some type of competitive advantage or to keep up with competitors. Therefore considerable focus is placed on how well these systems or tools are used (Yoon, 2009; Yoon, Lee, Hong & Kang, 2008). It follows that employers would wish to be aware of the end-user computing skill level of their employees.

### 2.3.2 Evaluating end-user computing competence

Studies have shown a gap between the computing skill expectation of an employer and the actual skill of an employee (Berezina et al., 2011; Bunker, 2010; Gibbs et al., 2010; Murray & Perez, 2014). A problem that both employers and those assessing their own computing skill face can be the ambiguity in definitions of computer literacy. Some regard computer literacy as being able to use specific and common workplace software applications, while others regard it as being able to navigate the Internet (Gibbs, et al., 2010; Murray & Perez, 2014; Perez & Murray, 2010).

Although the use of end-user applications is a requirement in many jobs, skill level may be at a very basic level and therefore the maximum benefit from using the technology is not achieved (Bunker, 2010; Eschenbrenner & Nah, 2014; Torkzadeh & Lee, 2003). Effective end-user computing capability within an organisation ideally includes effective task completion. This type of capability may be

related to the competency of an organisation as a whole (Bunker, 2010; Yoon, 2009). For example, in a report on the digital literacy standards in New Zealand organisations, Bunker (2010) found that, although the New Zealand government had introduced digital strategies into the education sector, there was little in place to support improving digital literacy in organisations. The findings of this report suggest that workplace digital competency levels are low, resulting in lost personal and organisation productivity.

Often the type of computing skill required in a workplace is assumed and not measured in any way (Murray & Perez, 2014). If measurement does take place, it will often involve some form of self-assessment (Gibbs et al., 2010; Grant, Malloy & Murphy, 2009; Gravill et al., 2006, 2001). Self-assessment is frequently used to assess end-user computing, in both educational and workplace settings. However, self-assessment has been found in other domains to be an inappropriate method of measuring computing knowledge when used in isolation as it is often subject to biases such as the above-average effect (Gravill et al., 2006, 2001, Grant et al., 2009; Stoner, 2009). When inaccuracies in self-assessment involve an over-estimation of skill the result may be that an employee is not performing at an expected or acceptable level (Gibbs et al., 2010; Grant et al., 2009; Gravill et al., 2006, 2001). Having reliable measurement of skill would mean that the constructs that make up this skill-set are less likely to be affected by social biases, and appropriate indicators would be available for measuring the impact of end-user skill in an environment such as the workplace (Torkzadeh & Lee, 2003). End-user computing competence has been defined as having a complete set of knowledge, computing skills and attitudes that combine to allow a user to complete tasks efficiently and effectively (Eschenbrenner & Nah, 2014; Suen, 2012; Leahy & Dolan, 2010; Yoon, 2009; Yoon et al., 2008). Such competence has an influence on how well an individual can apply IT knowledge when using software or systems required for completing workplace tasks (Eschenbrenner & Nah, 2014; Suen, 2012).

Various models of end-user competency have been proposed. For example Huff, Munro, and Marcolin (1992) endeavoured to create a model that would accurately measure end-user computing sophistication where sophistication is the level to which the software is used. For their study, they classified end-user computing knowledge and skill on three dimensions: breadth, depth and finesse. The dimension of breadth refers to the range of computing knowledge a person may have. Depth was used to classify how much a person knew about certain aspects of EUC. The final dimension, finesse, refers to an end-user's ability to apply their knowledge "creatively" in an end-user situation. Those who could be deemed true novices were those who had experience in only a

small number of the applications. Those who could be deemed true experts were those who had experience and knowledge in a wide range of applications and computing concepts. Experts also featured in the finesse dimension by rating themselves as highly creative.

More recently, Yoon (2009) attempted to produce a 'reliable' instrument to measure end-user competency in a business setting based on computing competencies defined in prior research. Yoon defines an end-user as someone who directly interacts with a computer in a business situation and defined end-user computing competency (EUCC) as being

*"a total set of knowledge, technology, skills and attitudes which function as action characteristics of an organisational member who can outstandingly and efficiently do his or her tasks in a computing environment" (Yoon, 2009, p. 47).*

According to Yoon (2009), from his review of prior research, end-user computing competency can be explained by four components: computing mind; computing knowledge; computing application and computing potential. Yoon (2009) surveyed end-users from a variety of different industries. The survey consisted of a questionnaire designed to measure end-user competency by asking respondents to rate their ability on a number of end-user tasks and included questions relating to computer security, hardware, software and network knowledge as well as some questions relating to Internet and computer use and etiquette. Questions were then assessed against the four criteria previously mentioned. An example of a question related to computer mind-set was "How many computer magazines do you subscribe to?" whereas computing knowledge questions included "How much do you know and understand computing technology, applications and computer systems?" All questions were presented using a 5 point Likert type system where the respondent could answer on a scale from 1(Not at all) to 5 (A great deal). Yoon (2009) concluded that this instrument was a valid and reliable measure of end user competency because it not only asked all the general "what can you do" questions, it also included the competency constructs that other researchers had identified.

Models, such as those promoted by Huff et al. (1992) and, more recently, Yoon (2009) have been useful in recognising the user as central in extracting the best from software or a system. However, these models rely on an individual's subjective self-rating of their computing skill, confidence using IT or knowledge of IT and it is not possible to assess computing skill reliably when a computer is not part of the assessment method (Stoner, 2009).

Previous research in self-assessment of skill in areas such as computer literacy has found differences between perceived and actual ability (Anderson, Benamati, Merhout, & Rajkumar, 2010; Ballantine, McCourt Larres, & Oyelere, 2007; Gravill et al., 2006). For example, Gravill et al. (2006) reported that participants with a greater breadth of experience using computer software had self-assessments more aligned to actual knowledge than those with a lesser exposure to IT. Gravill et al. (2006) used the cognitive skills dimension of a three-dimension user competence cube to represent the relationships between self-assessed knowledge of IT, procedural knowledge and declarative knowledge and the influence of experience on these factors. The three conceptualisation dimensions included in the cube were cognitive outcomes, skill-based outcomes and affective outcomes. Each dimension was measured using a combination of self-report, paper and pencil testing, a hands-on test and observer assessment. The cognitive dimension was identified by Gravill et al. (2006) as being most appropriate for their study because this dimension, which refers to the knowledge a user will have about technology and their use of it, comprised declarative, procedural and strategic outcomes that could characterise the incremental stages of knowledge attainment. In their study, experience factors included years of use, the breadth of use and a control or anchoring factor where two groups were given the same instruments but one had the self-assessment before the knowledge tests. Results from this study found that self-assessments were more closely related to procedural knowledge than to declarative knowledge and that varying the order of the self-assessment resulted in a closer alignment between self-assessment and declarative knowledge than with procedural knowledge. Their results also showed that those participants with greater exposure to technology (measured as years of use) were no more accurate in their self-assessment than those with fewer years' experience. The findings reported by Gravill et al. (2006) are interesting and relevant to both the areas of end-user computing and research in social biases. While Gravill et al. (2006) did not specifically look for cognitive explanations of the self-report results; their findings are in direct contrast to work in the area of the AAE and more specially the DKE. Kruger & Dunning (1999, 2009) contend that the AAE is influenced by a person's level of expertise in a particular domain. Kruger & Dunning (1999, 2009) say that those with low levels of expertise often do not recognise this, believe they have more expertise than they do and are unlikely not to recognise expertise in others. They also say the reverse is true, that those with more expertise may be more likely to under-estimate this in themselves, all of which is somewhat different to the results present by Gravill et al., (2006).

To measure skill and knowledge accurately without the need to rely on inaccurate self-assessments it is necessary to have some method of benchmarking skill level (Bunker, 2010; Gravill et al., 2006;

Leahy & Dolan, 2010). One way of providing a benchmark of skill is to require employees to attain some type of certification or standard (Bunker, 2010; McGill & Dixon, 2004; Vakhitova & Bollinger, 2011). Skill validation certification can be not only associated with high skills and therefore be of value to an employer, but it may also send signals about a person's motivation to keep up to date with changing technology and to improve their knowledge (Vakhitova & Bollinger, 2011).

There are a number of computing learning and testing systems available through educational institutions or accessible via the Internet. Some of these, including SAM (Skill Assessment Manager)<sup>2</sup> MOS<sup>3</sup> (Microsoft Office Specialist), and ECDL<sup>4</sup> have been used or recommended for use as industry standards on which to benchmark workplace computing skills (Bunker, 2010; Calzarossa, Ciancarini, Maresca, Mich & Scarabotto, 2007; Davis & Cleere, 2003; Grant et al., 2009; McLay & Brown, 2006; Panicos & Sotiris, 2010; Townley, 2004; Wallace & Clariana, 2005). Each of these end-user computing systems claims to have been informed through a rigorous development process by subject matter experts and to be quality assured (Leahy & Dolan, 2010). However, in some instances this type of learning system has been found to be inflexible in particular workplace situations (Gravill et al., 2006). Some employers value computing certification more highly than they value some degree qualifications (McGill & Dixon, 2004; Vakhitova & Bollinger, 2011). This may be because certifications give an assurance that a person has specific skills, whereas the skills gained in a degree may be regarded by some employers as more general (McGill & Dixon, 2004; Vakhitova & Bollinger, 2011 ). Some employers also believe that employees with certification will require far less workplace training than those without industry certification (McGill & Dixon, 2004; Vakhitova & Bollinger, 2011). Although these certifications are promoted as assuring workplace-ready practitioners, there are some disadvantages associated with them. Risks include the fast rate of technological change and graduates of these courses who may be unable or unwilling to keep up to date (Gravill et al., 2006; McGill & Dixon, 2004; Vakhitova & Bollinger, 2011). It is important to note that perceived skill level may be just as important as actual skill level in the effect it has on a person's attitude toward using and extending their use of technology (Torkzadeh & Lee, 2006).

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<sup>2</sup> <http://www.cengage.com/samoffice2013/>

<sup>3</sup> <http://www.microsoft.com/learning/en-us/mos-certification.aspx>

<sup>4</sup> <http://www.ecdl.com>

### 2.3.3 EUC workplace learning and training

The gap that often occurs between the expectation of computing knowledge that an employer may have and the actual or demonstrated knowledge of employees suggests that some type of EUC training should be an important aspect of the modern workplace (Berezina et al., 2011; Rondeau, Ragu-Nathan, and Vonderembse, 2006). EUC training usually involves one or more of three approaches: learning by oneself, learning from others, and learning with others (Korpelainen & Kira, 2010). The first two methods could be described as informal with choice that is more individual for the learner, whilst the latter, learning with others, typically describes a more formal group learning or training environment (Korpelainen & Kira, 2010).

In their review of literature on EUC training, Gupta, Bostrom and Huber (2010) found that the largest share of all corporate training pertains to EUC. In recent times, the requirement for EUC has escalated with many companies requiring end-user competence at all levels of the organisation (Gupta & Anson, 2014; Gupta et al., 2010). Typically, end-user training is focused on simple tasks, for novice users, but as technology has become more prevalent there is a greater need for more sophisticated training, for more complex problems tailored toward individual users (Gupta & Anson, 2014). Gupta et al. (2010) note that as training methods continue to evolve continued research is required in order to ensure that the training offered is fully meeting its purpose, and that learning, in an EUC environment, needs to become a part of the process of using the technology rather than comprising standalone events. Individual users each have specific training needs, which can mean that offering courses for large groups will not necessarily result in an overall increase in skill level (Gupta et al., 2010; Korpelainen & Kira, 2010).

The most common method of user training in end-user computing skills is learning by ones-self or self-training (Gravill et al., 2006, 2001; Korpelainen & Kira, 2010). Such training, however, is dependent upon self-selection that, in turn, depends upon a person wanting to update their skills and recognising that their skills need updating (Sitzmann, Ely, Brown & Bauer, 2010). Further, it is possible that someone who is self-taught has not been taught correctly or efficiently (Gravill et al., 2006; 2001). Even those users whose skill is acceptable on employment need to be encouraged to engage in on-going learning in order to keep pace with fast changing technology (Gravill et al., 2006, 2001). To be truly effective EUC training should include basic problem-solving techniques and abstract reasoning skills as well as specific technical instruction. This combination helps to ensure that effective learning by end-users can continue in a self-directed manner. The type and level of

training end-users receive can have an impact on how people learn, use and accept new software and IT systems.

Organisations without effective training strategies in place may face problems when their employees do not use information technology effectively and fail to transfer skills between different jobs and different software applications (Gallivan, Spitler and Koufaris, 2003; Rondeau et al., 2006). In their study Lawson et al. (2009) found that the participants they had identified as having expertise in the use of spreadsheets were more likely than those with little experience to have had some formal training using spreadsheets. They also found that for all participants in their study, experts and novices, workplace spreadsheet training was the exception rather than the norm. The most common reason given to explain this lack of training was a lack of time to fit training programmes into a working day. Training has been found to be most effective when the users have the ability and willingness to expand their knowledge and skill level (Laoledchai, Pek Wee Land & Low, 2008; Rondeau et al., 2006). However, training should not be seen as the total solution to the problem of low skill level. Gallivan et al. (2003) found that some employers regard sending employees on a training course as the complete solution for ineffective software knowledge and not just as one-step in the process. One limitation of offering workplace-training courses is that those who overestimate their ability may not believe that they need training so not sign up for the courses offered (Sitzmann et al., 2010).

## 2.3.4 Summary of section two

Section two of this literature review investigated the area of workplace end-user computing.

End-user computing has been defined as the type of computing that non-computing professionals do. This type of computing varies in the types of software used and the levels of user experience. The two most commonly used end-user applications in the workplace are word processors and spreadsheets but the level to which they are used varies widely between role and organisation. The literature has shown a gap between the skill level expectations that employers have and the skill level that some employees have. While these skills are required, they are often not assessed as they may have fallen into the category of soft-skills that employers expect. When skill is assessed this is often done by way of self-report. As the literature in section one of this literature review has shown, often self-reports are biased by social biases such as the above-average effect.

The following and final section of this literature review provides a summary of section one – perceptions of self-ability from a social perspective and section two- end-user computing.

## 2.4 Section three - Summary of literature

This chapter reviewed literature from social science and social psychology relating to self-perceptions, self-evaluations; social biases, personality and expertise. There is a wide range of material available in each of the areas. This review was most concerned with that pertaining to the areas of social biases evident in situations of social comparison. In the first section a review of literature relating to the social concepts of the self, self-evaluation, social biases, personality and expertise was presented.

The social bias known as the above-average effect has been found to have wide-ranging application and implications for people's judgments of their own abilities in socially significant behaviours (Dunning et al., 1989; Mattern et al., 2010; Matz & Hinsz, 2000; Sundstrom, 2008). The literature has shown that the above-average effect is sensitive to a number of influences. These influences include self-focus where a person will place greater importance on themselves than others in comparative situations and a lack of information about a domain. In situations where people do not have sufficient information about a domain but do not realise this are likely to make inaccurate self-assessments. A misrepresentation of skill level may have negative consequences for individuals, especially in areas where accurate skill assessment is critical. Inaccurate self-evaluations have been found to be motivated by self-enhancement factors or by cognitive process such as egocentrism, focalism, information deficiencies or the Dunning-Kruger effect and may be greater when a skill, task or domain is not clearly defined.

Self-perceptions of knowledge or skill in a particular domain may be affected by inaccurate self-evaluation, and by individual differences, such as personality or expertise. Although there is continuing debate about the number of trait dimensions necessary to define personality a comprehensive account of literature focussing on the five-factor model of personality was considered to be most pertinent. Many studies have identified positive and negative links between one or more of the five traits from the five-factor model of personality and the feelings, actions and behaviours of individual's in a variety of situations and social settings. There is evidence that the personality trait of conscientiousness is related to confidence, accurate self-assessment and the ability or desire for a person to improve knowledge while the trait of extraversion is related to overconfidence. In the studies reviewed, evidence has been found for relationships between



personality traits and job performance and personality traits and over-confidence. Specifically, extraversion was found to predict over-confidence in general knowledge in a multi-choice situation, whereas conscientious was seen to be significant in job satisfaction and job performance.

As with personality, the area of expertise is also wide-ranging and is relevant to individual differences between people. For the purposes of this study, literature which defined expertise in both conceptual and practical ways from both cognitive and knowledge engineering perspectives were reviewed. Several approaches to defining expertise and distinguishing expertise from competency were discussed. Studies have found that those considered expert in a domain are less likely to over-estimate their knowledge or ability in that domain relative to non-experts. Likewise, there is strong evidence to support the view that those with little competence in an area are not likely to recognise their lack of expertise or the expertise of others.

Section 1 of this chapter concentrated on a social science perspective, defining and explaining concepts related to the self, self-evaluation, social biases and individual difference that affect these biases. Social biases will occur in situations that are considered social settings. In Section 2, studies involving the use of computers in the workplace were discussed and literature from the domains of information technology, including information systems, was reviewed.

The workplace environment and, more specifically, the domain of end-user computing was chosen as it has become commonplace for people in workplaces to be responsible for their own computing. Often, the dominant way of assessing these skills is by some kind of self-report. The literature shows that end-user computing skills are important in a wide range of employment situations because workers are more likely to be responsible for their own computing than was the case in the past. Employers, from a range of domains, expect that employees, both new and existing, will be familiar with common software applications, such as spreadsheets and word-processing, but often there is little detail provided on specific uses required. For example, many roles require the use of spreadsheet software but this use could range from simple data entry to the creation of complex formulae. Because of the ubiquity of computing technology, computing skills have become part of the “soft skill” set required by employers and evidence of skill in this area is seldom requested with employers depending instead on a candidate’s self-assessment.

The literature shows evidence of flawed self-assessment in the domain of workplace or end-user computing. Further, much of the work in this area relies on comparisons between self-reported measures and instruments assessing declarative knowledge. The failing of only applying comparisons

between self-reports and declarative knowledge is that this knowledge structure relies on the ability to recall information but not necessarily how to apply that information in a procedural manner. For example, in a computing context this may mean that a person can recall the name of a function required to complete a spreadsheet formula but may not be able to competently, and effectively use that same function in an actual formula. Therefore, it is necessary to undertake further examination of procedural knowledge in this context rather than just declarative knowledge.

In sum, this review has shown that comparative judgment biases such as the above-average effect are prevalent in social settings, and that these biases may be explained by a number of motivational or cognitive process that are also likely to be influenced by individual differences such as expertise and personality. While evidence of the above-average effect is routinely discovered in common task such as driving, fewer studies have been undertaken specifically in the area of workplace or end-user computing. Further to this, the studies that have found evidence of overly optimistic self-reporting in this type of computing environment have not considered the influences of expertise and the personality traits of extraversion and conscientiousness, neither have they engaged directly with the AAE. Likewise, the work on the AAE, has not included the area of end-user computing which is clearly an increasingly pervasive area of skill and knowledge in workplaces, therefore has considerable implications for business outcomes.

These gaps in the literature suggest a need for an original approach in examining these over-estimations from the theoretical perspective of the above-average effect and in a domain, such as end-user computing, where this effect was not found to have been examined previously.

## Chapter 3     Method

### 3.1     Introduction

The purpose of this study is to explore the influence of a number of demographic and expertise factors and selected personality traits on occurrences of the above-average effect in an end-user computing context. Eight hypotheses have been developed in an attempt to answer the over-arching research question: *What individual differences, if any, are critical in instances of the above-average effect in the context of end-user computing?*

As discussed in the literature review (see Chapter 2), self-assessment techniques are frequently the only way a person's end-user computing ability is judged. However, as also discussed in the literature review, self-assessments are often flawed. One of the ways that self-assessments can be flawed is their susceptibility to cognitive biases such as the above-average effect. Occurrences of this effect are variously explained by cognitive processes such as egocentrism, focalism or the Dunning-Kruger effect or by motivational mechanisms such as the need to self-enhance. It was argued in Chapter 2 that individual differences such as personality and expertise factors might influence a person's self-assessment.

### 3.2     Research paradigm

Just as in other areas of interest in social science, research studies about the relationships between people and situations that may be affected by cognitive biases have been influenced by varying methodological orientations and positions (Bryman, 2012). The purpose of research is either to test a theory, or to use a theory to explain the results of research, by providing a rationale for the research and an explanation for facts or events (Bryman, 2012). However, social science research is not always easily explained in such a concise manner. Theories associated with social science research are often quite abstract in nature (Bryman, 2012). Researchers typically approach a problem guided by a particular paradigm or set of beliefs or assumptions (Cresswell, 2013). The research paradigm establishes the philosophical basis for the research, which can be defined in terms of an ontology (the nature of being or of what there is in the world) and an epistemology (a philosophy of knowledge and knowing). These paradigms then guide a researcher toward a methodology (how we know) (Bhattacharjee, 2012; Bryman, 2012; Johnson & Onwuegbuzie, 2004). Broadly speaking, research paradigms in social science can be broken down into the following

categories: positivism; post-positivism, interpretivism and pragmatism (Bryman, 2012; Clark, 2008; Wahyuni, 2012).

This study fits with post-positivism as this paradigm, like positivism, is reality oriented and assumes that there is a real world that can be understood, analysed and measured. Unlike positivists, however, post-positivists believe that such reality can never be known for certain, but an account of this reality is the goal (Bryman, 2012; Cresswell, 2013). Post-positivists believe that knowledge is a social phenomenon based on conjecture and observation rather than being based on unchallengeable foundations (Bryman, 2012; Cresswell, 2013). Quantitative methods are compatible with a post-positivist perspective, as they are useful for studies in which the hypothesis presupposes the variables, the research question and the study purpose (Borrego, Douglas & Amelink 2009). They allow for the study of relationships between variables and produce results which can be statistically verified (Borrego et al., 2009; Cresswell, 2013; Given, 2008; Johnson & Onwuegbuzie, 2004). In this study relationships between people and different demographic and cognitive variables, which may lessen or increase prevalence of the above-average effect, are investigated. Strengths of a quantitative approach include the ability to test existing theories through hypotheses that are constructed prior to data collection, and to provide quantitative data (Johnson Onwuegbuzie, 2004).

A multi-instrument approach was undertaken. This type of approach allows for the collection of data related to different constructs involved in the relationships being investigated (Nurani, 2009). Similar studies, such as those undertaken by Grant et al. (2009) and Gravill et al. (2001) also employed a multi-instrument approach to test hypotheses. Results from each of these studies indicate that this approach enabled the researchers to have confidence that the data collected was reliable and of high quality.

### 3.3 Participants

Typically, studies examining either the AAE or computer skill have recruited participants who are university students (Brown, 2011; Grant et al., 2009; Kruger & Dunning, 1999). For this study it was considered important that participants represent actual computer end-users. For this reason, participation was sought from people who, in their employment, are regular users of common end-user software for word processing and spread sheeting tasks. Members of this population are employed in a number of different organisations over many different disciplines (Holtzman & Kraft, 2010). Due to the increase over the last two or so decades in the extent and variety of the use of computer technology in the workplace it is difficult to define the exact characteristics of this

population. Nevertheless, there are certain occupational groups that tend to use computers (as end-users) more than others (e.g., administrative, accounting, research, etc.).

The nature of the hypotheses developed for this study (Section 1.2) leads to multiple and multivariate linear regression analysis. To achieve statistical power reasonably conservative parameters ( $\beta = .80$ ) and a medium effect size ( $f^2 = .15$ ) at a significance level of  $\alpha = .05$  it was determined that ninety participants is the minimum number required. Sample size is an important consideration for any study due to its effect on statistical power. Statistical power, in multiple regression, can generally be described as the probability that a statistical test will reject the null hypothesis, the ability of such a test to identify effects that actually exist (Baguley, 2004; Eng, 2003; Hair, Anderson, Tatham & Black, 1995). Hair et al. (1995) noted that for a test using multiple regression the number of observations should not fall below five for each independent variable. Other studies have suggested that a more conservative approach would be to use a minimum of ten observations for each independent variable (Bartlett, Kotrlik, & Higgins, 2001). For this study, to answer the research question in a reasonable manner, a maximum nine variables were used. Using reasonably conservative parameters, ninety-one participants were recruited. This number of participants ( $n = 91$ ) was considered sufficient for this study, given the number of variables, to produce results with sufficient statistical power so as not to be too specific to reduce the likelihood of the generalizability of the results (Bartlett et al., 2001; Hair et al., 1995).

Recruitment involved purposive or judgment sampling. This nonprobability method occurs when a researcher appeals to people, who meet particular criteria, from a particular population to participate in a study (Babbie, 2007; Guarte & Barrios, 2007; Moser & Kalton, 1971; Sibona & Walczak, 2012; Tongco, 2007). A purposive approach is acceptable in situations where the researcher has some knowledge of the population and a specific sample is required (Babbie, 2007). This approach was appropriate in this study where participation from employed computer end-users from a variety of job types was required. It would make little sense, in a study such as this, to seek participation from people who were not employed in roles where end-user computing was not used.

It is important that a researcher use the sampling method best suited to the constraints presented by a particular study, which can include time, money, availability (Sibona & Walczak, 2012). Although there are criticisms and limitations of this sampling method, in practical situations, purposive sampling can be as efficient as random sampling and can be used with a number of different data collection methods (Fowler, 2013; Palys, 2008; Tongco, 2007).

One of the main concerns related to this type of sampling method is it involves only those who wish to participate. As a consequence participants may either have motives to participate that conflict with the aim of the research project or be inclined to participate because of attributes which may prejudice the findings (Babbie, 2007; Fowler, 2013; Wallin, 1949). Self-selection (or volunteer) bias is often referred to as a problem in purposive sampling. This is because people who volunteer for a study may in some ways be different from the population that is the target of sampling and so not be representative of that population (Brownell, Kloser, Fukami, & Shavelson, 2013.). In fact, because of ethical concerns, all human participants in psychological studies in effect volunteer (i.e., 'opt-in') and so could be said to be self-selecting. Hence, the type of bias associated with self-selection can be found in any study where sampling is required. Nevertheless, it has been found to occur more in studies where the refusal rate to partake is high (Brownell et al., 2013). In this study, no person who was approached to take part refused to do so; this is a reasonably strong indication that the sample used was not affected by volunteer bias, assuming that the approach made to participants was itself not influenced by, for example, proficiency at end-user computing.

Further, although random sampling is often seen as the 'gold standard' of sampling methods, a true random sample, apart from being difficult to achieve, is not likely to be truly representative of a population due to the effect of low response rates (Gantz, 2015 ). However, when a sample is representative, it can be appropriate for the population it represents and can provide internal validity (Tongco, 2007). If a sample has a similar distribution as a known population then it is very likely that the sample is representative of the study population (Sibona & Walczak, 2012), thereby approximating randomness. The representativeness of the sample used for this study is outlined in sections 0 and 3.3.3. In terms of sampling it can be concluded, overall, that the sample used for this study was unlikely to have been self-selecting in a way that might reasonably be thought to prejudice the data collection and, consequently, compromise the validity of the conclusions drawn from the analysis of the data.

In practical terms, invitations were made, by email, to people from a variety of different organisations (Appendix 1). Some of these people were known to the researcher. They were approached on the basis that they might use the required software in their employment. Because the researcher was not always sure if a person did indeed use the required software there was no predetermined rationale to influence the study by only inviting those with known skill to participate. Other approaches included notices to participate sent with an email to organisations. It transpired that some of these notices to partake were placed on notice boards, from which the researcher was

contacted. Again, once it was established that the potential participant used the requisite software in their employment they were invited to participate. At no time during the recruitment part of the study, nor indeed during the study itself, were there any conversations between participants and the researcher about their level of use or skill. In fact, in order not influence the outcome of the study, the researcher was very careful in explaining participation as a method of finding out what type of skill sets were used ( for these particular software packages) in a range of different occupations. It should be reiterated that of those directly approached no one refused this invitation.

As described above, there was an element of snowball sampling that occurred, where some participants recommended the study to people of their acquaintance, who then contacted the researcher. Snowball sampling is sometimes referred to as accidental sampling and is appropriate for locating members of a specific population (Babbie, 2007). As with purposive sampling, there are concerns that snowballing will result in high incidences of a self-selection bias. Although a researcher can have very little influence over this type of recruitment, prospective participants in this study were required to make contact with the researcher. At the time of contact, the researcher briefly explained that the study was looking at the types of use different occupation types made of common end-user software (spreadsheets and word-processing) and asked again if a potential participant did actually use both of those software for their employment. Once software use was established and a desire to participate was indicated then a more detailed participation email was sent.

The participation email sent to prospective participants outlined the study and gave details of the level of participation required, including an estimation of the time commitment required. After a participant indicated they wished to participate, an appointment was made for them to commence the study. At the time of the study, participants were again given information about the study (Appendix 1). After receiving the study information participants were asked if they still wished to participate and, if so, were asked to complete and sign a consent form. At the completion of these formalities, the participants began the study by completing the questionnaire to collect demographic, expertise, self-assessment and personality data. On completion of the questionnaire, participants undertook the computer-based assessment of their word-processing and spreadsheet skills.

It is important to note that previous studies investigating biases such as the AAE and the DKE have used similar recruitment strategies. One of the most commonly used convenience samples available to researchers is that of undergraduate students. For example, Caputo and Dunning (2008), in their

study of imperfect self-assessment, recruited undergraduate students from a variety of psychology and human development courses who earned extra credit. An identical method of recruitment was used by Schlosser, Dunning, Johnson and Kruger (2013) in their investigation of explanations for the DKE. Likewise, in their investigation into occurrences of the DKE in aviation Pavel, Robertson and Harrison (2012) used student pilots and aeronautical engineers as participants. In none of these cases, was there concern expressed about instances of self-selection bias having contributed to findings.

### 3.3.1 Participant age

Participants ranged in age from 22 years to 64 years ( $M = 42.7$  years,  $SD = 11.38$  years) with a median age of 44 years. The general age distribution in this study conforms to the workforce age group distribution presented in the *Ageing Workforces and Ageing Occupations Working Paper* released by the NZ Ministry of Business, Innovation & Employment<sup>5</sup>(Figure 1).

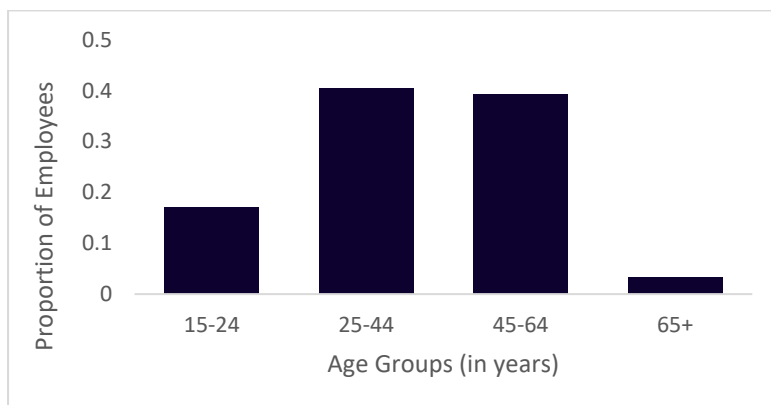


Figure 1 - NZ Labour force age group distributions 2011

Because no participants in this study were aged under 20, or over 65, the study median was slightly higher to that in the workforces report (41.9 years). See Figure 2 for the frequency distribution of participant ages for this study.

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<sup>5</sup> [http://www.dol.govt.nz/publications/research/ageing-workforces/ageing-workforces\\_03.asp](http://www.dol.govt.nz/publications/research/ageing-workforces/ageing-workforces_03.asp)



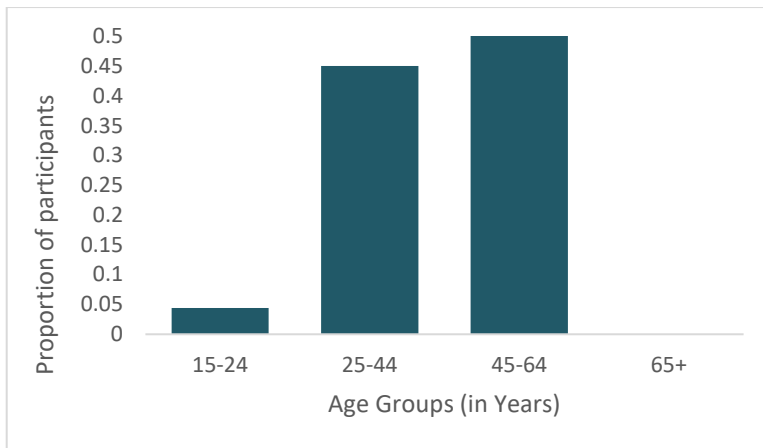


Figure 2 – Distribution of participant ages (years).

### 3.3.2 Participant gender

In this study, there were sixty-one female and thirty male participants. For the purposes of analysis this variable was coded as 1= Female and 0 = Male. Although this distribution is not necessarily a balanced representation of the gender split of this type of white-collar workforce (NZ Department of Statistics, 2013 - 51% males, 49% female), the gender split in this study is more representative of the largest occupation group in this study who identified as having administration roles. According to the Canterbury Labour Market report (2012, p. 59) 96% of those employed in occupations which could broadly be termed clerical and administrative workers were women.

The following sections (3.3.3 0 and 3.3.5) describe the demographic variables included as measures of a participants experience using end-user type applications.

### 3.3.3 Participant occupation

Participants were from a variety of different occupations and employed in a range of different industries. The distribution of occupations shows a good 'fit' to occupational groups in Canterbury, the geographical region (Canterbury NZ) in which the research was undertaken. According to the 2011 Labour Market and Economic profile – Canterbury pg. 24), at the time of recruitment, education and research professionals were ranked as the 3rd largest occupation in the region and combined office and administrative positions made up 8.2% of the total workforce or a ranking of second largest occupation group in the region. The distribution of occupations represented in this study is presented in Table 1.

Table 1 - Distribution of occupation types

| Occupation type        | Male | Female | Total | % of Total |
|------------------------|------|--------|-------|------------|
| Accounts               | 3    | 6      | 9     | 10%        |
| Administrator          | 2    | 18     | 20    | 22%        |
| Analyst                | 2    | 3      | 5     | 5%         |
| Education and Research | 13   | 13     | 26    | 29%        |
| Environmental planning |      | 2      | 2     | 2%         |
| Human Resources        |      | 2      | 2     | 2%         |
| ICT                    | 1    | 2      | 3     | 3%         |
| Librarian              | 1    | 3      | 4     | 4%         |
| Manager                | 5    | 2      | 7     | 8%         |
| Marketing              |      | 4      | 4     | 4%         |
| Misc.                  | 2    | 3      | 5     | 5%         |
| Project management     | 1    | 3      | 4     | 4%         |

Occupation was included and used as a measure of experience in using end-user applications. The rationale for this was that different occupations require different types and amounts of use for both of the applications used in this study. Therefore, it was considered that people in some occupations may have more experience at one or both applications than people in other occupations.

### 3.3.4 Computer usage and number of applications used in job.

Participants were asked to estimate how many hours, on average, they were required to use a computer as part of their employment. The average approximate time that people used a computer during a normal working week was 30.8 hours (SD 9.9). The range of hours of use was between a minimum of three hours a week to a maximum of 55 hours per week with the median value being 30 hours.

Hours of computer usage was used as one of the variable to measure experience using end-user applications in the workplace. This was included as the time spent using a computer may be influential in the improvement of skills for a user. Some people are required to use a computer for

the majority of their workplace tasks, while others only use a computer for a small amount of their work time.

Participants were asked to list the computer software packages they were required to use routinely as part of their occupations. Participants were able to choose as many categories as they wished. The mean number of applications used was  $M = 3.6$ ,  $SD = 1.52$ , the minimum number was two, the maximum number was eight and the median was three.

Figure 3 displays the frequency distribution of software application types used by participants.

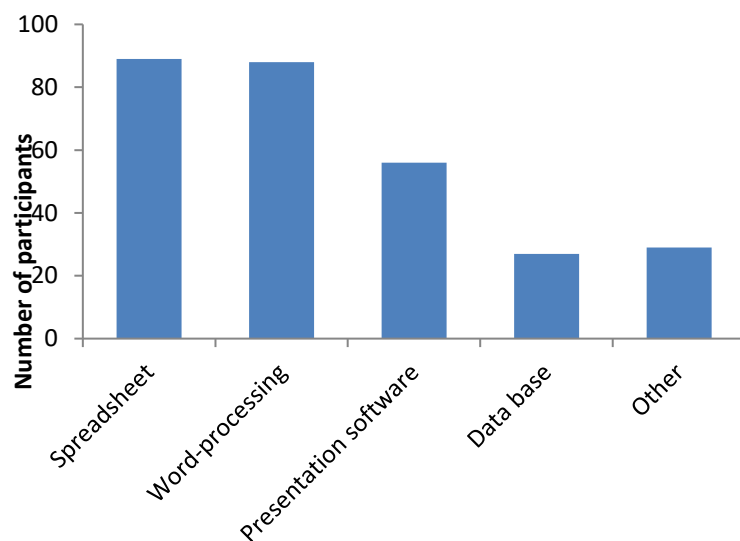


Figure 3 - Software application types used by participants for their employment

The “other” software included a mix of in-house systems, accounting packages, statistical packages, as well as CRM systems (customer relationship management).

The number of computing applications used was calculated for each participant and then displayed in a histogram to show the frequency distribution (Figure 4).

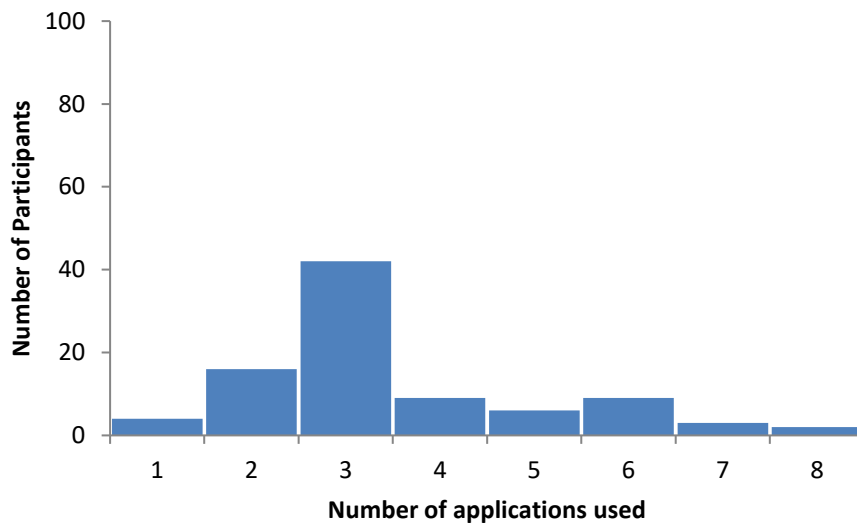


Figure 4 - Frequency distribution for number of applications used by participants

The number of applications a participant used for their particular job was used as one of the combination of variables to measure experience in EUC. It was thought that the greater number of different applications required for a job may be influential in improving a person's confidence and ability with using computers in general.

### 3.3.5 Modes of learning

Participants indicated (from the list shown in Appendix 2) how they acquired their computing skill. They were able to choose as many categories as they wished. The average number of mode of learning per participant was 3.26 (SD =1.25), with everyone naming at least one. The largest number of modes of learning was seven. The most cited method was self-taught, with eighty participants (88%) indicating they used this method. The distribution of training approaches is in Table 2.

Table 2 – Frequency of learning approaches

| <b>Mode of learning</b>                       | <b>Total Number</b> |
|---|---------------------|
| Community classes                             | 19                  |
| Friends, workmates etc.                       | 64                  |
| High school                                   | 21                  |
| ICDL (International Computer Drivers Licence) | 2                   |
| MOS (Microsoft Office User Specialist)        | 5                   |
| Online  | 31                  |
| Self-taught                                   | 80                  |
| Tertiary classes                              | 18                  |
| Workplace training                            | 51                  |

For the purposes of this study, data relating to modes of learning were reorganised and had a weighting applied to show the highest level of formal learning approach for each participant. The first step in this process was to organise the training approaches into formal and non-formal. Non-formal methods, typically self-directed in approach, included online, self-taught and help from peers (Korpelainen & Kira, 2010). The next step was to rank each of the formal modes of learning. Each of the modes was ranked to show the level of formality that employers would place on each. Tertiary training and the standardised testing systems (e.g. ICDL & MOS) were co-ranked as 1 because employers have been shown to place just as much relevance on industry certification as they have tertiary study (Vakhitova & Bollinger, 2011). Workplace courses were ranked as the next most important given that it is expected that this type of learning will be task specific (Gupta & Anson, 2014). High School computing classes were ranked lower than workplace courses. Prior to 2011 and the introduction of the Digital Technologies Curriculum into New Zealand secondary schools, computing was not a subject area in its own right and did not have academic credibility (Bell, Andreae & Lambert, 2010). Because computing was bundled in with other technology subjects it was not considered as attractive to students as it was seen as an area that had grown from typewriting classes and for which some teachers did not have the necessary technical knowledge (Thompson, Bell, Andreae & Robins, 2011 ;Bell et al., 2010). Community classes were the lowest ranked formal method. Often these types of computing programmes are low cost short courses that focus on introducing students to common software; generally, they offer no assessment or benchmarking

opportunities. Further, these classes are often held in community libraries, at high school night classes or by community groups. They provide tuition in key board skills, file management, emailing, Internet searching, editing photographs, etc. Table 3 shows the distribution for approaches to learning.

Table 3-Summary of approaches to learning computer skills

|   | <b>Mode of learning</b> | <b>N</b> |
|---|-------------------------|----------|
| 1 | Tertiary                | 18       |
| 1 | ICDL/MOS                | 5        |
| 3 | Workplace Courses       | 40       |
| 4 | High School             | 11       |
| 5 | Community Classes       | 3        |
| 6 | No formal training      | 14       |

Modes of learning was included as an experience variable. It was considered that those who had undertaken formal instruction in computing education may have more experience in using end-user applications than those who had only informal learning.

### 3.4 Instrumentation

The multi-instrument approach taken in this study involves the use of three instruments to collect four types of information. Results from each of these instruments are combined to tell an overall story. The four separate types of data are demographic, self-assessment, personality and skill assessment.

A questionnaire was created for the collection of demographic data. Data collection using a questionnaire approach allows a researcher to collect data from a sample of a population and then using statistical analysis to generalise the results for the entire population (Borrego et al., 2009).

Two Visual Analogue Scales (VAS) were created and used for the estimation of the extent of end-user computing knowledge, self-assessment of end-user computing knowledge and assessment of the average computer end-user's end-user computing knowledge. A visual analogue scale (VAS) is a psychometric response scale used to measure items that are often subjective (Funke & Reips, 2006;

Marsh-Richard, Hatzis, Mathias, Venditti, & Dougherty, D.M, 2009; Parkin & Devlin, 2004). Respondents indicate their agreement or level of measure by placing a mark along a continuous line.

Two skills assessments were created to incorporate workplace tasks involving the use of MS Excel and MS Word. These instruments were used as a method for participants to demonstrate their skill using these two end-user applications.

In addition to the instruments created for this study, the Big Five Inventory (BFI) was used to collect personality trait data from participants (Benet-Martinez & John, 1998; John, Donahue & Kentle, 1991; John, Naumann & Soto, 2008).

The following sections describe each of the instruments in detail.

### **3.4.1 Background questionnaire**

A number of variables were included to test the notion that an above-average effect is less likely to be evidenced as the level of participant expertise increases (Kruger & Dunning, 1999). Participants were asked to provide demographic information, some of which was used to measure experience (Sections 3.3.3, 3.3.4, and 3.3.5). Demographic information refers to the statistical data collected about a particular population and helps to distinguish one participant from another, assisting researchers in being confident that the sample is representative of the study population and allowing for a sample to be quantified in a statistical manner. The demographic information collected for this study was:

- Age;
- Sex;
- Occupation.

The characteristics of the study sample for each of these demographic variables representative of the sample is explained in Sections 3.3, 3.3.3, 3.3.4 and 3.3.5. As noted in Section 3.3 participants in this study were recruited on the basis that they used the spreadsheets and word-processing applications for their employment. Participants represented a number of different occupations in a number of different industries.

The rationale for using the variables mentioned is an attempt to ensure that the sample used is representative of a working population although as noted in section 3.3.2 there is a gender imbalance in this study with twice as many females than males participating, it should also be

reiterated that the largest employment group was that of secretarial and administration workers, a group dominated by females. There is evidence in the literature to suggest that males may be more confident in their use of technology than females (Sainz & Eccles, 2012). Likewise, it is necessary to include age in a study such as this one, where the range in a normal workforce will be spread generally between the late teens to the mid-sixties (usual retirement age). Given that those who are in their early to mid-twenties have not known a time without computers, age is an important personal factor, which may be an influence in occurrences of the AAE in an EUC context.

A number of measures were collected for assessing participants' experience in computing against their perception of their level of knowledge. This information included information about their workplace computing. The literature suggests that as a person's level of expertise increases that it is likely that the over-estimation of self-assessment decreases (Kruger & Dunning, 1999, 2009).

Workplace expertise indicators collected included:

- The number of hours a week participants would use a computer in their employment;
- Modes of learning used to acquire their computing skill;
- The different computing applications used in their employment.

Expertise, in part, can be increased due to experience in using a particular software. Experience can be related to the amount of time a person may spend using a particular software, or technology in general (Ericsson, 2014) or the type of educational experience a person has in a domain (Herling & Provo, 2000). In turn, experience and expertise may come about due to the extent of exposure a person has to a number of different types of software packages (Gravill et al., 2006).

### 3.5 Assessing perceptions of EUC knowledge

This section describes the method used to assess a participant's perception of three things:

- Perception of the breadth of the domain of EUC.
- Self-assessment of EUC knowledge.
- Perception of the EUC knowledge of an AEU.

#### 3.5.1 Method used to measure perceptions of EUC knowledge

Three measures of perception were used in this study. Each of these perceptions were measured using a visual analogue scale (VAS). The measures of perception were:



- The extent of the domain of end-user computing as a subsection of computing as a whole ( $EoD_{EUC}$ );
- Self-assessment (SA);
- Estimation of the knowledge of the average computer end-user (AEU).

The VAS was chosen in this study because of the ability to gather more accurate measures than would be possible by using a discrete scale which, in turn, means that a greater range of statistical analyses can be applied to the measurements collected (Parkin & Devlin, 2004; Funke & Reips, 2006). VAS is also sometimes credited with being easier for a participant to understand than a discrete scale (Marsh-Richards et al., 2009; Funke & Reips, 2006).

Two instances of the VAS developed after three comprehensive pilot studies, representing a 1000 page book about computing, were used in this study. The first line was used to establish a participant's estimation of the  $EoD_{EUC}$  and the second line as a method of self-assessment and assessment of the average computer end-user. The lines presented to the participants are reproduced in Figure 5.

Suppose that the line below represents all the pages in a thousand-page book, and that this book contains all that is known about computing. If the section on office type software began on the first page, please indicate (by marking a T on the line below) how many pages in this book you believe would be this type of computing.

1 Page 1000 Pages

---

The line below is the expanded section between 1 and T that you just indicated on the first line. Please indicate (by marking an I on the line below) how many pages you think you know about common office type software.

1 Page T

---

Also on the second line (above) please indicate using an X, how much you believe the average person knows about common office type software.

Figure 5 - Visual Analogue Scales and accompanying questions used in study

The Extent of Domain ( $EoD_{EUC}$ ), in the context of this study, refers to the extent (or breadth) of knowledge that a person believes makes up the domain of end-user computing as a subsection of

computing as a whole. The purpose of including this measure was to establish a person's awareness of the world of computing.

The area of computing includes many sub-domains, one of which is EUC. The intent was to produce a measure of the relationship between how people conceptualise the area of EUC within the domain of computing and how they perceive their own knowledge of EUC and that of an average computer end-user. This was seen as a way of determining if a person's self-perception of their knowledge of skill in a sub-domain is in any way connected with their belief about the size of the domain as a whole.

To measure this participants were asked to place a mark (T) on the first line to represent how much of all computing they believed was represented by the domain of end-user computing. This line, using the analogy of a book written about "all of computing" as a reference point, was used to judge the participant's perception of how much of the knowledge about computing as a whole is represented by the subset of end-user computing. This measurement was used to help determine a person's awareness of the breadth of end-user computing within the context of computing as a whole. This was seen as an important way of understanding if people with a greater appreciation or awareness of the greater domain of computing may also be aware that EUC is just a part of this, and although relatively small does extend further than they may be aware. The assumption is that those who place their mark closer to the beginning of the line are demonstrating an awareness of the extent, depth and variation within computing as a whole and, hence, that such awareness will apply to their awareness of the extent, depth and variation within EUC. For example, it was assumed that a person who placed their mark at 900 pages was a person with little awareness of the depth of the domain of computing. They are signalling that they believe there is little more to know about computing than EUC (or their interpretation of what EUC is). Whereas, it is assumed that someone who placed their mark at 100 pages or less may have a greater awareness of how little space each of the subdomains of computing, specifically EUC, would occupy. However, of course, these assumptions may be entirely wrong and it may be that a person who places their mark near the beginning of the line believes there is little to know about EUC computing. Conversely, those who place their mark near the end of the line, signalling that EUC makes up a lot of all computing may themselves have good EUC skill. In general, people who are aware that domains are large are more likely to be aware that a sub-domain of the larger domain ( in this case EUC) is also larger than they might suspect. Such people are also more likely to be more cautious in their perception of the extent of their knowledge than a person who is inclined to that domain knowledge is small. The assumptions made for this study are based on the literature on the AAE and the DKE effect, which

says, that self-reports can be the result of a lack of domain information which reinforces a person's belief in their own knowledge in or of that domain (Brown, 2012, Kruger & Dunning, 1999, 2009).

### **3.5.2 Measuring self-assessment and estimations of the average computer end-user's knowledge**

Participants were next asked to place a mark (I) on the second line (a scaled version of the first line). This line was said to represent what a participant believed represented the extent of the domain of EUC, with their estimation of T being the end point. On this line, they placed a mark (I) to represent how much they believed they knew about EUC. This measurement was used to determine a person's self-assessment of their EUC knowledge. The final part of this task required participants to place a second mark (X) on the second line. This mark was to represent how much they believe the average computer end-user would know about EUC.

Typically, when making a self-assessment, a person is inclined to measure their ability against a reference point such as the average computer end-user in their peer group (Krizan & Suls, 2008). In the case of this study, participants were recruited on the basis that they are required to use end-user software such as spreadsheet and word-processing applications as a part of their employment. Consequently, the field of reference for participants in this study was considered other people who also use computers. A manipulation check was undertaken. This check involved randomly selecting 10% of the study population ( $n = 9$ ) and asking them to indicate, from a list of three choices, their interpretation of the average computer end-user, as related to the study. The three choices they were given were:

1. People in general who use a computer.
2. People required to use a computer as part of their job.
3. Those in the wider population (including children and retired folk) including those who do not use a computer.

The results of this manipulation check showed that, for this study, the average computer end-user was interpreted as "those who required to use a computer as part of their job."

Figure 6, Figure 7 and Figure 8 present a graphical representation, for three example participants, of how the I and X marks would appear on the first line, given T as the endpoint. For the purposes of this study, the measure of  $EoD_{EUC}$  was used as an indicator of a participant's expectation of the

breadth of knowledge available in the domain of EUC. This measure was then used as a way of exploring the Dunning-Kruger effect compared with self-assessments and AEU measurements.

The darker points represent the actual marks made on lines and the lighter marks are how they would transform. The arrows show the direction of transformation. Examples A and B are cases of people with identical estimations for I and X. However, these examples have very different estimations of T. The examples are useful in illustrating the influence of T for people with similar X and I estimations.

The Dunning-Kruger effect for Example A (Figure 6) will be greater than that of Example B (Figure 7) even though the gaps between the self-assessment and AEU assessment were similar on line two. It is expected that any Dunning-Kruger effect is likely to be more apparent in situations where a person has a greater  $EoD_{EUC}$  estimation than another person does, even when the self-assessments and EAEs for both people appear similar as in the example being illustrated here.

Example A

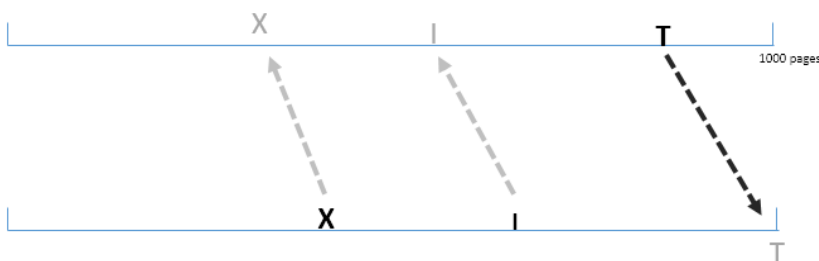


Figure 6 - Example A representation of mark transformations on VAS

Example B

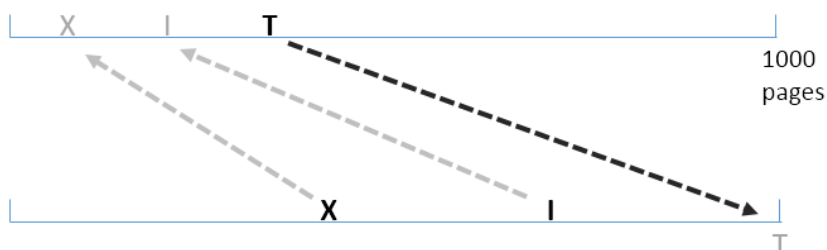


Figure 7 - Example B representation of mark transformations on VAS

The self-assessment and AEU assessment illustrated in Example C (Figure 8) appears, compared with the previous example, to be the one with the largest gap yet the T value for this example was much smaller. This person is less likely to be affected by the Dunning-Kruger effect as the person in Example A (Figure 8 ) may be.

Example C:

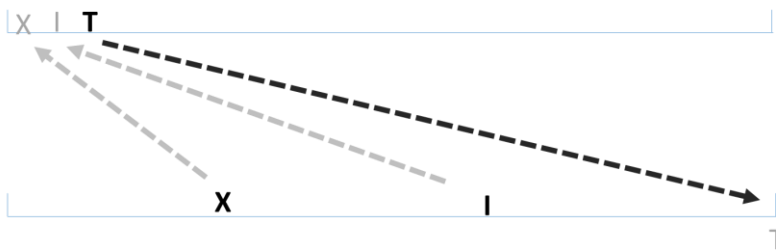


Figure 8- Example C representation of mark transformations on VAS

The VAS instruments, described in Section 3.5.1, were the result of an iterative development and evaluation process that is described in the following sections.

### 3.6 Detailed development and evaluation of VAS instrument

The methods used to create a VAS suitable for the purpose of this study involved an iterative process. This process comprised three comprehensive pilot tests resulting in the VAS being significantly altered for improvement after each iteration. For each pilot study a small sample of employed people who regularly used EUC in the workplace.

#### 3.6.1 VAS Pilot1

The purpose of the pilot was to test the use of the visual analogue scale as an alternative to discrete scales more commonly used as a self-report and perception measures.

Pilot Study 1 involved the testing of a VAS created as a comparison model. Participants were shown one of two different lines, each said to represent the sum of knowledge in either nature or driving. This instrument was tested with 12 participants, seven females and five males. For each version, driving or nature, there were six participants. Participants were shown one of the lines and then asked to draw a similar line to represent the sum of knowledge they believed existed for the domain of computing. Participants were then asked to indicate, by placing marks on the line, what they considered their level of knowledge about computing and what they considered to be the level of knowledge most other people had about computing.

The results for the two quite different versions (nature or driving) were very similar in many aspects. In particular, for each version, some participants struggled to understand the instruction. While the comparison was intended as a guideline, several people mistook this intention. Some participants thought they were being asked to indicate their knowledge in the nature or driving areas and others

thought they were being asked to indicate how much of the line (driving or nature) they thought would be computing. It was considered that the level of task ambiguity evident in this task was too great and led to an exaggerated above-average effect. An above-average effect is more likely to occur when the task or domain being assessed is broad leading to confusion and ambiguity of requirements (Kruger & Dunning, 1999). Of the twelve participants, only three rated their own knowledge of computing as lower than what they perceived an average computer end-user would have. One person thought that their rating was the same as the average. All of these four participants were female. The use of the term “most people” caused confusion with some people. This confusion was evidenced through comments made and questions asked by participants, as to what “most” meant. The results from this pilot were mixed with the comparison example causing an unacceptable level of confusion for the users while the actual approach using the VAS appeared to work well.

It was considered that, given that the domain of computing is broad, it would be beneficial to run a second pilot, this time making the target domain more specific. The reasoning for using the same approach but making the comparison domain more specific was to ensure that the approach of using the VAS was the correct approach as this was difficult to assess accurately in the first pilot given the level of explanation required.

Full details of this pilot are in Appendix 5.

### **3.6.2 VAS Pilot2**

A second VAS instrument was created and piloted. For pilot study two 10 users not involved in VAS Pilot 1 were recruited. As for VAS Pilot1, the second pilot study involved testing a version of a visual analogue scale. In a similar manner to VAS Pilot1, the participants in the VAS pilot 2 were also shown a reference line to use as a guide. The participants were instructed to assume that the reference line represented “all there was to know about computing”. The five male and five female participants were asked to place a mark on this line to indicate how much they considered the knowledge about computing was specifically related to end-user software such as MS Office. Participants were subsequently asked to make two further marks on the line, one to represent their own knowledge of this type of software and a second representing how much they thought most other people knew about this type of software.

Although the comparison in pilot two was more specific than in pilot one, a marked above-average effect was still present. In this pilot study three of the participants believed that their knowledge was

lower than the average computer end-users. All these three participants were female. What was a little different in this study was that the person who considered himself to be at the average level, was male and a computing student. In pilot one, no male participants considered their knowledge was lower than the average knowledge.

Although no statistical significance can be taken from the results of this pilot, given the low number of participants, six of the ten participants' considered their knowledge of end-user software is equivalent to more than half of all there is to know about computing. Although there was less confusion caused using the Pilot 2 version than for the previous version the level of ambiguity that resulted in a marked above-average effect was considered to have been too great to be considered a reliable measure. Due to this, it was decided that further refinement was required. Full test details of this pilot are in Appendix 5.

### **3.6.3 VAS Pilot3**

A third version of a VAS was created and piloted with eight participants none of whom had been involved in either of the previous two pilot studies. Participants were again shown a line. In an attempt to reduce some of the ambiguity present in previous versions, the endpoints of this line were represented as being pages in a book. Participants were told that the line represented a 1000 page book containing all there was to know about computing. They were asked to mark on the line how many pages, from page 1, they believed this book would have relating to all there is to know about end-user computing. A second line was shown to participants. This line represented an expanded version of the previous line with their mark representing the end point. The participants were asked to mark, on the second line what they believed to be their knowledge of end-user computing and what they believed to be the knowledge of the average person. The term 'average person' was a replacement for the term "most other people" used in the previous two pilots. This replacement was made in an attempt to reduce any ambiguity surrounding people's interpretation of what 'most people' meant. For this pilot there were four female and four male participants.

Participants appeared comfortable with the analogy of the 1000 page book. Far fewer questions were asked by participants using this version of the VAS about the task requirement than had been asked for the previous versions. The results did indicate an above-average effect although this was not as pronounced as in the previous two pilots. Another difference in the results of this study was only one person believed their level of knowledge was lower than that of the average person. Overall, the differences between self-assessments and perceptions of others were smaller than in

the previous studies. This result would suggest that, given a more defined type of instrument, participants were more likely to make a more realistic judgment than when the boundaries were undefined to them. Using the third version of the line with the book analogy, participants' average rating of their knowledge of computing was a mere 14% compared with the average of the 39% result from pilot 1 and the 58% from pilot 2. This adds weight to the conclusion that as the test gets more specific then the ratings become more realistic.

Full test details of this pilot are in Appendix 5.

### **3.6.4 Implementation of VAS instrument**

The results from the third and final VAS instrument pilot test provided a less marked result than the previous pilots had. While still present, the above-average effect was much less pronounced than for the previous pilots. As previously mentioned, the lower above-average effect may have occurred because a more defined task was presented than in the previous two pilots. Studies into the above-average effect have found that it is likely to be less pronounced in situations where a task is well defined, leaving little room for participants to make different interpretations (Kruger & Dunning, 1999, Krizan & Suls, 2008). The results from the third pilot test signalled that this version was a conservative option to use for the data collection purposes in the main study.

The next instrument required for this study was one to measure personality. The following section introduces the concept of personality and the instrument used for this study.

## **3.7 Personality**

Personality refers to the variations in characteristics, behaviours and thoughts that make a person unique. Studies of personality have resulted in the creation of the widely used Five-Factor Model (FFM) (Digman, 1990). This model was introduced as a comprehensive framework by which personality traits are classified into five central areas considered to incorporate the essential personality traits.

The FFM measures, for an individual, the extent to which their personality is made up of each of the five traits: openness, conscientiousness, extraversion, agreeableness and neuroticism. Each of the traits which make up the five-factor model have some influence over how people act in, and react to, different situations (Costa & McCrae, 1992; Digman, 1990; Markus & Wurf, 1987). Several well-established measures have been constructed for covering the five factors of personality. These



measures include a mixture of longer and shorter version instruments. An example of a longer version would be the Revised NEO Personality inventory (NEO-PI-R) consisting of 240 items (Costa & McCrae 1992). Shorter versions consisting of 60, 44, 10 or 5 items also exist. While it is generally accepted that the longer versions have better psychometric properties than the shorter measures, a long version is not always practical as it can take between 45 minutes and an hour to complete and the detailed results may not always be relevant for the purpose of use (Hahn, Gottschling & Spinath, 2012; Gosling et al., 2003). In situations where personality is not the focus of attention, but just one factor, a short version BFI can provide the level of overview required (Gosling et al., 2003).

For the purposes of this study, a shorter version of the five-factor personality model was used. The version chosen for this study was the forty-four item Big Five Inventory (BFI) constructed by John, Donahue and Kentle (John, Naumann & Soto, 2008; John, Donahue & Kentle, 1991; Benet-Martinez & John, 1998). The BFI requires participants to complete 44 statements using a five point Likert-type response scale. The use of statements leads to more consistent results than found for the use of single adjective items in some other instruments (John et al., 1998). The items are distributed among the five traits of Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism. All five factors have been found to have convergent and discriminant validity across instruments meaning this instrument is a concise measure (McCrae & John, 1992). The results from this measure will give an estimate of the degree to which a person displays each of the five traits. For this study, only the factors of Conscientiousness and Extraversion will be reported as there is evidence that suggests that, of the five factors, these two are likely to be influential in occurrences of an above or below average effect. Extraversion was chosen for this study as previous work has found positive relationships between this trait and overconfidence and no relationship between this trait and accuracy (Schaefer et al., 2004). Agreeableness has been found to be related to confidence and openness related to accuracy (Schaefer et al., 2004). However, because conscientiousness has not been found to predict either confidence, overconfidence or accuracy and has been linked to job performance it is considered, relative to this study, that those high in conscientiousness are likely to make more accurate self-report judgments than those low in this trait (George & Zhou, 2001; Schaefer et al., 2004). The descriptive statistics from each of the five traits from this study are shown in Table 4.

Table 4 – Descriptive statistics for BFI traits

| <b>Trait</b>      | <b>M</b> | <b>SD</b> |
|-------------------|----------|-----------|
| Extraversion      | 3.31     | 0.7       |
| Conscientiousness | 3.95     | 0.54      |
| Openness          | 3.54     | 0.46      |
| Neuroticism       | 2.47     | 0.67      |
| Agreeableness     | 4.00     | 0.56      |

For the purposes of this study, only the results from the traits of conscientiousness and extraversion were taken into account. These two traits were identified from the literature, (Section 2.2.1), as being the two most likely to have some association with a person’s perception of his or her computing ability compared with demonstrated ability.

The results for extraversion and conscientiousness items in this study were internally consistent with Cronbach’s Alpha scores of 0.85 and 0.78, respectively. Cronbach’s alpha reliability usually ranges between 0 and 1 with the following rules of thumbs provided in Gliem & Gliem (2003, p. 87) “>.9 – Excellent, \_ >.8 – Good, \_ >.7 – Acceptable, \_ >.6 – Questionable, \_ >.5 – Poor, and \_ <.5 – Unacceptable”

The 44 item BFI was chosen for this study. This is a 44 item shorter version of the 240 item Neo-Pi, and has been well used and validated for studies where personality is one part of data collection and time for participation is a factor (John, Naumann & Soto, 2008; John, Donahue & Kentle, 1991; Benet-Martinez & John, 1998). When measures of personality were first defined it was considered that the identified traits were mutually exclusive (John & Srivastava, 1999). However, further work identified ‘fuzzy boundaries’ existing between each trait (John & Srivastava, 1999). The instrument chosen has been widely used and has been found to be reliable both internally and externally. Although only the traits of Extraversion and Conscientiousness were considered for this study, at no time was only using these two traits from an instrument considered. As noted, there is a school of thought that the boundaries between each of the traits is blurred (John & Srivastava, 1999), but the most practical reason for not adapting the instrument was the reluctance to disrupt an instrument previously found to be internally and externally consistent and reliable. Given that this instrument is

a short version (44 items) the time taken to complete four rather than two of the traits was deemed to be negligible for participants.

### 3.8 Skill assessment

The fourth area assessed in this study was that of the demonstrated end-user computing skill level for each of the participants. Skill level was assessed using two end-user computing instruments: a word processing assessment and a spreadsheet assessment. These two types of software application were chosen due to their requirement for many different workplace occupations (Hansen & Hansen, 2010).

The instruments used were developed for this study using a development process following a Design Research Approach (described in detail in Appendix 4). Researchers involved in applied fields, such as the design of Information Technology applications, are both researchers and designers. They often draw on theories from several domains and require a pragmatic approach. One such pragmatic method is the Design Research Approach (Hevner, Park, & Ram, 2004; Wang & Hannifin, 2005). The Design Research Approach, commonly used in learning sciences, does not replace methodologies from the other domains involved, instead it utilises relevant parts of each (Wang & Hannifin, 2005). The iterative nature of a research design approach means that instruments created using this approach will please both the researchers and users alike (Hevner et al., 2004; Wang & Hannifin, 2005, McLaren & Burjis, n.d).

Typically a, Research Design approach consists of five stages (Hevner et al., 2004):

1. Problem identification;
2. Solution development proposal;
3. Outline of potential implementation of the proposed approach;
4. Evaluation of the approach;
5. Conclusions as to effectiveness of the approach.

The first four stages of the research design approach taken in the development of the skill assessment instruments are discussed in the following sections.

### **3.8.1 Skill-assessment development**

One intention of this study was to compare the self-assessment of a participant's end-user computing knowledge with their demonstrated ability. To assess the demonstrated end-user skill it was decided to use word-processing and spreadsheet applications as representative of the types of software commonly required in most workplaces (Panko, 2013; Holtzman & Kraft, 2010; Hansen & Hansen, 2010; Lawson et al, 2009; Baker, et al., 2008).

There are a number of proprietary computer skills tests available for assessing end-user computer skills. These tests include the ICDL/ECDL (International/ European Computer Drivers Licence) and the Microsoft testing system (MOUS). Both the Microsoft system and the ICDL/ECDL are used by some as a standard for the assessment of computer skill level (Bunker, 2010; Gravill et al., 2001, 2006). However, systems such as ICDL or MSMOUS are based on learning systems that test skills and knowledge based on full knowledge of a package (Gravill et al., 2001, 2006). Due to the package nature of these systems, it is difficult to isolate a particular set of tasks for testing (Gravill et al., 2001). The package nature of these testing systems often means that they may not be unbiased in nature because people in a workplace may not need to have the full set of knowledge from a package to complete their tasks but the testing system tests all aspects and returns results based on this. In addition, the on-line presentation of the test is often in a simulated environment with only partial functionality available (Panicos & Sotiris, 2010). In this study, the aim was to present a subset of Word-processing and Spreadsheet tasks representative of workplace tasks that a user could complete using a number of different methods. For these reasons, it was concluded that a bespoke testing system would provide more flexibility than a proprietary system and that developing an instrument from scratch would provide the opportunity to subject the systems to a thorough and robust content validation process.

The 'trade-off' between using a propriety test and creating a bespoke application was that this took a considerable amount of time and resources to develop. This has means that the instrument development part of this study in effect became a substantive aspect of the overall study. Devotion of this effort was, however, concluded to be necessary to ensure targeted assessment of skills that ranged from 'easy' (and expected) to 'difficult' (likely to be at the upper end of skill level). Also, a bespoke instrument could target tasks that most accurately reflect specific workplace requirements rather than overall skill across the breadth of tasks available in the software packages (not all of

which would be necessary in workplace settings). The development process is explained in the following section with technical detail available in Appendix 4.

### **3.8.2 Skill assessment instrument content development**

Two automated assessment instruments were created, using MS Excel and MSWord, and automated using VBA (Visual Basic for Applications).

Two development processes were undertaken simultaneously. These processes were:

- The development of the automated instrument;
- The development of the instrument content.

The technical development process involved in the creation of the automated instruments is described in detail in Appendix 4.

The development of the instrument content involved a content validity approach comprising inter-rater reliability testing. An inter-rater approach using panels of experts was undertaken to develop content for the instruments. A two-panel approach using a multi-stage iterative process was used during instrument development. The stages involved were:

- Task classification development;
- Task development;
- Assessment testing by panel;
- Task rating by panel;
- Adjustment of tasks based on panel feedback.

The first step in creating the content for each instrument involved identifying and defining the categories of skill or task for each of the applications tested. The categories were defined initially using the author's personal experience in teaching end-user computing and then comparing these with the skills tested in the ECDL/ ICDL tests ([www.ecdl.org](http://www.ecdl.org)). Finally, these categories were evaluated by an independent academic expert in EUC. The categories determined by the process are shown in Table 5.

Table 5 - Classifications for spreadsheet and word-processing assessments

| <b>Spread-sheet Classification</b> | <b>Word-Processing Classifications</b> |
|------------------------------------|--|
| 1. Cells and formatting            | 1. Text and paragraph formatting       |
| 2. Functions and formulas          | 2. Styles                              |
| 3. Charting                        | 3. Numbered lists                      |
| 4. Sorting and Filtering           | 4. Tables                              |
| 5. Validation and protection       | 5. Page Layout                         |

The second stage in this process involved the development of the tasks in each category to be included in the final instruments. A content development process was undertaken in two stages using the two separate and independent panels of end-user computer experts.

The first panel were tasked with testing the instruments by completing the assessment as a user would. Comprising ten users for the word processing test and eleven for the spreadsheet test, the panels were a mixture of academic experts and industry experts (Table 6).

The academic panel members were people currently involved in teaching the use of productivity of software at a tertiary level. The expert users were people with experience using this type of software to a high level in their jobs. They were identified as the “go to people” in an organisation, those who others would ask for help. Identification of panel members were made in a variety of ways; some people were identified by way of an organisation expert list, others by recommendations from peers.

Table 6 - Make-up of SS and WP Expert Panel 1

| <b>Spread-sheet Experts</b>    | <b>11 Users</b> |
|--------------------------------|-----------------|
| Academic Expert                | 3               |
| Expert user                    | 8               |
|                                |                 |
| <b>Word Processing Experts</b> | <b>10 Users</b> |
| Academic Expert                | 3               |
| Expert user                    | 7               |

Panel 1 was divided into two sub panels: spreadsheet experts and word processing experts. None of the panel members belonged to both panels. The members of Panel 1 were each asked to take the tests under the same conditions as participants in the main study. The time to complete each task was recorded and a recording of the screen was made. Members of these panels were asked to complete a questionnaire rating the content and difficulty of each task.

A second panel of end-user specialists (Panel 2) was formed to assess the objectives of each task in each instrument. The reason for having a second panel was to ensure that an independent view of the content objectives was made by people who had no exposure to the test instrument. Panel 2 consisted of seven members, all involved in the teaching or workplace training of end-user computer skills (Table 7).

Table 7 - Expert panel 2

| <b>Expert User Panel 2</b>  | <b>7 Users</b> |
|-----------------------------|----------------|
| Corporate computer trainers | 5              |
| Academic End-user teacher   | 2              |

Panel 2 members were not required to complete the tests but were asked to rate each of the skills

being tested as either essential to test or not essential to test. Panel members were also asked to judge each skill as to whether or not it was one every user should have or one that only an expert would be expected to have. Panellists from both panels were asked to suggest any skills that they thought were essential to test but had been omitted from the original instruments. All of these suggestions were taken into account and both instruments were altered to accommodate minor changes.

Following a round of development and piloting of instruments two assessments were created. These instruments were a fifteen-task spreadsheet assessment and an eleven task word-processing instrument. The spreadsheet assessment evolved from an initial sixteen-item instrument. The final instrument was created by adjusting the included tasks based on suggestions from panel members and adding other tasks seen as relevant. The word-processing test evolved from a twelve task instrument, that was piloted, to the more streamlined version used in final testing. Tasks used in each assessment are outlined in Table 8 and Table 9 .

Table 8 - Spreadsheet assessment tasks for final instrument

---

**Spread-sheet skills test tasks**

1. Basic Cell formatting.
2. Using a simple Sum function.
3. Using a Count function.
4. Using a conditional function to count values meeting a criteria.
5. Using Text Functions.
6. Using a fixed cell reference in a formula.
7. Create a pivot table with one summary value
8. Using a conditional function to return value.
9. Naming a Cell.
10. Creating a simple Column chart using adjacent ranges
11. Creating a one series column chart with numeric values as the x axis.
12. Sorting multi column data.
13. Using a Lookup function in a formula.
14. Using a simple filter.
15. Create a validation rule



Table 9 - Word-processing assessment tasks for final instrument

**Word processing tasks**

- 
1. Applying basic paragraph formatting.
  2. Changing a paragraph's alignment
  3. Copying formatting between paragraphs.
  4. Indent a paragraph.
  5. Creating multi-level lists.
  6. Applying pre-set styles to text.
  7. Modifying a pre-set style.
  8. Inserting text and page number into page footer
  9. Updating tables
  10. Positioning an image within a block of text.
  11. Working with sections within a document.

To ensure internal validity, the results from each of the panels was subjected to a two-part content validity analysis. First, they were assessed using an item content validity index ( $C_{VI}$ ). The results from the Item  $C_{VI}$  were then analysed for chance agreement by linking these results with a kappa-like index adjusted to take into account chance agreements on relevance as outlined in Polit, Beck & Owen (2007).

The Item  $C_{VI}$  is calculated by counting, for each item, the number rated as relevant divided by the actual number rated.

$$C_{VI} = \frac{R}{N}$$

**Equation 1 - Content Validity Index**

Where:

R = number of relevant rating choices

N = the number of experts

The probability of agreement between panel members occurring by chance (Pc) is calculated using the formula for a binomial random variable with one specific outcome (Polit et al., 2007). In this case, the specific outcome is the chance that experts will randomly select a relevant rating.

$$P_c = \left[ \frac{N!}{A!(N-A)!} \right] r^N$$

**Equation 2 - Probability of chance**

Where:

A = the number of tasks rated as relevant

r = the number of tasks rated as relevant ratings divided by the total number of rating choices

The Kappa index was used to define the level of agreement of item relevance between panel members over and above any agreement that occurred by chance. This index is calculated as:

$$\kappa = \frac{C_{VI} - P_c}{1 - P_c}$$

**Equation 3 - Polit's modified kappa**

The strength of the modified kappa ( $\kappa$ ) as compared with the values used by Polit et al. (2007) is shown in Table 10.

Table 10 –Modified Kappa evaluation (Polit et al., 2007).

| $\kappa$    | Evaluation          |
|-------------|---------------------|
| < 0         | Poor agreement      |
| 0.01 – 0.39 | Slight agreement    |
| 0.40 – 0.59 | Fair agreement      |
| 0.60 – 0.74 | Good agreement      |
| >= 0.75     | Excellent agreement |

Results from the content validity analysis indicated the items both panels agreed were relevant to use in a test of this nature. This analysis also confirmed the level of difficulty for each of the tasks. The mean kappa results from the two panels are displayed in Table 11 and Table 12.

Table 11 - Content Validity Kappa results for Word- processing assessment development testing

| <b>Task</b> | <b>K</b> | <b>Evaluation</b> |
|-------------|----------|-------------------|
| 1           | 0.93     | Excellent         |
| 2           | 0.93     | Excellent         |
| 3           | 0.93     | Excellent         |
| 4           | 0.93     | Excellent         |
| 5           | 0.82     | Excellent         |
| 6           | 0.87     | Excellent         |
| 7           | 0.87     | Excellent         |
| 8           | 0.77     | Excellent         |
| 9           | 1.00     | Excellent         |
| 10          | 0.82     | Excellent         |
| 11          | 0.95     | Excellent         |

Table 12 - Content Validity Kappa results for spreadsheet assessment development testing

| <b>Task</b> | <b>K</b> | <b>Evaluation</b> |
|-------------|----------|-------------------|
| 1           | 0.93     | Excellent         |
| 2           | 0.93     | Excellent         |
| 3           | 0.88     | Excellent         |
| 4           | 0.78     | Excellent         |
| 5           | 0.63     | Good              |
| 6           | 0.95     | Excellent         |
| 7           | 0.73     | Good              |
| 8           | 0.71     | Good              |
| 9           | 0.66     | Good              |
| 10          | 0.93     | Excellent         |
| 11          | 0.83     | Excellent         |
| 12          | 0.93     | Excellent         |
| 13          | 0.75     | Good              |
| 14          | 0.82     | Excellent         |
| 15          | 0.75     | Good              |

### 3.8.3 Design of assessment instrument screens

It was felt that examples of the actual tasks screens may be help the reader of this thesis to better understand the manner in which the assessment was undertaken. Such examples are shown in the figures in this section.

The start screens from both assessments are shown in Figure 9. Both of these include an explanation for the user of the overall process.

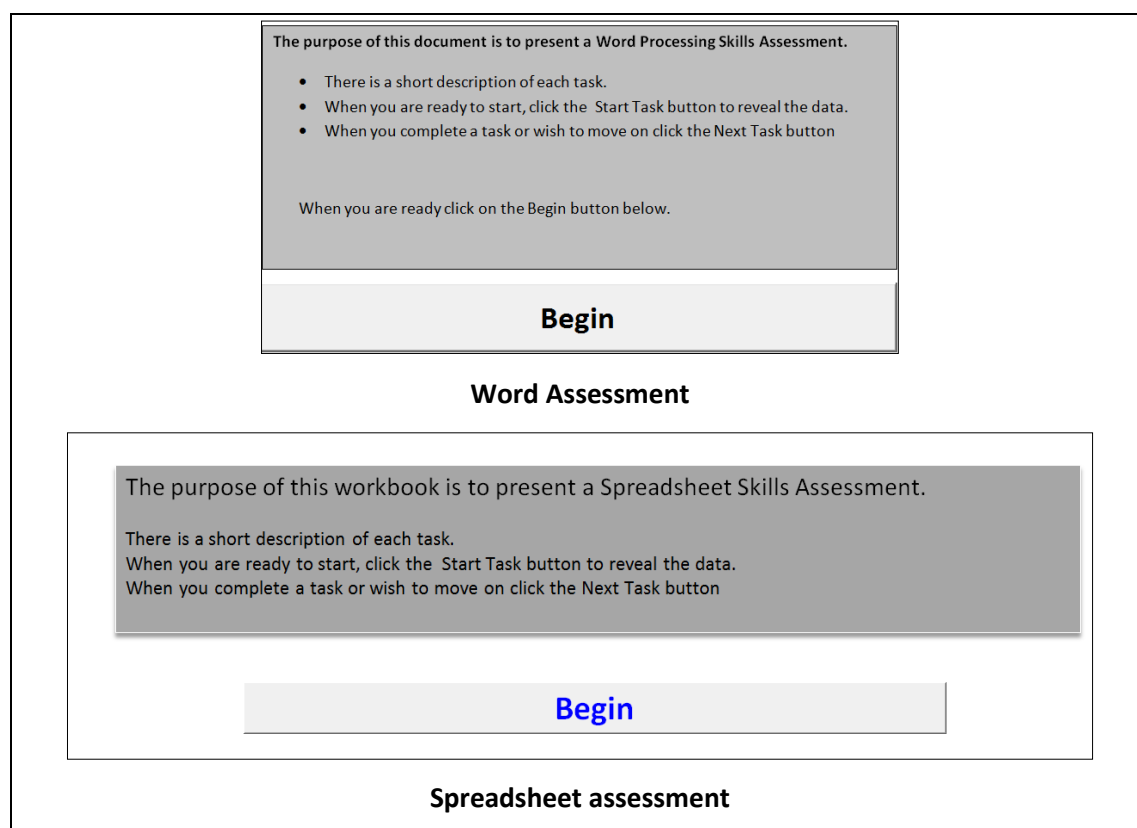


Figure 9 - Start pages for the Word and Spreadsheet assessments

The Task1 screens for both assessments are shown in Figure 10 (word-processing) and Figure 11 (spreadsheet). Each task is then presented to the participant. First, the task is described as shown below. When the participant is ready, they can press the Start Task button to reveal the data and record the start time.

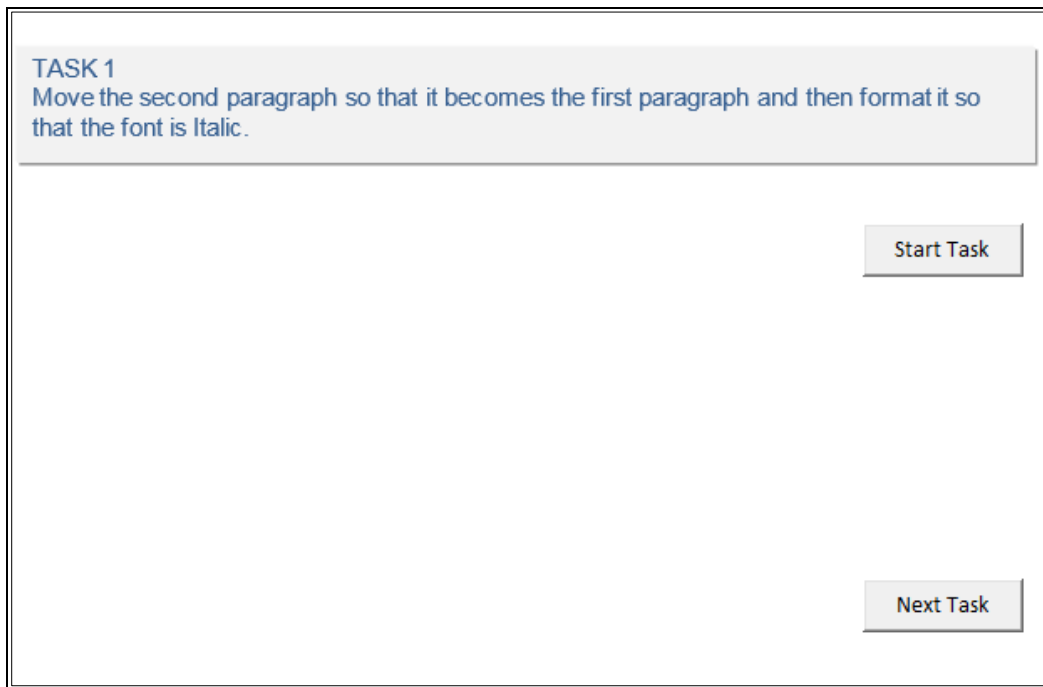


Figure 10 – Task 1 screen for Word assessment instrument

Once the start button is pressed, the participant would see two paragraphs of nonsense text. They would be expected to highlight the second paragraph and move (drag) it above the original first paragraph. They would then be expected to use the Italic button (or short-cut Ctrl I) to change the font style to italic.

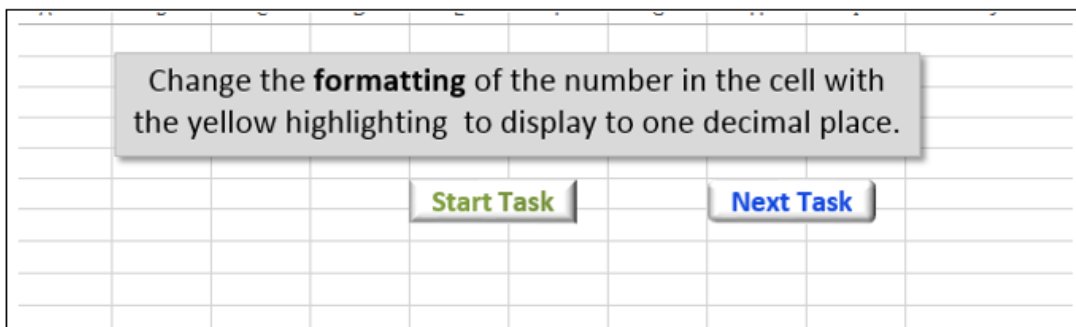


Figure 11- Task 1 screen for spreadsheet assessment instrument

Once the Start Task button is pressed the participants would see a number displayed to three decimals places. They would be expected to decrease the decimals by highlighting the cell containing the number and then by using the decrease decimal button to remove two decimals places.

Alternatively participants may choose to right-click and then choose format from the in-context menu. From this position, they could also choose the number of decimals to display.

For both instruments, clicking the start button resulted in the following:

- The current time being recorded
- The text or values required for the task being made visible
- The start button being disabled – preventing the user re-clicking

If the participant did not wish to attempt a task, he or she could press (click on) the **Next Task** button before pressing (click on) the **Start Task** (the task time would then be recorded as “skipped”). The participant could also press the **Next Task** button at any time during the task if they wished.

For both instruments, clicking the **Next Task** button resulted in the following:

- Recording of the current (stop) time
- Moving to the next page/worksheet

### **3.8.4 Implementation of skill assessment instrument**

Overall, the instruments used for development testing performed well except for a few minor technical issues easily solved prior to use for data collection. The instruments used in the actual testing were adapted using information gained from the development stages.

The Word processing instrument used for testing was an eleven item assessment and the spreadsheet assessment was a fifteen task automated instrument. The process undertaken to develop the automated skill assessment instruments is explained in detail in Appendix 4.

### **3.8.5 Evaluation of combined instruments**

Subsequent to the development stage, the skill assessment instruments were combined with the other instruments in this study and tested as one instrument. This final pilot was multi-purposed. The first aim was to test the instruments as a whole in order to get a sense of how the different parts worked together and the time required for an average participant. Another, and very important, aim was to test the automated assessments on people not considered experts to get a sense of the range of task level presented. This process, involving users considered representative of the main participant population, worked well. The results revealed minor technical issues with the automated tests that could be rectified prior to the actual testing.

### 3.9 Data Collection

As outlined in Section 3.3 study participants completed three instruments collecting four types of data. The data were collected from each participant in one session. Either participants came to Lincoln University or the researcher visited the participant at their place of employment in the Christchurch area.

The following was the process carried out with each participant:

- The background to the project was explained to the participant;
- Participants were given a description of the project to read;
- Participants were asked if they were happy to go ahead with project and if so given consent form to complete;
- Participants were asked to complete the demographic questionnaire, perception measures and the personality inventory;
- On completion of the written component participants were informed that they would undertake the skill assessment using the automated assessments;
- Participants were asked which assessment - spreadsheet or word-processing - they would prefer to do first;
- The researcher started the screen recording – using screen recording software to record mouse movement;

The purpose of recording the screen when participants were completing the skill assessment was so the researcher could view the route a participant took to complete a task without the need to interfere with the actual process.

- Participants began the assessment by reading the introductory screen and following the instructions.
- Participants were asked to complete the tasks that they knew how to perform. Therefore, although this was not closed book as such, no participants searched for an answer. A small number of participants (fewer than five) did comment that for tasks they did not know about, if they needed to use these for work, they would search for the answer.



At the completion of the data collection stage the data from each of the instruments were entered into one main data collection worksheet. This included demographic data, skill assessment data, perception measurement data and personality variable data for extraversion and conscientiousness.

### 3.10 Summary of instrument development

The following sections provide a summary and illustration of the journey taken in creating, testing and validating the instruments used in this study.

#### 3.10.1 Perception Measure Development and Validation

As discussed in the previous section development of perceptions measures involved a lengthy development and validation process making use of three separate pilot studies. Three studies were necessary in order to produce an instrument that was clear for participants, where both the task and the instrument were neither ambiguous nor caused confusion. At the conclusion of each of the pilot studies, two sources of data external to the actual task were analysed for task clarity: the number of questions asked of the facilitator; and “talking out loud” by participants or inability to complete the task. Pilot One’s task definition proved unclear for most of the ten participants. A revised definition in Pilot Two caused fewer issues. Finally, a more strictly defined version of the task description in Pilot Three showed none of the previous issues. This process is shown in Figure 12

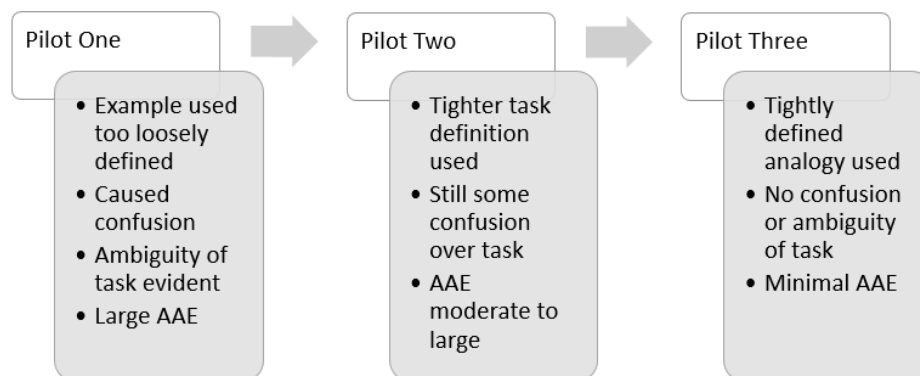
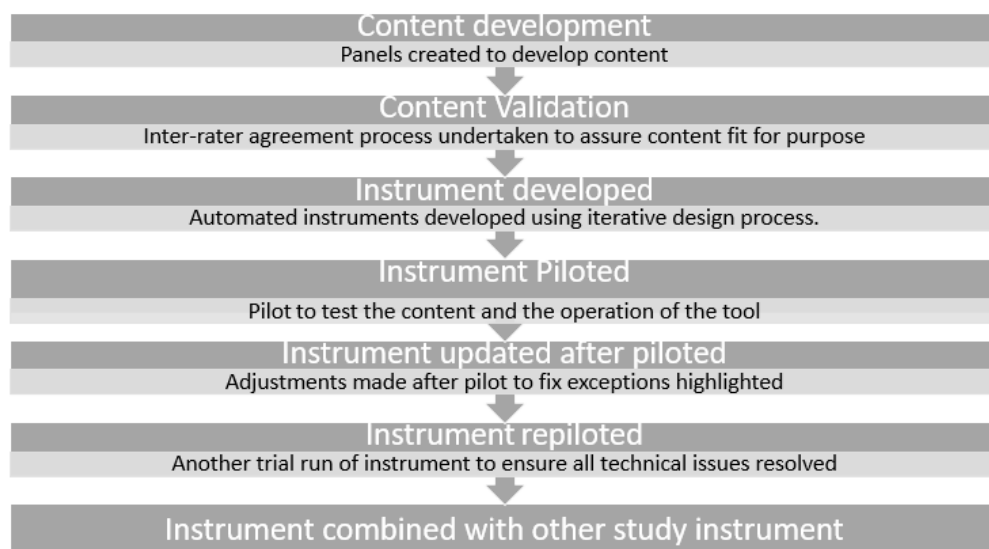


Figure 12 - Measure of perception development process

#### 3.10.2 Skill Assessment Development and Validation

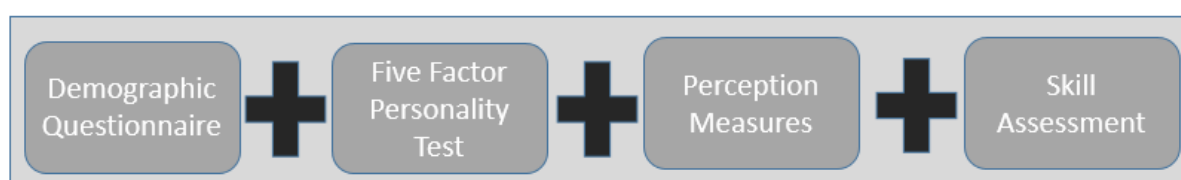
The development of the skill assessment instrument was undertaken in several stages. These stages are illustrated in Figure 13.



**Figure 13 - Development process of skill assessment instruments**

### 3.10.3 Pilot of combined instruments

The final stage of instrument development and piloting combined the instruments into a single battery, then administered this battery to a new group of participants. These participants were recruited to work through this combination in the order that the study's target participants would do so. This process is illustrated in Figure 14.



**Figure 14 - Combined instrument**

The methods used to enter the data, varied for each of the instruments, are described below. This final set of participants reported no significant issues with understanding the procedures or completing the battery.

## 3.11 Analysis method

All data were entered into a computer spreadsheet. The data from the demographic and perception measures were entered manually. Measurements of the marks made on the VAS were recorded and

entered manually. Marks for each of the perceptions measures were converted from millimetres (as measured) into equivalent pages and, for self-assessment and estimation of the AEU, also into proportion of pages based on an individual's measure for T.

Each participant completed the spreadsheet skill assessment using their own workbook. As each task was completed, attempted or skipped a time was entered into the final data collection sheet (hidden from participants. This worksheet included a series of formulae designed to enter the answer given for each task. Conditional formatting was used to add a colour for correct, skipped or attempted for each task. It is important to note that initial analysis of assessment tasks was undertaken for each participant, for each task, as they were completed in the application. This procedure entailed a combination of spreadsheet formulae (both user-defined and inbuilt) along with VBA (Visual Basic for Applications) automation. The user-defined functions used in the process included methods to identify cell formatting, to paste formula as text , identify any filtering on a worksheet and if data validation existed on a particular worksheet. The automation used at task level involved the copying and pasting of the start and finish time for each task as well as the data entered by the participant in the answer cell. A VBA macro was written to transfer the completed data, including conditional formatting into a worksheet in the data collection workbook.

For the word processing assessments times taken to record the task completion were kept in a table at the end of the document and hidden from the participants. This information, for each participant was copied and pasted into the main data collection workbook using VBA automation.

The information from the BFI personality inventory was entered into a separate worksheet for each participant. Formulae were used to extract data for each trait and average these for each participant to give an overall score for each trait. A spreadsheet macro was used to loop through each worksheet and copy and paste the data for the extraversion and conscientiousness traits into the main data collection worksheet.

The process described here lessened the time taken to access each task for completeness and correctness. Further information about this is included in Appendix 4.

Analysis of data was carried out using a combination of Excel and the SPSS statistical package. These analyses included standard descriptive analyses (mean, median, frequencies, and standard deviation) as well as analysis of variance techniques and the creation of graphs and charts.

Associations between the perception measures and the scores for demonstrated ability, expertise and personality variables were examined using multiple regression analysis. This analysis was used to identify and describe the extent, direction and strength of relationships between several independent variables and a dependent variable. In research involving several different variables, it may be that several predictor variables simultaneously affect a dependent variable. In these cases, multiple regression analysis is a suitable method for analysing these interactions (Babbie, 2007). Multiple regression returns results for the combined influence of several independent variables as well as the individual influence of each variable on one dependent variable (Hair et al., 1995). This method provides more accurate results than if several separate simple regressions were applied (Hair et al., 1995). To counteract any influence of the number of variables on the effect size the adjusted  $R^2$  calculation is reported. It should be noted that it is possible to have a low  $R^2$  value with a significant P value. In a multiple regression equation this may be a result of only one of multiple regressors being of substantive interest and the others being control variables. In some situations, it is possible that the control variables are not important and may cause the r-square to be non-significant and low. However, the coefficient of one (or more variable) may be significant. These values are reported for any rejected hypotheses in Section 4.4.

The Pearson product-moment correlation coefficient was used to identify relationships between pairs of variables. This statistical test is used to measure the amount of linear dependence between two variables (Babbie, 2007). The correlation coefficient ranges from -1 to 1. A value of 1 implies that in a linear sense variable 'a' fits perfectly with variable 'b' with all points lying on a line for which as variable a increases so does variable b. A value of -1 implies a negative relationship. A value of 0 implies no relationship between variables.

The demographic variables include sex that was re-coded using a dummy variable following the procedure described in Myers (1990). Females were coded as 1 and males 0. Although categorical data should not routinely be used as predictor variables, for this study the combination of demographic variables was considered important as qualitative factors, in this type of study, can cause influence (Myers, 1990). Because sex has been found, in previous studies, to be associated with over-confidence (Burnett, Beckwith, Wiedenbeck, Fleming, Cao, Park & Rector, 2011) it was considered important to include in this study. Descriptive statistics such as mean, median and standard deviation were used to describe the demographic and expertise variables.

### 3.12 Ethical considerations

This research project, including all pilot and development testing, received ethical approval from the Lincoln University Human Ethics Committee (2012-25).

Although the data collected related to someone's workplace skill no information was available to anyone other than the researcher and no reported data were identifiable as coming from any particular individual participant. All participation in this study was purely voluntary with participants free to withdraw their information at any time until analysis of data had commenced. All participants completed a project consent form prior to beginning the study. Participants were considered to have participated on completion of all of the instruments. There was no information collected that could identify any of the participants. All information provided by the participants was kept securely, and was only accessible by the researcher.

The following chapter (Chapter 4) presents and describes, in detail, all results collected in this study. Discussion of results is in Chapter 5.

## Chapter 4 Results

### 4.1 Introduction to results

The purpose of this chapter is to present the results of the methods employed to gather data. All findings will be presented and these and the statistical tests used to analyse them, described. Full discussion regarding the implications of these findings is present in the following chapter (Chapter 5).

Chapter 4 will be presented in five sections including this introductory section (4.1).

Section two (4.2) reports participant characteristics. This includes demographic features, workplace expertise measures and personality trait results for extraversion and conscientiousness.

Section three (4.3 ) presents the findings from the skills assessments. These are presented both by application (i.e., MS Excel or MS Word software) and as a combination of both assessment measures.

The fourth section (4.4) is separated into sections for each of the hypotheses  $H_1 - H_8$  as described in Section 1.2. The data were examined using Pearson's product model correlation coefficient and multiple regression analyses in order to identify the factors that are associated with a person's self-assessment (SA), estimation of the knowledge of the average computer end-user (AEU) and extent of domain (EoD<sub>EUC</sub>). Findings are shown both in graph and table format. Regression results are reported using standardised beta statistics, adjusted  $R^2$  for the multiple regression analysis and R and P statistics for bivariate correlation analysis.

Section 4.4 explores the above-average effect and the DKE in relation to the demographic, expertise and personality variables as related to the hypotheses.

The final section (4.5) of this chapter provides a summary of results.

All findings presented in this chapter are considered and discussed in detail in the discussion chapter (Chapter 5).

## 4.2 Participant characteristics

Ninety-one participants were recruited for this study on the basis that their current employment required them to use spreadsheets and word-processing software. Selection criteria are described in full detail in Section 3.3 in the Methods chapter.

### 4.2.1 Demographic and expertise variables used in analysis

The demographic and expertise variables used in analysis included:

- Sex
- Age
- Occupation
- Hours of computer use
- Number of software packages used
- Computer skills learning approaches
- Extraversion
- Conscientiousness

The rationales for the use of each of these variables is given in detail in Section 3.3 in the Methods chapter. The demographic, expertise and personality variables were analysed with respect to the perception measurements:

- Self-assessment
- Estimation of the Average computer End-user (AEU)
- Estimation of extent of the domain of end-user computing (EoD<sub>EUC</sub>).

## 4.3 Skill assessment results

The information in the following sections outlines the results from the end-user assessments using MS Word (11 tasks) and MS Excel (15 tasks). All participants (n=91) completed both the spreadsheet and word-processing assessment. The combined assessment result returned a study mean of (14.5 tasks correct from a total of 26 tasks). Results from each assessment will be presented individually as well as results that take into account a participant's results for the combined assessment exercise.

### 4.3.1 Spreadsheet assessment results

The spreadsheet assessment consisted of fifteen tasks comprising a mixture of levels and included ones that everyday users of this software should be able to complete, and those that expert users could complete. The tasks were decided on during the creation of this instrument and were developed in cooperation with panels of people with experience in end-user computing. This process is described in detail in Section 3.8.

The results for the spreadsheet items in this study were internally consistent with a Cronbach's Alpha score of 0.82 (See Section 3.7). Table 13 presents a summary of the results for the spreadsheet assessment.

Table 13 - Summary of spreadsheet results

|                       |           |
|-----------------------|-----------|
| Mean number correct   | 7 (47%)   |
| Median number correct | 6 (40%)   |
| Standard deviation    | 3.6 (24%) |
| Max number correct    | 15 (100%) |
| Min number correct    | 2 (13%)   |

Table 14 displays the breakdown of results in the four categories: Correct, Incorrect, Inspected but not attempted and skipped. Tasks are described in Table 33 in Appendix 3.



Table 14 – Proportion correct for each spreadsheet task

| Task number | Difficulty level<br>1: everyone;<br>2: experts | Proportion correct<br>( n = 91) | Proportion inspected<br>and skipped | Proportion incorrect | Proportion skipped<br>without inspection |
|-------------|--|---------------------------------|-------------------------------------|----------------------|--|
| Task 1      | 1  | 0.96                            | 0                                   | 0.04                 | 0  |
| Task 2      | 1  | 0.97                            | 0.02                                | 0                    | 0.01                                     |
| Task 3      | 1  | 0.48                            | 0.47                                | 0.03                 | 0.02                                     |
| Task 4      | 2  | 0.26                            | 0.46                                | 0.24                 | 0.04                                     |
| Task 5      | 2  | 0.18                            | 0.70                                | 0.04                 | 0.08                                     |
| Task 6      | 1  | 0.36                            | 0.26                                | 0.30                 | 0.08                                     |
| Task 7      | 1  | 0.42                            | 0.20                                | 0.14                 | 0.24                                     |
| Task 8      | 2  | 0.35                            | 0.34                                | 0.05                 | 0.26                                     |
| Task 9      | 2  | 0.12                            | 0.80                                | 0.01                 | 0.07                                     |
| Task 10     | 1  | 0.78                            | 0.16                                | 0.02                 | 0.04                                     |
| Task 11     | 2  | 0.34                            | 0.29                                | 0.21                 | 0.16                                     |
| Task 12     | 1  | 0.59                            | 0.32                                | 0.07                 | 0.02                                     |
| Task 13     | 2  | 0.20                            | 0.65                                | 0.04                 | 0.11                                     |
| Task 14     | 1  | 0.78                            | 0.16                                | 0.02                 | 0.04                                     |
| Task 15     | 2  | 0.19                            | 0.65                                | 0.01                 | 0.15                                     |

*Note: the shading in the rows indicates the skills rated as expert skills (47% of total tasks available).*

For each task, participants were presented with a written on-screen description. If they chose to press the start button, the data required for the task would be presented. The data were not revealed to participants who chose to skip the task. The rationale behind not displaying the data at the first step for each task was the need to run the behind-the-screen timing mechanism for each task. The time taken to read and understand the requirement of a task was not taken into account. As can be seen in Table 14 , tasks 1, 2, 10 and 14 had the highest correct completion rate (ranging from 78% to 98% of participants). Participants were least successful on task nine with only 12% of participants completing it successfully. Tasks seven and eight were each skipped by 25% of the participants.

Figure 15 shows the number of participants who correctly completed the different tasks. It is perhaps not surprising that the tasks labelled as basic had a higher frequency of correct completion than the expert tasks.

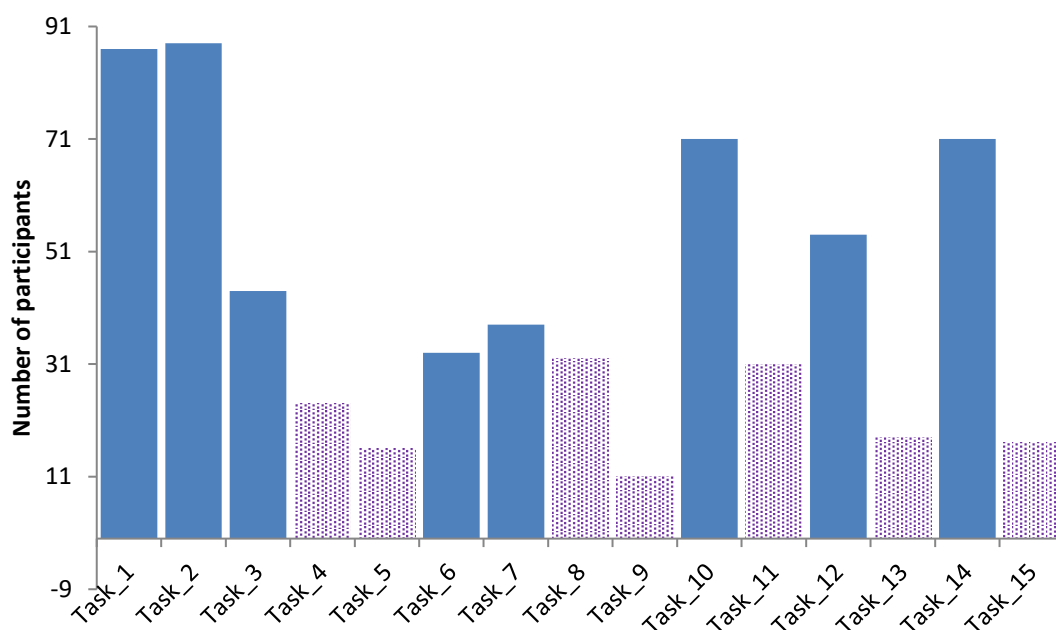


Figure 15 - Numbers Correct for Spreadsheet Tasks

**Note:** Expert tasks bars have lighter shading

Figure 16 depicts the frequency with which participants successfully completed a particular number of tasks in the spreadsheet assessment. Of the 91 participants 30 (33%) completed only four of fifteen(27%) or fewer tasks correctly. Twenty participants (22%) correctly completed ten of fifteen tasks (66%) or more of the assessment. The lowest number completed correctly was two of fifteen tasks by three participants. Five participants correctly completed all fifteen of the spreadsheet tasks.

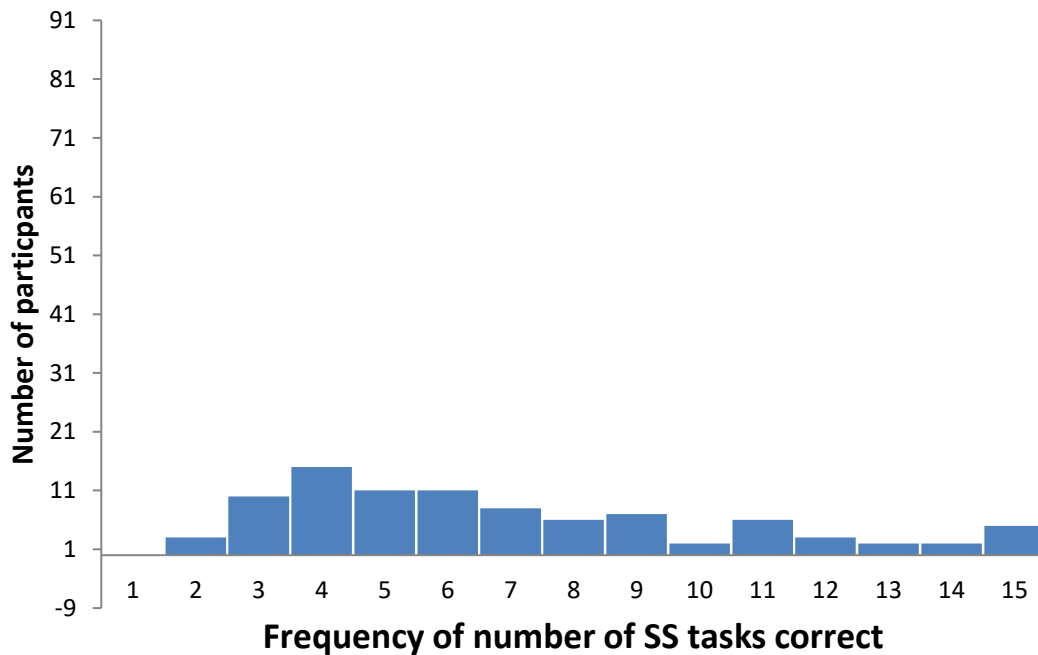


Figure 16 - Spreadsheet tasks correct frequency

#### 4.3.1.1 Study participants compared with expected average

The panel involved in the development stage of this instrument (Section 3.8) ranked eight (53%) of the spreadsheet tasks as being tasks regular workplace users should be able to complete.

In this study the average completion was 7.05 of fifteen tasks (47%), SD 3.45 of fifteen tasks (23%). These tasks were a mixture of those considered basic by the panel and those considered moderately advanced.

Fifty-seven participants (63%) had a demonstrated score less than the study average (47%) Of those 57 participants with a score lower than other participants in the study ,36 (63%) had a self-assessment greater than their estimation of the average person

Although 34 participants had a spreadsheet result equal or greater than the panel expectation of 53%. Interestingly, only ten participants (11%) correctly completed all the tasks rated as basic by the panel. This means that the other 24 completed a mixture of basic and moderately advanced tasks.

No one task was answered correctly by all participants, with two of the basic tasks being completed correctly by less than half the participants (Task 6 (36%) and Task 7 (42%)). The average completion for the eight basic rated tasks was 5.4 tasks (67%). Fourteen (15%) participants correctly completed all basic tasks. Five participants correctly completed all 15 spreadsheet tasks. Of the expert spreadsheet tasks, tasks 8 and 11 had the highest correct proportion with 32% of participants completing each correctly. The tasks with the lowest rate of correct response were those tasks ranked as expert tasks by the development panel.

#### **4.3.1.2 Spreadsheet assessment result and time taken**

Times for each task, regardless of correctness, are displayed in full in Appendix 3. When a participant clicked the start button for each task a timestamp was recorded in the background, another timestamp was recorded when a participant moved from one task to another. Participants were unaware that time was being recorded and as such, it is not considered that this caused a distraction to participants.

Figure 17 displays the times recorded by each participant for the spreadsheet assessment against the number that participants completed correctly.

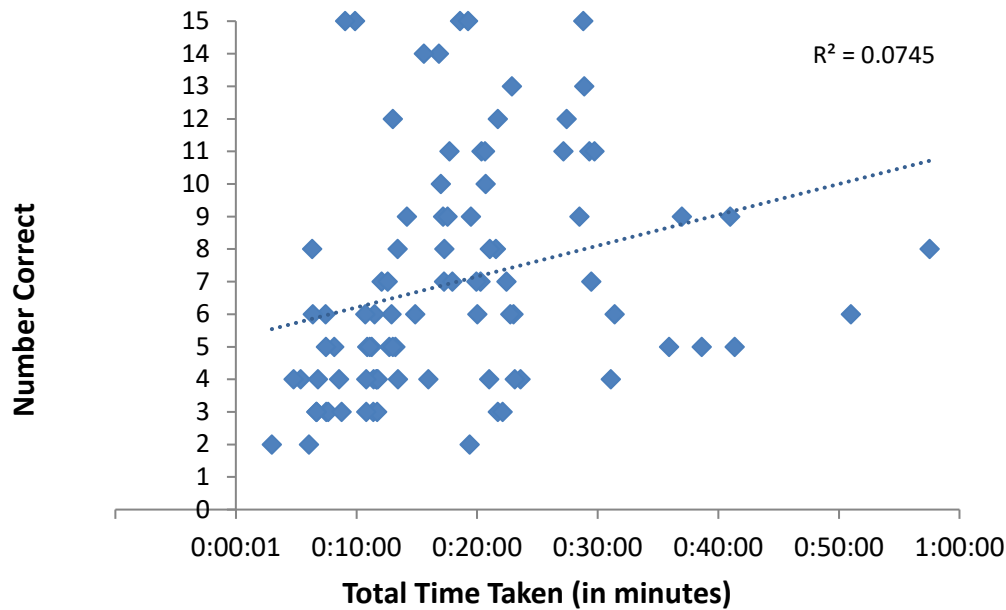


Figure 17 - Time taken to complete spreadsheet assessment and number correct

The minimum time taken working on the spreadsheet assessment was 00:02:59 with a corresponding two tasks (13%) correct compared with the maximum time taken of 00:57:32 with a correct completion of eight tasks (53%). The overall average time of completion for this assessment was 00:18:07 (SD 00:10:14). The average time of completion for the five participants who correctly completed all 15 spreadsheet tasks was 00:17:07 ranging from 00:09:03 to 00:28:49 (SD 00:08:05).

The spreadsheet assessment result was significantly correlated with the time taken to complete this assessment ( $R = 0.26$ ,  $N = 91$ ,  $p = 0.012$ ). This analysis suggests that taking a longer time was not a guarantee of completing a high number of tasks, as those with the highest scores (the experts) did so in relatively short times.

#### 4.3.1.3 Spreadsheet assessment result and measures of perception

A multiple regression analysis was conducted to evaluate how well the measures of perception were associated with a person's spreadsheet assessment score. The linear combination of the three predictor variables was significantly related to a person's spreadsheet assessment score,  $F(3, 87) = 6.55$ ,  $p \leq 0.000$ .

The Adjusted  $R^2 = 0.156$  indicates that approximately 16% of the variance of the spreadsheet assessment score can be accounted for by the linear combination of the measures of perception.

Table 15 presents standardised Beta weights to indicate the relative strength of the individual predictors.

**Table 15- Associations between spreadsheet assessment and measures of perception**

| Predictor       | beta  | t     | p     |
|-----------------|-------|-------|-------|
| Self-assessment | .470  | 3.64  | 0.000 |
| EoDEUC          | -.20  | -1.84 | 0.069 |
| AEU             | -.421 | -3.15 | 0.002 |

Both the perceptions of self-assessment and estimations of an AEU were significant as predictors of the spreadsheet assessment score. Based on this analysis it may be tempting to conclude that a person's perception of the breadth of knowledge available about end-user computing has any influence over their spreadsheet score, however judgments about relative importance of variables are difficult because of the correlations shown between each of these and the overall omnibus effect. The positive association between spreadsheet ability and self-assessment suggests that those with more expertise using this application may underestimate their knowledge in the EUC domain. People with more expertise sometimes believe that their expertise is the norm (Kruger & Dunning, 1999, 2009). Although not significant, the negative association between estimation of the breadth of the domain and spreadsheet ability also suggests that those with a greater demonstrated skill will have a more conservative view of the domain.

#### **4.3.2 Word-processing assessment results**

The word-processing assessment consisted of eleven tasks. Tasks were a mixture of those with which everyday users should be familiar and more difficult ones for experienced users. The tasks were determined during the creation of this instrument and were developed in cooperation with panels of people with experience in end-user computing. This process is described in detail in Section 3.8.

No tasks in the word-processing assessment were skipped by any participants and results were assessed as correct or incorrect. No person completed all tasks correctly and the lowest number of tasks completed correctly was three of eleven tasks. The tasks and their level of difficulty are shown in Table 29 in Appendix 3. The study mean for this assessment was seven out of a possible eleven tasks 7.6 tasks of 11 (69%) (SD = 2.5 tasks of 11 (23%)). The results for the word-processing items in this study were at an acceptable level of internal consistency with a Cronbach's Alpha score of 0.65 (See Section 3.7). Table 16 provides a summary of the descriptive results for the word-processing assessment.

Table 16 – Summary of word-processing results

|                                |     |
|--------------------------------|-----|
| Mean number of tasks correct   | 7.6 |
| Median number of tasks correct | 8   |
| Standard deviation             | 1.8 |
| Max number of tasks correct    | 10  |
| Min number of tasks correct    | 3   |

Table **17** shows the breakdown of results for the word-processing assessment. The results show, for each task, the level of difficulty (basic (1) or expert (2)) and the proportion correct and incorrect. Unlike the spreadsheet assessment, no tasks in the word-processing assessment were skipped by any participant. No one task was completed correctly by all participants and no participant correctly completed all the tasks.

Table 17 - Proportion correct for each task

| Task number | Difficulty level | Proportion Correct | Incorrect |
|-------------|------------------|--------------------|-----------|
| 1           | 1                | 0.96               | 0.04      |
| 2           | 1                | 0.91               | 0.09      |
| 3           | 1                | 0.67               | 0.33      |
| 4           | 1                | 0.85               | 0.15      |
| 5           | 2                | 0.76               | 0.24      |
| 6           | 1                | 0.90               | 0.1       |
| 7           | 2                | 0.38               | 0.62      |
| 8           | 1                | 0.82               | 0.18      |
| 9           | 1                | 0.99               | 0.01      |
| 10          | 2                | 0.60               | 0.4       |
| 11          | 2                | 0.32               | 0.68      |

Note: the shaded rows indicate expert skills.

For each task, participants were presented with an on-screen description of the task. If they chose to press the Start button, the data required for the task would be presented. The rationale behind not displaying the data at the first step for each task was the need to run the behind the screen time mechanism for each task. The time taken to read and understand the requirement of a task was not taken into account.

The results for correct task completion by number of participants are shown in Figure 18. Similar to results from the spreadsheet assessment, there was a higher completion rate for the basic tasks than for the expert level tasks.



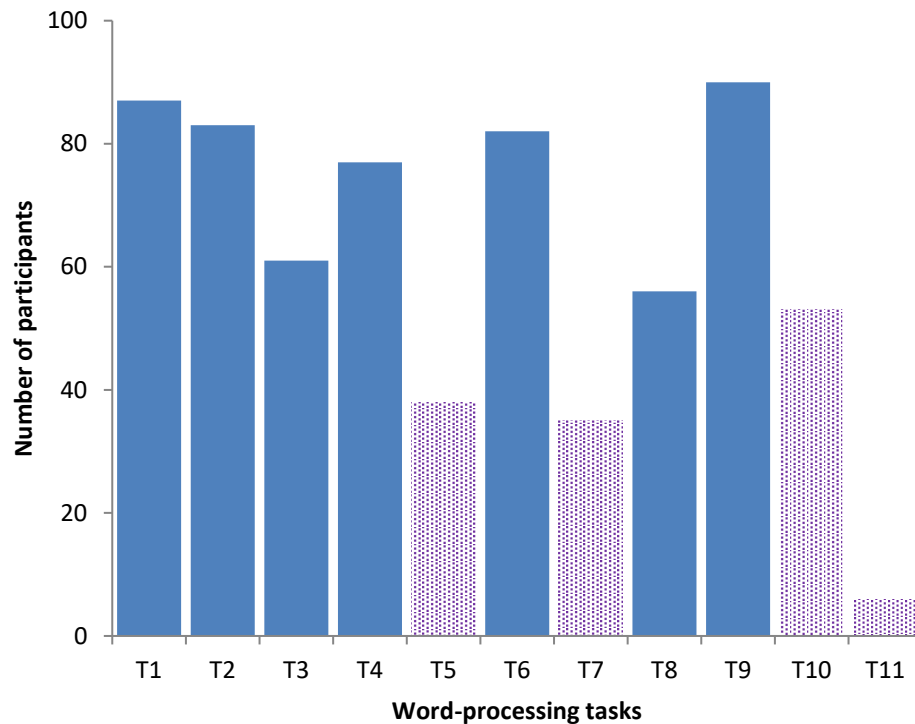


Figure 18 – Numbers of participants correctly completing each word-processing task

**Note:** Expert task bars have lighter shading

The number of correctly completed tasks are displayed as a frequency distribution in Figure 19. This graph clearly shows that no participant completed all eleven tasks correctly; it also shows that the minimum number completed was three of eleven tasks by two participants. It is interesting to note that, unlike the spreadsheet assessment, the results are skewed toward the high end of number of tasks.

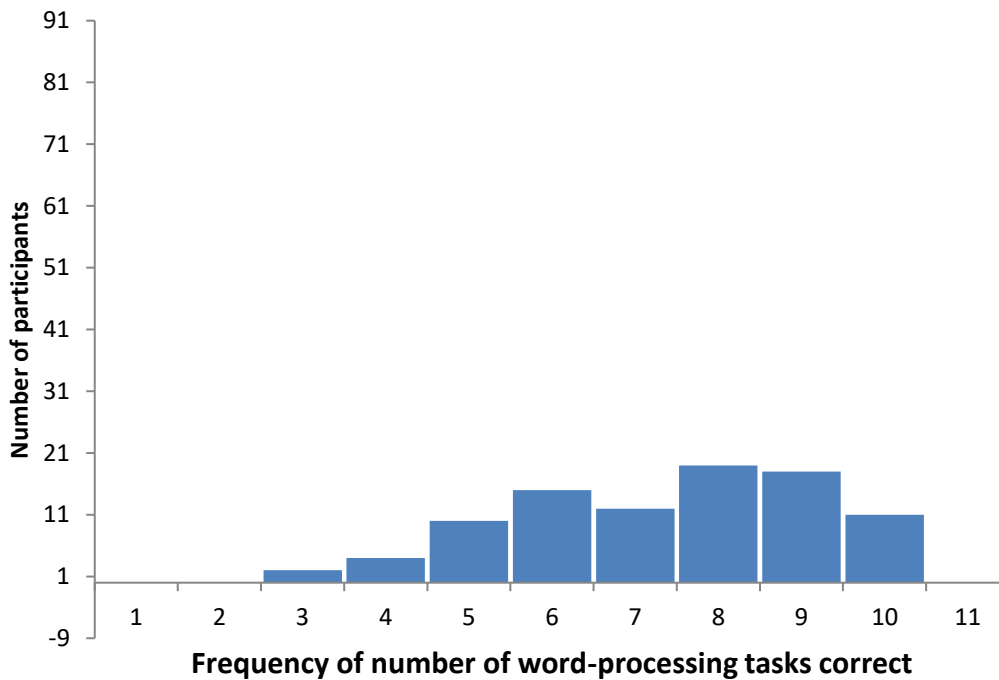


Figure 19 - Frequency for number of correct word-processing tasks

#### 4.3.2.1 Study participants compared with expected average

The panel involved in the development stage(Section 3.8) of this instrument ranked seven word-processing tasks of the eleven (67% of the tasks) as being tasks everyone who performs end-user computing in workplaces should be able to complete. In this study, the average completion was higher than this, ( $M = 7.59$  tasks of 11 (69%),  $SD = 1.9$  tasks of 11 (17%)). However, 43 participants (47%) scored lower than the study average for this assessment. Of these 43 participants 27 (63%) believed their knowledge was greater than the average computer end-user.

Of the tasks rated as expert tasks only task 8 was completed correctly by more than half of the participants (58%). Task 11 was only completed correctly by 7% of participants. No one task in this assessment was completed by all participants although only one participant failed to complete task nine. The average completion rate for the seven basic tasks was 5.9 tasks (84%). Thirty-five (38%) of participants completed all the basic tasks and while no one completed all tasks in this assessment 11 participants (12%) completed 10 of the 11 tasks (90%).

#### 4.3.2.2 Word-processing assessment result and time taken

As with the spreadsheet assessment, the time each participant took to complete a task was recorded in the background of the application. Participants were unaware of the timing process and it was considered that this background process had no effect on a participant being able to complete any of the tasks. Figure 20 displays the times recorded by each participant for the word-processing assessment against the number that each participant completed correctly.

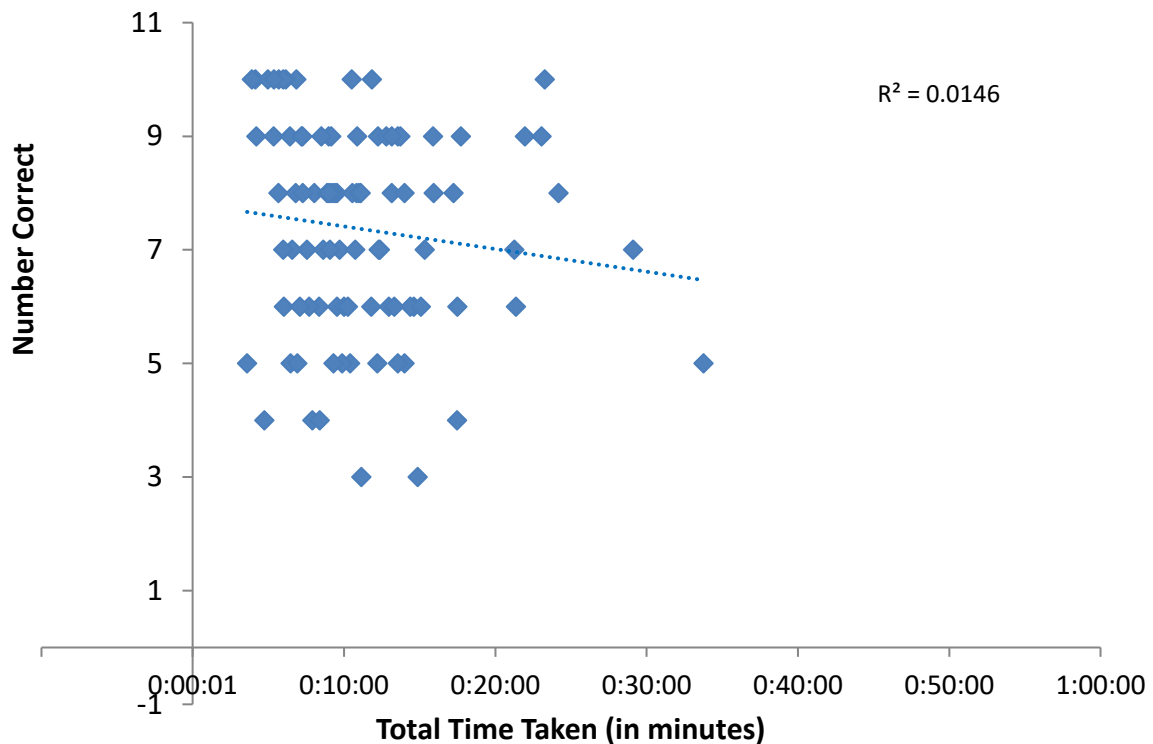


Figure 20 Number Correct and Time taken to complete WP assessment

The minimum time taken to complete the word-processing assessment was 00:03:36 with a corresponding number correct of five of 11 tasks or 45%. The longest time taken by a participant for this assessment was 00:33:46 with a corresponding number correct of also five of 11 tasks or 45%.

There was no correlation between time taken to complete the word-processing assessment and the score received for the word-processing assessment. ( $R = 0.12$   $N = (91)$   $P = 0.26$ ).

#### 4.3.2.3 Word-processing assessment result and measures of perception

A multiple regression analysis was conducted to evaluate how well the measures of perception predicted the word-processing assessment score. The linear combination of the three predictor variables were significantly related to a person's word-processing assessment score,  $F(3, 87) = 2.991$  ( $p = 0.035$ ). The adjusted  $R^2 = 0.062$  indicates that approximately 6% of the variance of the word-processing assessment score can be accounted for by the linear combination of the measures of perception. Table 18 presents standardised Beta weights to indicate the relative strength of the individual predictors.

**Table 18 - Summary of associations between word-processing assessment and measures of perception**

| Predictor       | beta   | t      | p     |
|-----------------|--------|--------|-------|
| Self-assessment | 0.367  | 2.695  | 0.008 |
| AEU             | -0.318 | -2.254 | 0.027 |
| EoDEUC          | -0.183 | -0.825 | 0.398 |

The association between the estimation of the extent of the domain of EUC was the only variable that was not a significant predictor of Word-Processing ability. Self-assessment and estimations of an AEU were both individually significant in this association. Based on this analysis it may be tempting to conclude that a person's perception of their ability or knowledge of EUC does not have an influence over their word-processing score. However, judgments about the relative importance of variables are difficult because of the correlations shown between each of these. There were negative associations between estimations of the AEU. These findings suggest that a person with high demonstrated ability with word-processing have a high estimations of their ability but a lower estimation of the average person. There was a significant associations between the measures of perception and demonstrated word-processing ability.

### 4.3.3 Combined assessment results

The results from the spreadsheet assessment and the word-processing assessment were combined to give a total correct for each participant as a percentage. A frequency distribution for combined results data is shown in Figure 21.

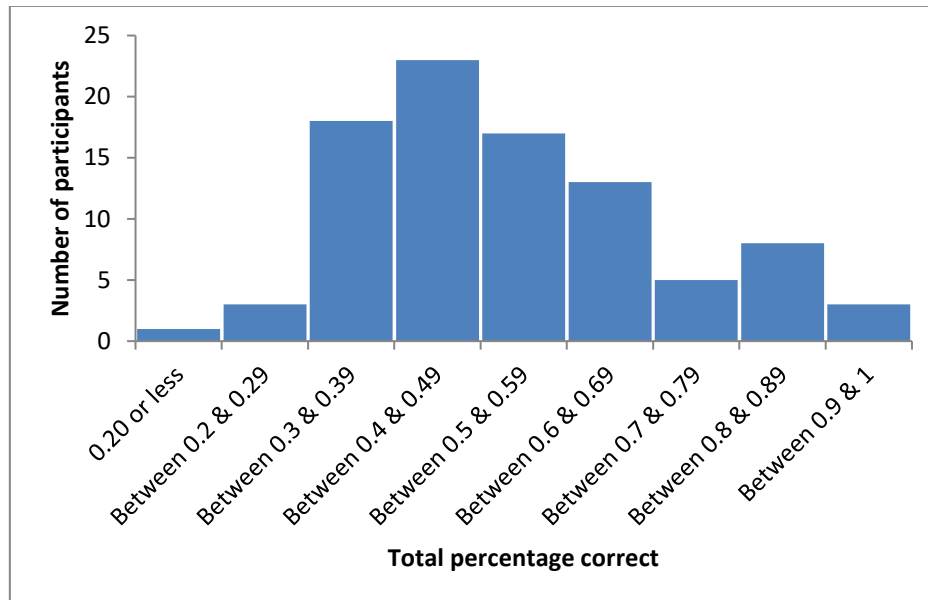


Figure 21 - Frequency distribution of total percentage correct

The graph shows a relatively normal distribution consistent with a study mean of 55% (SD.18) and Median of 54%. Results for each participant's combined assessment plotted against the total time taken by each participant to complete the assessments are displayed in (Figure 22).

No statistically significant relationship was found: ( $R = 0.15$ ,  $F(1, 89) = 1.12$ ,  $p = .28$ ).

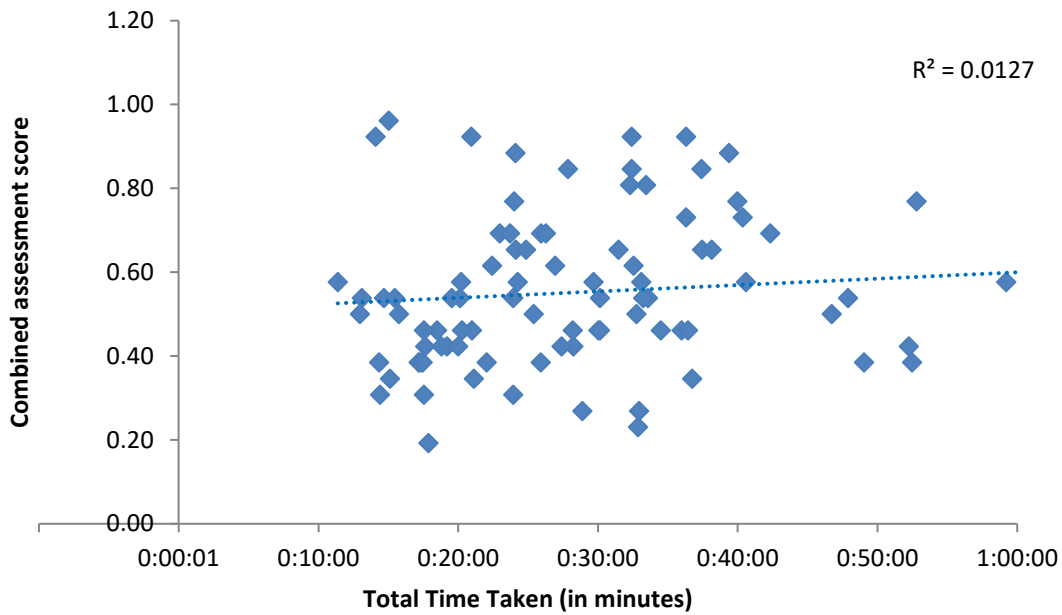


Figure 22- Association between total time taken and combined assessment score

Expert ratings from the panel involved in the development of the assessments highlighted seven word-processing and eight spreadsheet tasks as being basic tasks that should be correctly completed by “everyone who uses these applications for their employment”. The tasks rated as those everyone should be able to do were 58% (16 of 26 )of the tasks available. Results from the demonstrated skill assessments show that the average number correct for the participants in this study was slightly lower at 14 of 26 tasks ( $M = 55\%$ ,  $SD = 18\%$ ). The result includes both basic and advanced tasks. The findings specifically related to the tasks labelled basic showed a study mean of 5.4 (67% of basic SS tasks) and 5.85 (84% for basic WP tasks), with an overall average of 74% for basic tasks alone.

The overall results for all tasks were grouped by occupation and the average correct for each group along with the average age within the groups is presented in Table - **18**.

Table - 18 Assessment results by occupation

| Occupation                |        |     |                    |     |     | SS         | WP         |
|---------------------------|--------|-----|--------------------|-----|-----|------------|------------|
| Area                      | Number | Age | EoD <sub>EUC</sub> | SA  | AEU | assessment | assessment |
| Accounts                  | 9      | 45  | 259                | 100 | 82  | 0.62       | 0.61       |
| Administration            | 20     | 45  | 339                | 155 | 107 | 0.33       | 0.67       |
| Analyst                   | 5      | 41  | 123                | 10  | 9   | 0.69       | 0.85       |
| Environmental<br>Planning | 2      | 34  | 457                | 197 | 229 | 0.43       | 0.77       |
| HR                        | 2      | 40  | 213                | 88  | 72  | 0.37       | 0.55       |
| ICT                       | 3      | 37  | 128                | 60  | 20  | 0.87       | 0.70       |
| Library                   | 4      | 45  | 307                | 111 | 101 | 0.33       | 0.68       |
| Management                | 7      | 51  | 174                | 81  | 58  | 0.41       | 0.61       |
| Marketing                 | 4      | 30  | 200                | 72  | 76  | 0.40       | 0.59       |
| Misc.*                    | 3      | 43  | 348                | 243 | 172 | 0.44       | 0.67       |
| Project                   | 4      | 37  | 183                | 87  | 69  | 0.33       | 0.68       |
| Research &<br>Academic    | 26     | 42  | 211                | 101 | 63  | 0.53       | 0.69       |
| Self-employed             | 2      | 58  | 178                | 52  | 24  | 0.30       | 0.55       |

*\*Participants in the occupations represented by only one person were grouped together in the miscellaneous category*

Occupation was significantly correlated with demonstrated spreadsheet ability, estimation of the breadth of the domain (EoD<sub>EUC</sub>) and estimation of the average computer end user's knowledge. These correlations are shown in Table 19.

Table 19 - Significant correlations for participant occupation

|            |             | Estimation of |                    |       |
|------------|-------------|---------------|--------------------|-------|
|            |             | SS Results    | EoD <sub>EUC</sub> | AEU   |
| Occupation | R value     | -.317**       | .214*              | .226* |
|            | Probability | .002          | .042               | .031  |
|            | Number      | 91            | 91                 | 91    |

These findings suggest that people in certain occupations will have more use of spreadsheets and more skill using them. They also suggest that people in certain occupations may be more aware of the breadth of the domain and more aware of the skills of their peers.

The following sections presents findings from the self-perception measures used in this study.

#### 4.4 Above average effect

This study investigated the above average effect from two perspectives. The first perspective involved the measurement of perceptions. The first perception measurement, using a visual analogue scale, was of the participant's estimation of the extent of the domain of end-user computing (EoD<sub>EUC</sub>) (see Section 3.5). A second visual analogue scale was used to measure self-assessment and estimations of the average computer end-user (AEU) (see Section 3.5). The second perspective was the comparison of self-perceptions with demonstrated ability.

The following section presents findings showing evidence of the above-average effect . This is extended further by exploring the Dunning-Kruger Effect as an explanation of the above-average effect in Section 4.4.2.



#### 4.4.1 Tests of the above-average effect

##### 4.4.1.1 Test for $H_1$

**$H_1$**  *A person who uses end-user software as part of their employment will believe their computing skills to be better than the average computer end-user.*

The results in this section describe how individual participants rated their own ability compared with their perception of the ability of the average computer end-user. Table 20 shows the breakdown of self-assessments compared with a person's estimation of average computer end-user (AEU).

Table 20 - Self-assessments compared with AEU

| SA less than Average Computer<br>End-user | SA greater than Average<br>Computer End-user |
|---|--|
| 17 (19%)                                  | 74 (81%)                                     |

A significant correlation was found between a person's self-assessment of end-user computing knowledge and their estimation of the same knowledge for the average computer end-user ( $r = 0.73$ ,  $(N = 91)$   $p \leq 0.001$ ). This relationship is shown in Figure 23.

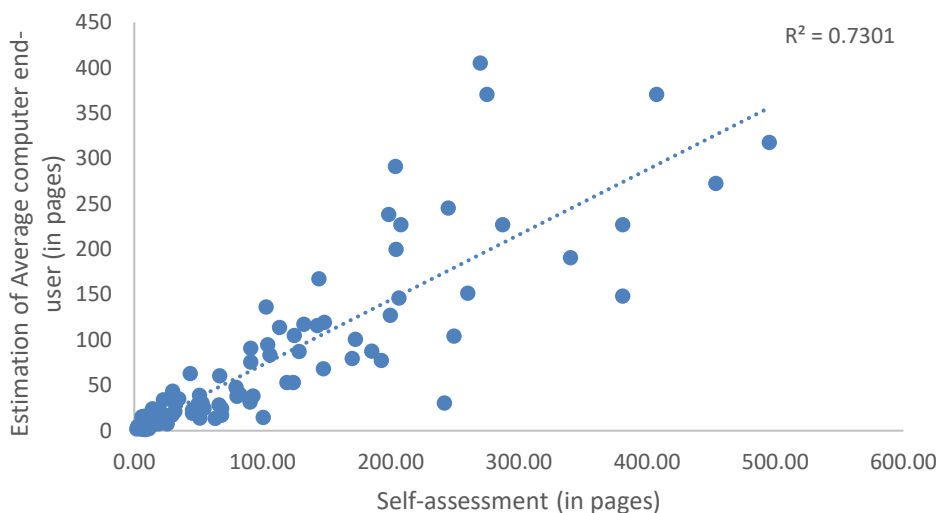


Figure 23 - Comparison of self-assessment with estimation of average computer end-user

Figure 24 displays a frequency distribution depicting differences between self-assessment of EUC knowledge and an estimation of the average computer end-user. This chart (Figure 24) shows that as a proportion of a participant's estimation of the breadth of the domain of EUC, the maximum proportion of self-assessed EUC was between 75% and 85% and that the similar maximum was estimated for the AEU .

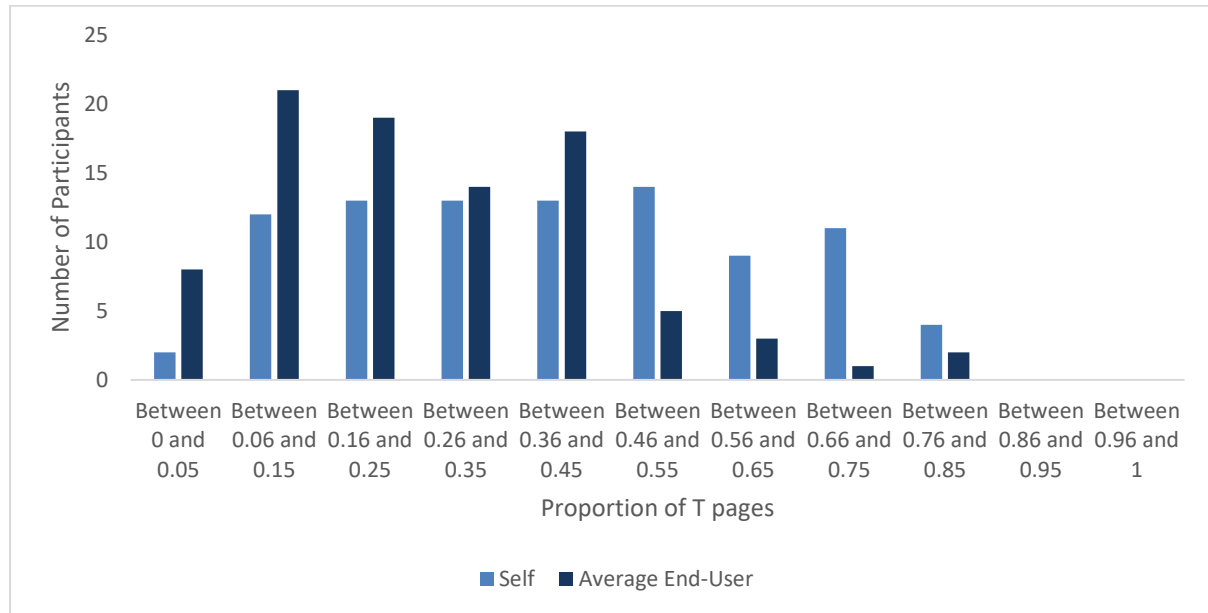


Figure 24 – Frequencies of self-reported EUC knowledge and that of average computer end-user

In order to quantify the difference between individuals' self-assessment and their perception of the knowledge of the average computer end-user, an additional measure was calculated and named Measure of AAE.

$$AAE = \text{Self-assessment} - AEU = I - X$$

**Equation 4 - AAE.**

The study average for Self-Assessment (I) as a proportion of estimation of the breadth of the domain of EUC (T) was M= 0.39 (SD 0.21), Median = 0.39 The maximum self-assessment as a proportion of the estimation of the breadth of the domain was 0.826 and the minimum estimation was 0.043.

The study average for estimation of the average computer end-user (X) as a proportion of estimation of the breadth of the domain of EUC (T) was M = 0.266 (SD 0.179), Median as a proportion of estimation of the breadth of the domain of EUC (T) was 0.23 . The maximum estimation of the average computer end-user as a proportion of the breadth of the domain of EUC (T) was 0.78 and the minimum was 0.02.

The average calculated AAE as a proportion of estimation of the domain of EUC (T) was 0.13 (SD = 0.165) with the maximum difference as a proportion of the estimation of the breadth of the domain of EUC (T) was 0.61 and with a minimum difference of -0.183. To interpret these results, it is useful to separate the results into three groups shown in Table 21.

Table 21 - Participant groups showing degree of above-average effect

|         |          |   |
|---------|----------|---|
| Group 1 | (n = 24) | Same or lower than the average computer end-user.   |
| Group 2 | (n = 58) | Difference between self and average computer end-user between 0 and 100 equivalent pages. |
| Group 3 | (n = 9)  | Difference between self and average computer end-user more than 100 equivalent pages      |

A relationship, confirmed by regression analysis, was found between a participant's self-assessment and the Measure of AAE ( $R = 0.30$ ,  $F(1, 89) = 37.57$ ,  $p \leq 0.001$ ). This relationship is shown in Figure 25 and can be described as how people's self-reported EUC knowledge is associated with their estimation of an AEU.

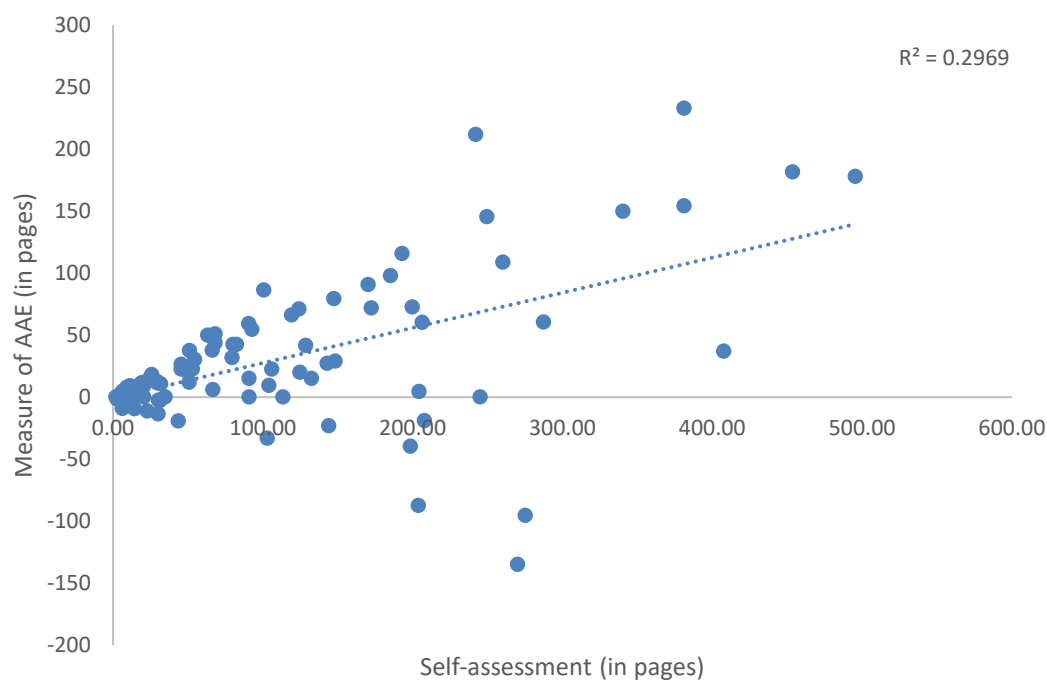


Figure 25 - Relationship between self-assessment and measure of AAE

These results show support for the acceptance of H<sub>1</sub>.

#### 4.4.1.2 Test for H<sub>2</sub>

**H<sub>2</sub> A combination of age, sex, experience, extraversion and conscientiousness is associated<sup>6</sup> with a person's self-rating of their own EUC ability in comparison with their ratings of the average computer end-user.**

A multiple regression analysis was conducted to evaluate how well expertise factors and demographic factors predicted occurrences of the above-average effect. The predictors were age; sex; conscientiousness; extraversion; learning approach; hours of computer use; occupation and number of SW applications used and the criterion variable was the calculated AAE value. The linear combination of the predictor variables was not significantly related to occurrences of the above-average effect,  $F(7, 83) = 1.972$ ,  $p = 0.069$ . Table 22 presents standardised beta weights to indicate the relative strength of the individual predictors.

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<sup>6</sup> Associated, in statistical terms, refers to any relationship between measured quantities that renders them statistically dependent (Hair, 1995).

Table 22 - Summary for predictors of AAE in end-user computing

| Predictor                        | Beta   | t      | Sig.  |
|----------------------------------|--------|--------|-------|
| Age                              | -0.007 | -0.060 | 0.952 |
| Sex                              | -0.263 | -2.346 | 0.021 |
| Conscientiousness                | 0.120  | 1.064  | 0.291 |
| Extraversion                     | -0.208 | -1.964 | 0.050 |
| Learning Mode                    | -0.009 | -0.081 | 0.936 |
| Hours of computer use            | 0.175  | 1.577  | 0.119 |
| Number of software packages used | -0.010 | -0.089 | 0.929 |
| Occupation                       | 0.075  | 0.650  | 0.518 |

Two of the predictor variables, Sex and Extraversion did produce individual negative significant associations with the occurrences of the AAE. This may mean that a person's sex, along with low scores for the trait of extraversion, are associated with occurrences of the above-average effect in an end-user computing context. However, the overall omnibus effect of this analysis produced a non-significant result. Based on this analysis and because the hypotheses is testing the association of a combination of variables working together to explain the strength of the calculated AAE no support was found for the acceptance of H<sub>2</sub>.

Given the non-significant result and in order to assess how close to the actual population the study sample is, the process of bootstrapping was undertaken. Bootstrapping is a resampling technique that uses random sampling with replacement by taking samples of the actual data, and calculating the population's parameter for each sample to derive a sample distribution. Bootstrap information is displayed in Table 23.

Table 23 - Bootstrap information for relationship between individual differences and the AAE

|                   |         | Bias  | Std. Error | Sig. (2-tailed) | Lower   | Upper  |
|-------------------|---------|-------|------------|-----------------|---------|--------|
| AAE               | 16.777  | 1.625 | 19.979     | .415            | -17.706 | 60.479 |
| Age               | -.006   | -.001 | .196       | .974            | -.411   | .364   |
| Sex               | -10.081 | .014  | 4.508      | .029            | -18.542 | -1.502 |
| Conscientiousness | 3.755   | -.235 | 3.934      | .344            | -3.684  | 11.869 |
| Extraversion      | -5.413  | -.086 | 2.609      | .046            | -10.796 | -.342  |
| Learning Approach | -.272   | -.078 | 1.287      | .845            | -2.824  | 2.210  |
| Hours use         | .290    | .011  | .229       | .218            | -.157   | .726   |
| Number SW apps    | .013    | -.105 | 1.297      | .993            | -2.724  | 2.362  |

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

The bootstrap analysis shows very little variance in significance values between these data and that presented using the study sample only. This suggests the study sample is representative of the greater population. Given the strength of the P value, the null hypotheses cannot be rejected. The p value of 0.069 suggests that for there is a 7% chance that the null hypothesis is not true and there is no relationship between individual differences and the difference between self-report and estimations of an AEU.

#### 4.4.1.3 Test for H<sub>3</sub>

**H<sub>3</sub> Self-perceived computing knowledge will be greater than demonstrated computing ability.**

Each participant completed a spreadsheet assessment (15 tasks) and a word-processing assessment (11 tasks). Assessments were created using an expert panel approach, which has been described, in section 0. The results for the spreadsheet items in this study were internally consistent with a Cronbach's Alpha score of 0.82 (See Section 3.7). Likewise the results for the word-processing assessment showed an acceptable level of internal consistency with a Cronbach's Alpha score of 0.65 (See Section 3.7).

Results for each assessment for each participant were combined to give a combined assessment result (Section 4.2, Equation 1). This result is a combination of a participant's spreadsheet and word-processing assessment results as a proportion of the total number of tasks. Figure 26 shows a relatively normal distribution of results for the combined assessment results.

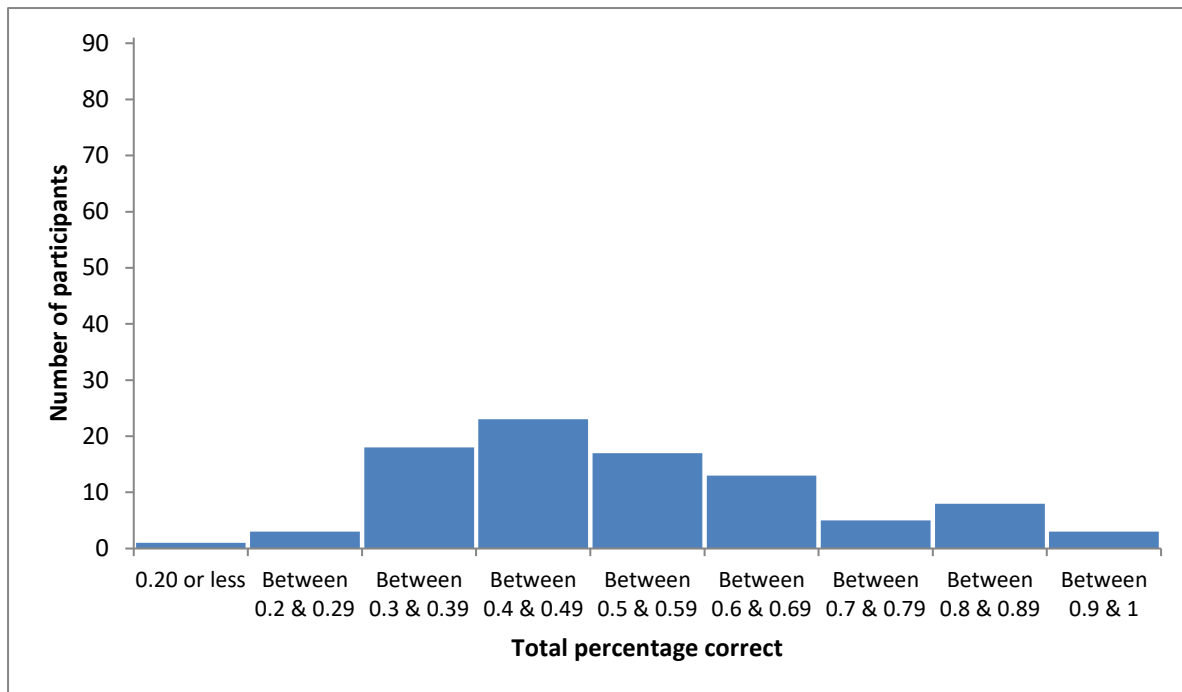


Figure 26 - Distribution of combined assessment results

Table 24 is a matrix developed to organise participant's self-rating compared with the average computer end user grouped by participant's demonstrated ability relative to the average for the study sample. This table shows that 67 (74%) participants believed their end-user computing knowledge to be greater than that of the average computer end-user. Fifty-three (58%) participants had lower demonstrated score than the study average. Of these 53 participants 33 (62%) believed their EUC knowledge to be greater than that of the average computer end-user.

Table 24 - Contingency table of self-assessment and combined assessment results

| Combined Assessment | Self-Assessment                 |                                 |
|---------------------|---------------------------------|---------------------------------|
|                     | below average computer end-user | above average computer end-user |
| Below average       | 20                              | 33                              |
| Above average       | 4                               | 34                              |

To assess relationships between these variables, a Chi<sup>2</sup> analysis was undertaken. Chi<sup>2</sup> analysis assumes a simple random sample, a categorical variable and at least five observations in each level of the variable (Babbie, 2007). As discussed in section 3.3, while not straightforwardly random the sampling approach approximates randomness. The variable ‘perception of knowledge of average end-user’ is categorical (‘above’ or ‘below’) and there are more than five observations at each level of the variable. Chi<sup>2</sup> is therefore an appropriate analysis to perform on these data.

The Chi<sup>2</sup> calculation is used to ascertain a significant difference between expected and observed frequencies in one or more of the categories, and if there is a difference, is this due to a variation in the sample or due to an actual difference? In the case of this study, the null hypothesis would be “the data are consistent with a specified distribution” where the specified distribution in this case is equal at each level of the matrix (i.e., there is no relationship between the variables). The results from this analysis confirm a statistically significant relationship and rejection of the null hypothesis,  $\chi^2(1, N=91) = 8.4$   $p = .0037$ .

An alternative way of looking at the raw data is to compare the study results with those expected by the panel of experts. Of the fifteen tasks in the spreadsheet assessment, seven were labelled moderately advanced, leaving eight in which everyone using the application should be competent. Similarly, of the eleven Word assessment tasks, four were labelled as moderately advanced, seven basic. A breakdown of the study results compared with the panel ranking is shown in Table 25.



Table 25- Breakdown of study results compared with panel expectations

| Assessment         | Number<br>of tasks | Mean Tasks<br>completed | Number<br>Greater<br>than Study<br>Average | Panel<br>Expected<br>mean | Number<br>completing<br>1 or more<br>advanced<br>tasks | Mean #<br>Advanced<br>Tasks (%) |
|--------------------|--------------------|-------------------------|--|---------------------------|--|---------------------------------|
| Spreadsheet        | 15                 | 7.0 (47%)               | 33 (36%)                                   | 8 (53%)                   | 49 (53%)   | 3 / 7 (43%)                     |
| Word<br>Processing | 11                 | 7.3 (67%)               | 48 (53%)                                   | 7 (64%)                   | 72 (79%)   | 2/4 (50%)                       |

The data from the study were further tested using multiple regression analysis to test for associations between perception measures and demonstrated ability. When the end-user assessments were considered together the association between the linear combination of self-assessment and estimation of the AEU were significantly associated with demonstrated ability.  $\text{adj}R^2 = 0.150$ ,  $F(2, 88) = 8.937$ ,  $p \leq 0.000$ .

Table 27 presents standardised beta weights to indicate the relative strength of the individual predictors.

**Table 27 - Summary of perception predictors of demonstrated ability**

| Predictor         | beta   | t      | p     |
|-------------------|--------|--------|-------|
| Self-Assessment   | 0.486  | 3.763  | 0.000 |
| Estimation of AEU | -0.508 | -3.929 | 0.000 |

Results indicate that self-perception measures have an association with demonstrated end-user computing ability. Overall, the analysis indicates support for the acceptance of  $H_3$ .

#### 4.4.1.4 Test for H<sub>4</sub>

**H<sub>4</sub> A combination of age, sex, experience, extraversion and conscientiousness are associated with estimations of the computing ability of the average computer end-user.**

A multiple regression analysis was conducted to evaluate how well expertise, individual differences and demographic factors predicted occurrences of the above-average effect. The predictors were: age; sex; conscientiousness; extraversion; learning mode; hours of computer use, number of SW applications used, occupation, and demonstrated ability. The criterion variable was the perception value estimation of the average computer end-user's ability (AEU). The linear combination of the predictor variables was significantly related to a person's perception of the average computer end-user,  $\text{adj}R^2 = 0.107$ ,  $F(9, 81) = 2.201$ ,  $p = 0.03$ . The adjusted  $R^2$  value indicates that approximately 10% of the variance of AEU can be accounted for by the linear combination of the measures included.

It should be noted that, although the adj R-squared value appears low, this is not uncommon in multiple regression analysis. Important conclusions can be drawn about how changes in the predictor values are associated with changes in the response values. The significant predictor value (in this case  $p=0.03$ ) represents the mean change in response of one variable while still holding the remaining predictors constant.

Table 26 presents standardised beta weights to indicate the relative strength of the individual predictors. Only the association between age and AEU was individually significant. Based on these analyses it is tempting to conclude that the only useful predictor of the AEU was age with the negative association suggesting that younger people may have a more conservative view of an AEU's knowledge than older participants. However, judgments about relative importance of predictors are difficult because they are correlated but it is difficult, from the results in Table 26 to make any assumptions about individual variables relationships with the dependent. However, as the result suggest, this combination of variables is significantly associated with a person's estimations of the AEU's computing knowledge.

Table 26 - Summary for predictors of AEU's EUC knowledge

| Predictor                        | Beta   | t      | Sig.  |
|----------------------------------|--------|--------|-------|
| Age                              | -0.286 | -2.47  | 0.015 |
| Sex                              | 0.098  | 0.861  | 0.392 |
| Conscientiousness                | 0.210  | 1.88   | 0.063 |
| Extraversion                     | -0.040 | -0.364 | 0.717 |
| Learning Mode                    | -0.132 | -1.266 | 0.209 |
| Hours of computer used           | 0.021  | 0.187  | 0.852 |
| Number of software packages used | 0.045  | 0.413  | 0.681 |
| Occupation                       | 0.183  | 1.622  | 0.109 |
| Demonstrated EUC                 | -0.218 | -1.727 | 0.088 |

Overall, the analysis indicates support for the acceptance of H<sub>4</sub>.

#### 4.4.2 Tests of the Dunning-Kruger Effect

The following four hypotheses were developed to test for evidence of the DKE.

##### 4.4.2.1 Test for H<sub>5</sub>

**H<sub>5</sub> A person's self-assessment of end-user computing skill will be associated with their awareness of the breadth of the domain of EUC.**

Participants' perception of how much of all computing could be classed as EUC was measured using a visual analogue scale as described in Chapter 3 (Methods). In this study, this measure is referred to as the Extent of Domain (EoD<sub>EUC</sub>).

The histogram (Figure 27) represents the distribution of the participants' perception of how many pages of a 1000 page book about computing, would be dedicated to end-user computing. (Median = 200; Mean = 247, SD = 191).

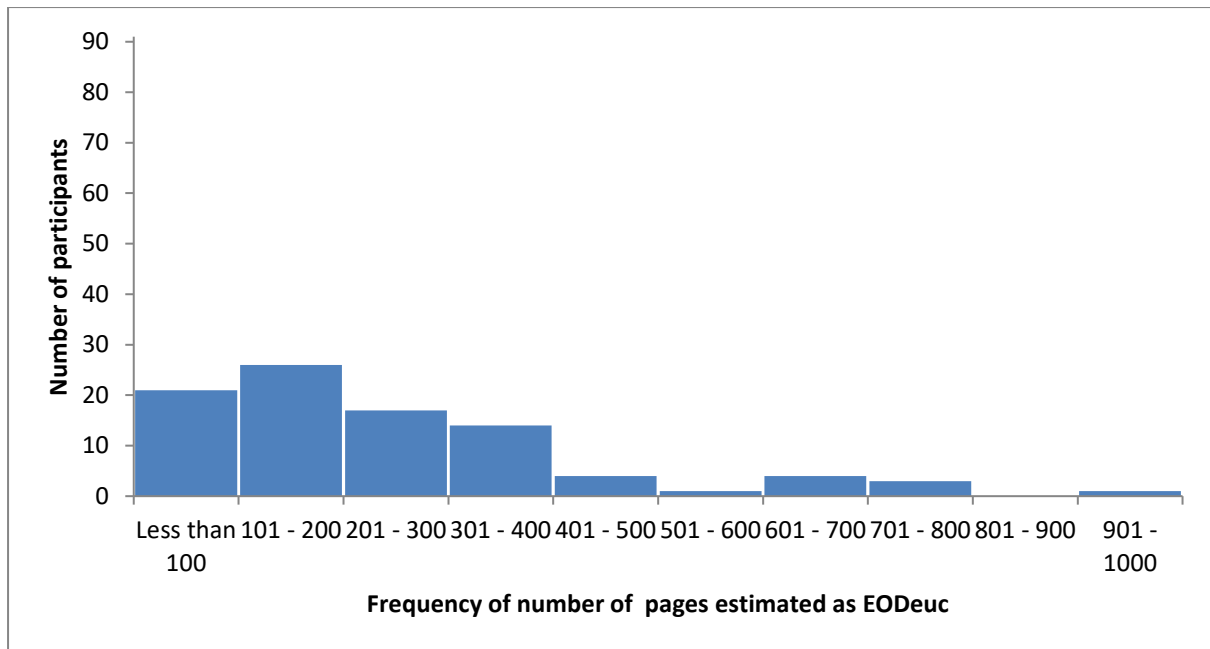


Figure 27 - Frequency distribution of Extent of domain of end-user computing

Once a participant had made their estimation on the line regarding their perception of the breadth of the domain of EUC, their mark (T) was transferred as the endpoint on an identical line. On this second line participants were asked to mark (I) to indicate how much of EUC out the pages they had indicate for T they believed they knew. This process is outlined in detail in Section 3.5.

This information has been created as frequency distribution of the proportion I pages for each participants estimation for T. This distribution is displayed in Figure 28.

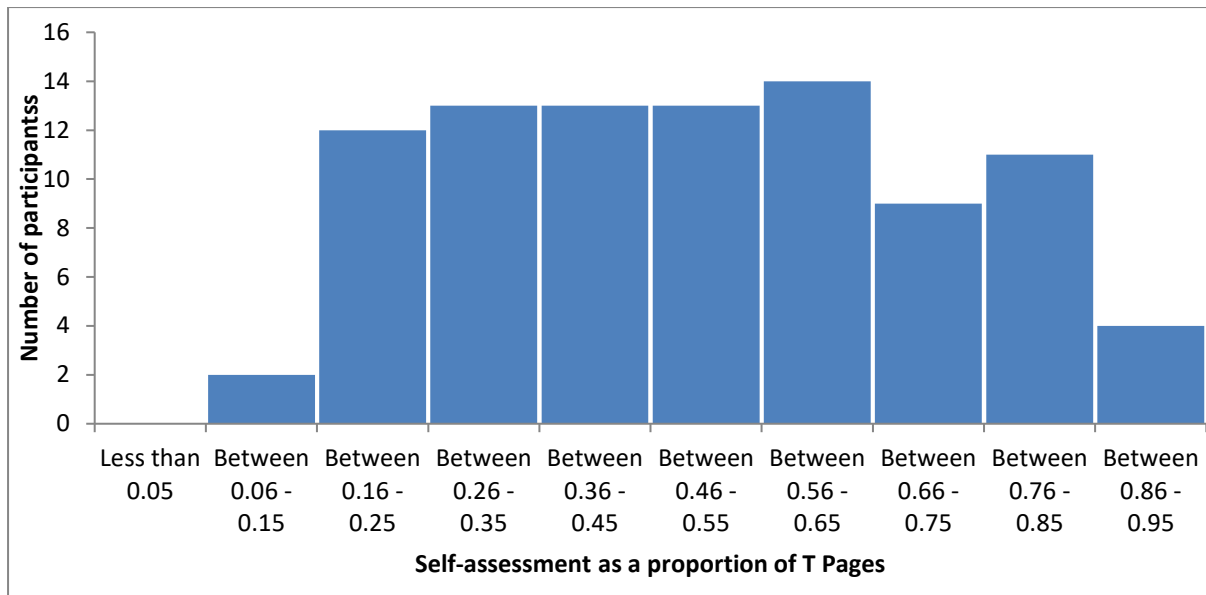


Figure 28 - Frequency distribution of self-assessment as a proportion of breadth of EUC

Regression analysis shows that there is a significant positive correlation between a person's estimation of the breadth of a domain ( $EoD_{EUC}$ ) and self-assessment: : ( $R = 0.31$ , ( $N=91$ )) =,  $p = 0.002$ ,- This result suggests that a person's self-assessment is associated with their estimation of the breadth of a particular domain, in this case end-user computing. In other words, and related to the example used in this study, a person who believes that the sub domain of EUC occupies a great deal of the space in the domain of computing, may also be likely to be excessive in their assessment of their own knowledge in the sub domain (EUC) than someone who appears to be more aware of the domain of computing. This relationship is shown in Figure 29 and shows support for the acceptance of  $H_5$ .

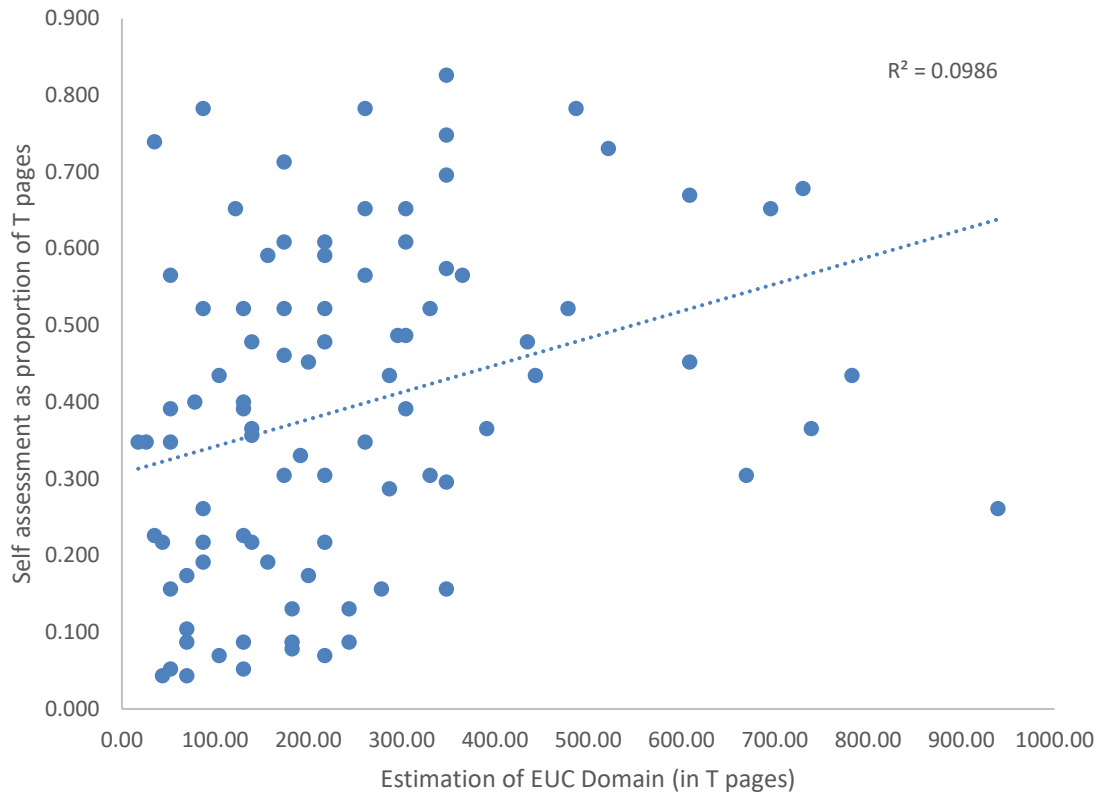


Figure 29 - Association between perception of  $EoD_{EUC}$  and self-assessment

#### 4.4.2.2 Test for $H_6$

**$H_6$**  The difference between people's self-reported EUC knowledge and their estimation of the knowledge of an average computer-end-user is associated with awareness of the breadth of EUC.

Participants placed marks on two lines as explained in Section 3.5. The mark (T), on the first line, represented a participant's estimation of the breadth of the domain of end-user computing ( $EoD_{EUC}$ ). Two marks on the second line were made to represent self-assessment (I) and estimation of the average computer end-user (X). The difference between estimation of an AEU and the self-assessment was calculated as a proportion of the number of equivalent self-assessed pages.

There was no significant correlation between the difference of self-report in equivalent pages and estimation of the ability of an AEU in equivalent pages and an estimation of the breadth of the domain of EUC in pages,  $r(n=91) = 0.075$ ,  $p = 0.480$ . This finds no support for the acceptance of  $H_6$ .

The association between the calculated AAE and the estimation of the breadth of the domain of EUC is displayed in Figure 30.

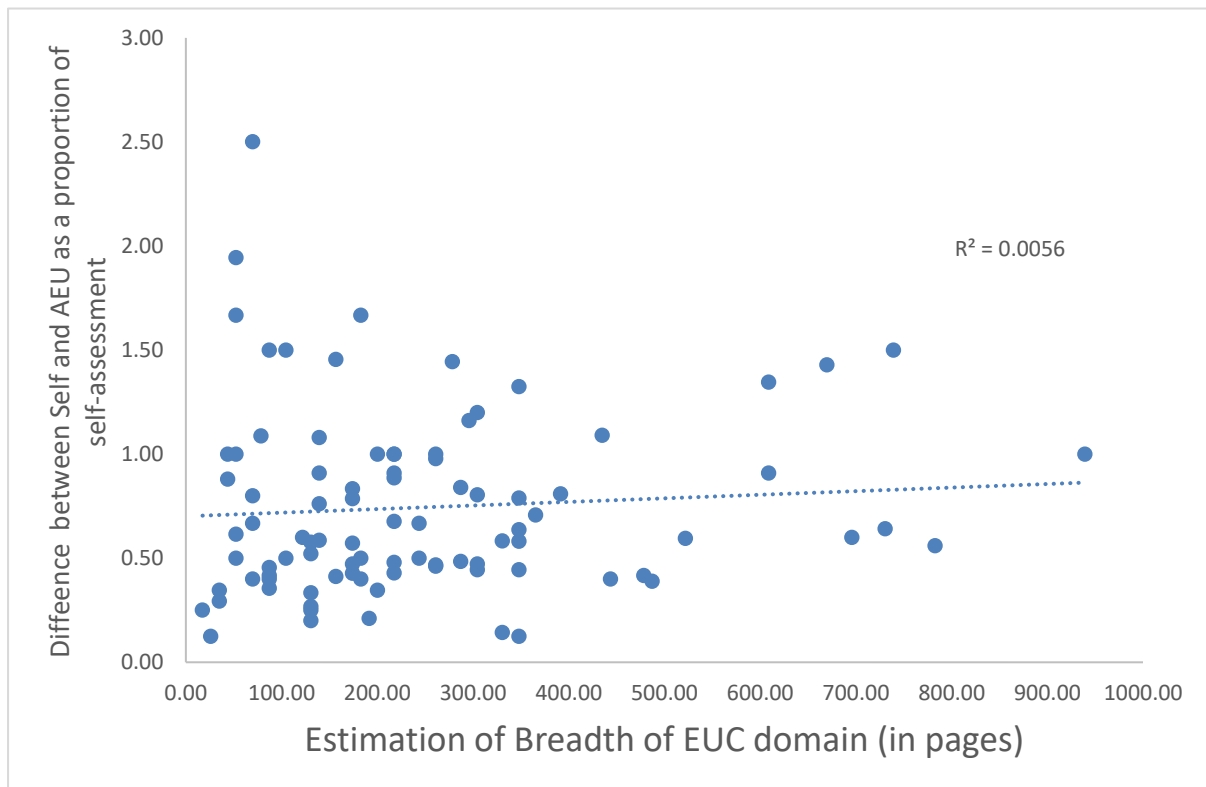


Figure 30 - Association between perception of  $EoD_{EUC}$  and the differences between a self-report and estimations of the AEU.

Figure 26 suggests that the estimations a person makes of an AEU compared with themselves are not significantly associated with that person's awareness of the breadth of the domain of EUC.

Given the non-significant result and in order to assess how close to the actual population the study sample is, the process of bootstrapping was undertaken. Bootstrapping is a resampling technique that uses random sampling with replacement by taking samples of the actual data, and calculating the population's parameter for each sample to derive a sample distribution. Bootstrap information is displayed in Table 27.

Table 27 - Bootstrap information for association between DKE and AAE

| Model | B      | Bias  | Std. Error | Sig. (2-tailed) | 95% Confidence Interval |         |
|-------|--------|-------|------------|-----------------|-------------------------|---------|
|       |        |       |            |                 | Lower                   | Upper   |
| AAE   | 32.791 | 5.007 | 52.719     | .518            | -50.733                 | 160.988 |

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

#### 4.4.2.3 Test for $H_7$

***$H_7$  A person's demonstrated EUC knowledge will be associated with their estimation of the breadth of EUC.***

There was no association between demonstrated spreadsheet and word-processing ability, and a person's estimation of the breadth of the domain of EUC,  $\text{adj}R^2 = .026$ ,  $F(2,88)=2.214$ ,  $p=.115$ . Table 28 presents standardised beta weights to show the relative strength of each of the predictors that are shown graphically in Figure 31. This graph shows that there is little or no relationship between the Word score and estimation of the breadth of the domain but that there is between the spreadsheet result and estimation of the breadth of the domain. This may mean that people will generally gain a better result using a word-processing application than a spreadsheet. This may be due to the level of functionality available in a spreadsheet application that requires some level of skill or knowledge to use, whereas, using a word-processing application it is a simple operation to enter some text and add some level of formatting.



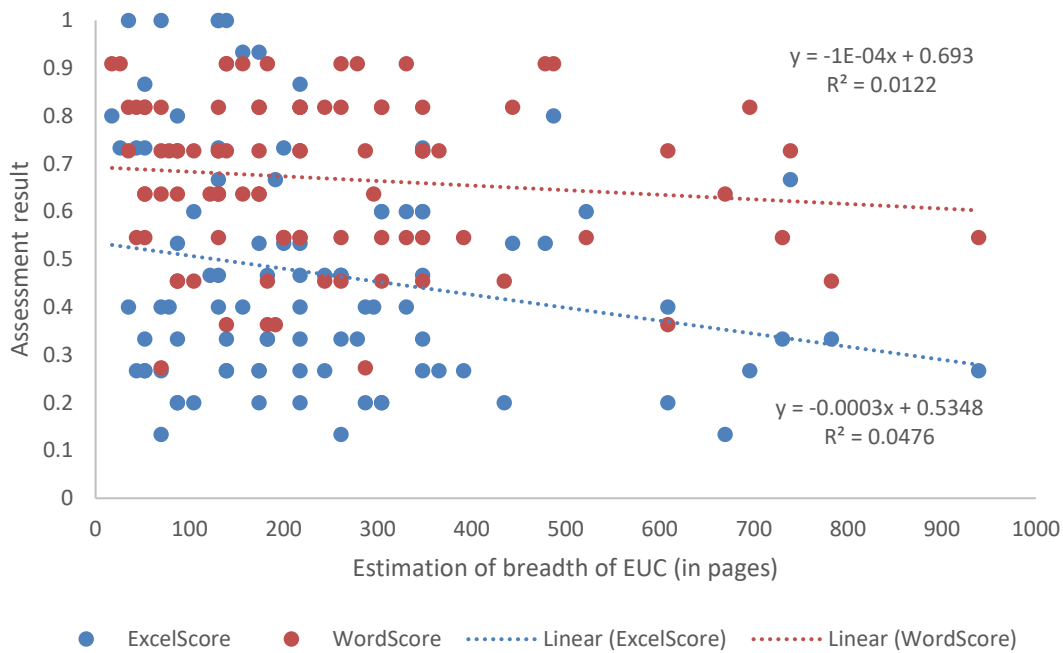


Figure 31 - Relationship between assessment results and estimation of breadth of the EUC domain.

Table 28 - Results of association between demonstrated ability and  $EoD_{EUC}$

|           | beta  | t      | p   |
|-----------|-------|--------|-----|
| SS Result | -.210 | -1.819 | n.s |
| WP Result | -.018 | -.158  | n.s |

Given the non-significant result and in order to assess how close to the actual population the study sample is, the process of bootstrapping was undertaken. Bootstrapping is a resampling technique that uses random sampling with replacement by taking samples of the actual data, and calculating the population's parameter for each sample to derive a sample distribution. Bootstrap information is displayed in Table 29.

Table 29 - Bootstrap information for relationship between Estimation of DoEUC and Demonstrated EUC

|                 | B        | Bias   | Std. Error | Sig. (2-tailed) | 95% Confidence Interval |         |
|-----------------|----------|--------|------------|-----------------|-------------------------|---------|
|                 |          |        |            |                 | Lower                   | Upper   |
| DoEUC           | 338.0902 | -2.778 | 85.42      | 0.002           | 170.677                 | 514.219 |
| Spreadsheet     |          |        |            |                 |                         |         |
| Result          | -168.833 | 1.441  | 71.35      | 0.022           | -308.454                | -20.881 |
| Word-Processing |          |        |            |                 |                         |         |
| result          | -20.7953 | 1.082  | 116.125    | 0.868           | -248.265                | 206.248 |

The bootstrap analysis shows very little variance between these data and that presented using the study sample only. This suggests the study sample is representative of the greater population.

Given the strength of the P value, the null hypotheses cannot be rejected. The p value of 0.115 suggests that for there is approximately an 11% chance that the null hypothesis is not true and there is no association between individual differences and the difference between self-report and estimations of an AEU. However, the omnibus effect of this combination of variables support the rejection of  $H_7$ . Test for  $H_8$

***$H_8$  Perceptions regarding the estimated breadth of the EUC domain are associated with a person's computing ability combined with demographic and expertise factors and levels of extraversion and conscientiousness.***

A multiple regression analysis was conducted to evaluate how well expertise, individual differences and demographic factors predict occurrences of the Dunning-Kruger effect. The predictors were : age; sex; conscientiousness; extraversion; learning approach; hours of computer use; the number of SW applications used and the assessment results. The criterion variable was the perception value, Extent of Domain ( $EoD_{EUC}$ ). The linear combination of the predictor variables was not significantly related to a person's perception of  $EoD_{EUC}$ ,  $F(9, 81) = 1.825$ ,  $p = 0.076$ . The adjusted  $R^2$  value was 0.076 indicating that approximately 8% of the variance of  $EoD_{EUC}$  can be accounted for by the linear

combination of the measures included. Table 30 presents standardised beta weights to indicate the relative strength of the individual predictors.

Table 30 Predictors of EoD<sub>EUC</sub>

| Predictor              | beta  | t      | p    |
|------------------------|-------|--------|------|
| Age                    | -.213 | -1.800 | .075 |
| Sex                    | .049  | .418   | .690 |
| Occupation             | .219  | 1.754  | .072 |
| Conscientiousness      | .234  | 2.051  | .042 |
| Extraversion           | -.013 | -.114  | .907 |
| Learning approach      | -.116 | -1.069 | .264 |
| Hours of computer use  | .100  | .847   | .412 |
| Number SW used         | .033  | .293   | .770 |
| Total Assessment Score | -.209 | -1.629 | .107 |

Conscientiousness was the only individual variable that had an association with the EoD<sub>EUC</sub>. This may suggest that people with a high level of conscientiousness will be more conservative, perhaps more accurate, in their estimation of the breadth of the domain of EUC. However, the overall omnibus effect of this analysis produced a non-significant result.

Given the non-significant result and in order to assess how close to the actual population the study sample is, the process of bootstrapping was undertaken. Bootstrapping is a resampling technique that uses random sampling with replacement by taking samples of the actual data, and calculating the population's parameter for each sample to derive a sample distribution. Bootstrap information is displayed in Table 22.

Table 31 -Bootstrap information for relationship between expertise, individual differences and demographic factors and the Dunning-Kruger effect

|                       | Bias | Std. Error | Sig. (2-tailed) | 95% Confidence Interval |      | Lower    | Upper   |
|-----------------------|------|------------|-----------------|-------------------------|------|----------|---------|
|                       |      |            |                 |                         |      |          |         |
| Age                   |      | -3.543     | -.095           | 1.786                   | .048 | -7.246   | -.267   |
| Sex                   |      | 18.678     | 2.606           | 39.895                  | .635 | -57.045  | 101.988 |
| Occupation            |      | 11.321     | .347            | 6.278                   | .074 | -.103    | 23.889  |
| Conscientiousness     |      | 81.206     | -.539           | 44.209                  | .069 | -7.131   | 164.293 |
| Extraversion          |      | -3.433     | -.760           | 25.383                  | .909 | -54.724  | 46.201  |
| Learning Approach     |      | -15.228    | 1.178           | 12.867                  | .246 | -38.698  | 10.157  |
| Hours of computer use |      | 1.797      | .096            | 2.496                   | .457 | -3.316   | 7.139   |
| Number of SW used     |      | 3.944      | -.594           | 16.050                  | .809 | -27.778  | 35.191  |
| Demonstrated EUC      |      | -222.156   | 4.574           | 144.287                 | .117 | -513.477 | 75.624  |

The bootstrap analysis shows very little variance between these data and that presented using the study sample only. This suggests the study sample is representative of the greater population.

Given the strength of the p value the null hypothesis cannot be rejected The p value of 0.076 suggests that for there is approximately an 8% chance that the null hypothesis is not true and there is no relationship between individual differences and the occurrences of the DKE. Based on this analysis and because the hypothesis is testing the association of a combination of variables working together to explain the relative strength of the association there is no for the acceptance of  $H_8$ .

#### 4.4.3 Bi-variate correlations between predictors of AAE and DKE

Simple correlation analyses were performed between the variables used as predictors for the biases AAE and DKE. Table 32 highlights the positive and negative correlations between predictor variables. Full results from these correlations are in displayed in Table 38, which is located in Appendix 3.

Table 32 - Significant associations between predictor variables

| <b>Positive correlations between</b>       | <b>r</b> | <b>p</b> |
|--|----------|----------|
| Age and the number of SW applications used | .218     | .038     |
| Age and conscientiousness                  | .291     | .012     |
| Sex and extraversion                       | .212     | .043     |
| Sex and conscientiousness                  | .262     | .012     |
| WP & hours of SW use                       | .337     | .001     |
| <b>Negative correlations between</b>       |          |          |
| Occupation and hours of SW use             | -.312    | .003     |
| Occupation and approach to learning        | -.224    | .033     |
| Occupation & SS                            | -.317    | .002     |
| Age & SS                                   | -.217    | .039     |
| Sex & SS                                   | -.337    | .001     |
| Extraversion & SS                          | -.309    | .003     |
| Extraversion & WP                          | -.255    | .015     |

## 4.5 Summary of results

This chapter began by presenting and outlining the results from the collection of demographic, expertise and personality data. These results were provided to offer information relevant for interpreting the results from the perception-measure data collection and the associations involved between these two sets of data.

The results from the skill assessments suggest a variation in skill levels for people who use this type of software as part of their employment. Generally, word-processing demonstrated ability was at a higher level than for demonstrated spreadsheet ability, although no one person correctly completed the word-processing assessment. Self-assessment measures indicate that more participants rated their skills above that of the average end-user than were above-average on the skill assessment tasks. Results also suggest that participants in this study had a skill level lower than might be expected by EUC SMEs.

The following is a summary of how each hypothesis was or was not supported by the analysis of results in this chapter.

### 4.5.1 Hypotheses developed to test for AAE

**H<sub>1</sub>      A person who uses end-user software as part of their employment will believe their computing skills to be better than the average computer end-user.**

The results support the acceptance of H<sub>1</sub>.

Raw results from the data showed that the majority of participants (81%) ranked their EUC knowledge greater than they ranked the EUC knowledge of the average computer user. Statistically significant evidence was found for the above-average effect when comparing self-assessment with the AEU.

Using a measure for the AAE (Section 3.5) statistical evidence was found for a relationship between self-assessment and the AAE.

**H<sub>2</sub> A combination of age, sex, experience, extraversion and conscientiousness is associated<sup>7</sup> with a person's self-rating of their own EUC ability in comparison with their ratings of the average computer end-user.**

The results show no support for the acceptance of H<sub>2</sub>.

Statistically significant evidence showed that a *combination* of demographic, expertise, and personality factors could not be used as a predictor for the above-average effect. However, individually participant's sex and levels of extraversion were found to be significant predictors in this relationship.

**H<sub>3</sub> Self-perceived computing knowledge will be greater than demonstrated computing ability.**

The results support the acceptance of H<sub>3</sub>.

Several approaches were taken in analysing the data related to this hypothesis and there was statistically significant evidence to show that demonstrated ability will differ from self-assessed ability in end-user computing tasks. A Chi-squared analysis showed a significant variance in observed and expected values with respect to self-reported computing knowledge and demonstrated computing knowledge . Multiple regression analysis confirmed that there was a significant association between self-report and demonstrated skill. Finally, the results from this study were lower than those expected by the subject matter experts involved in the instrument development process.

**H<sub>4</sub> A combination of age, sex, experience, extraversion and conscientiousness are associated with estimations of the computing ability of the average computer end-user.**

The results support the acceptance of H<sub>4</sub>.

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<sup>7</sup> Associated, in statistical terms, refers to any relationship between measured quantities that renders them statistically dependent. [Is there a citation that could be used here to support this definition? That would be great to have.]

Statistically significant evidence confirmed that a combination of demographic, expertise, and personality factors could be used as a predictor for the above-average effect. A participant's age was found to be a significant predictor for this relationship.

#### **4.5.2 Hypotheses developed to test for DKE**

**H<sub>5</sub> A person's self-assessment of end-user computing skill will be associated with their awareness of the breadth of the domain of EUC.**

The results support the acceptance of H<sub>5</sub>.

Statistically significant evidence showed support for a positive association between a person's self-assessment and their estimation of EoD<sub>EUC</sub>.

**H<sub>6</sub> The difference between people's self-reported EUC knowledge and their estimation of the knowledge of an average computer-end-user is associated with awareness of the breadth of EUC.**

The results show no support for the acceptance of H<sub>6</sub>.

No significant statistical evidence was found to support the DKE (based on perception measures) as a possible explanation for occurrences of the above-average effect in EUC. That is, a person's estimation of the average person was more likely based on what they believe they themselves know about EUC rather than what they believe there is to know about EUC.

**H<sub>7</sub> Perceptions regarding the estimated breadth of the EUC domain are associated with a person's demonstrated computing ability.**

The results show no support for the acceptance of H<sub>7</sub>.

No significant statistical evidence was found to support DKE based on an association between a person's demonstrated computing ability and their estimation of EoD<sub>EUC</sub> of EUC.



**H<sub>8</sub>      Perceptions regarding the estimated breadth of the EUC domain are associated with a person's computing ability combined with demographic and expertise factors and levels of extraversion and conscientiousness.**

The results show no support for the acceptance of H<sub>8</sub>.

The results did not demonstrate that the combination of expertise, demographic and personality traits predicts the DKE.

The results from this chapter are discussed in detail in the following chapter.

## Chapter 5 Discussion

### 5.1 Introduction

The purpose of this study was to assess influences of expertise, demographic factors and individual differences on occurrences of the above-average effect in an end-user computing context. For this study, eight hypotheses were developed to test the over-arching research question “*What individual differences are critical in instances of the above-average effect in the context of end-user computing?*” The first four hypotheses related directly to the above-average effect while the remaining four were designed to test for the presence of the Dunning-Kruger effect.

Aligned with expectations, there was evidence of an above-average effect in both the comparisons between a person’s self-assessment relative to an estimation of skill of a perceived average computer end-user, and when comparing perceptions of EUC knowledge with demonstrated skill. Contrary to expectations, the combination of expertise, demographic and personality traits did not predict an above-average effect. There was mixed support for the Dunning-Kruger effect as an explanation for some instances of this bias in an end-user computing context. Although estimations of the skill level of an average-computer end-user were correlated with a person’s self-assessment, there is not sufficient evidence to say that estimations of an average computer end-user’s skill were directly caused by a person’s self-assessment or that a person’s self-assessment was caused by their view of the average person.

This chapter presents a detailed discussion of these findings in five sections including this introductory section. Section 2 discusses implications and limitations of the findings for understanding the AAE. Section 3 considers the extent to which the findings support the explanation of the DKE for occurrences of the AAE. In section 4, the discussion turns to the domain of end-user computing, and how findings are relevant to issues in this domain. The chapter concludes with a summary section that will emphasise the main contributions from this study to the above-average effect and to the domain of end-user computing.

## 5.2 Implications and limitations in understanding the above-average effect

Findings from the four hypotheses used to test for occurrences of the AAE confirmed the existence of this social bias in self-assessment in the context of EUC. This effect was present in both comparisons between a person's self-assessment relative to estimations of the skill of a perceived average computer end-user, and when comparing expectations of EUC knowledge with demonstrated skill.

Participants in this study were recruited because of their use of common place end-user computing software as part of their employment. This is an important point to emphasise at the start of the discussion of this study's findings since one concern – common to many studies of the AAE – may be that, because of self-selection, any sample may comprise computer end-users who are, in fact, of above average ability. If true, this would undermine the main finding of this study, and others, as concerns the AAE. However, a manipulation check (see Section 3.3) confirmed that when making estimations of an average end-user, participants were assuming that the average person *used computers in a similar manner to themselves*. Also, as demonstrated in Section 3.3.3, the final sample was broadly in line with the occupational distribution of computer end-users in the Canterbury, New Zealand, region. Further, as detailed in 3.3 the participant selection process was based solely on the criterion of using end-user computing as part of one's job. Similarly, the participant recruitment process, when considered in detail, provides no evidence that recruitment proceeded on any grounds that would have biased the sample towards more skilled and knowledgeable end-users. Robust testing of the results was undertaken using bootstrapping methods for the regression and correlation analysis. Bootstrapping, which randomises many examples of a study population, returned results comparable, in all cases, to those returned for the study sample. For these reasons two conclusions are strongly suggested: The sampling and recruitment process led to sampling that approximated a true random sample; hence, the final sample is highly unlikely to have been biased towards computer end-users who, overall, were more highly skilled and knowledgeable than the average end-user. A further, related point in (post hoc) support of these conclusions is that the development of the VAS instruments resulted in more conservative measures of any possible AAE than measures often used in studies of the AAE. In other words, the VAS would appear to mitigate against the influence of any sample bias towards higher skilled participants.

This section will begin by discussing the uniqueness of the domain chosen and its suitability for tests of the AAE. It will then consider the relationship between personal factors such as sex, age, expertise and personality with occurrences of the AAE.

At its very heart, the AAE arises from a disconnect between self-perceptions and a real-world confusion about very different variables that have become conflated. Many studies investigating the AAE ask participants to make estimations about their ability relative to that of an average peer or group of peers. These estimations are then compared with results from actual assessments, often with disparities in the results indicating that self-reports are inaccurate (Mattern , 2010; Pavel et al., 2012). A similar approach to that used in other studies of the AAE was taken in this study where participants made self-assessments of their knowledge and that of average end-users and were then given the opportunity to demonstrate their ability using SW applications.

Not only has this phenomenon been found across tasks but also across measures (Ehrlinger et al., 2008 ). For example, Ehrlinger et al. (2008) found occurrences of overly optimistic self-assessment in relation to absolute performance over a series of five experiments using five separate samples each using differing measures. In conclusion, Ehrlinger et al. (2008) concluded that over the five experiments the constant they found was that those with less competence in a domain had more confidence in their ability compared with how they saw others. Relative to their peers the poor performers believed their performance to be better. These experiments were conducted in everyday situations where participants would receive regular feedback about performance; however, the poorly performed seemed less likely to use the feedback to improve their skill or knowledge. One criticism of studies of the AAE including this study, may be that the instruments used to compare perceptions with ability are not being assessed on the same scale. While understandable, such a criticism would be true of many other studies of the AAE (e.g., Ehrlinger et al., 2008; Kidd & Monk 2009; Kruger & Dunning, 1990, 2009; Mattern et al., 2010). Perception measures are frequently taken on scales that differ from measures of actual skill or ability. This is simply an aspect of the phenomenon under study. What is of interest in studies of the AAE, is not whether people generally overestimate their *performance* at a particular skill but, by contrast, how their assessed skill or knowledge compares to their perceptions of their relative ability with others who have that skill or knowledge. Further, unlike those other studies which used discrete scale measures, the development and use of a VAS specific to this study was an attempt to ensure that perception measurements were as fine grained as possible. This aligns the perception measure, in terms of granularity, with the fine-grained task-based measures of performance used in this study.

Occurrences of the AAE in this study are consistent with other studies, which have found this bias in domains or activities considered routine, easy or loosely defined (Brown, 2012; Kidd & Monk 2009; Sundstrom, 2008; Williams & Golivich, 2008). For example, Kruger & Dunning (1999,2009) conducted studies with university students using grammar testing. Having the necessary skills to write in a grammatically correct manner is an everyday occurrence for students, and one in which they receive regular feedback. However, in their studies Kruger & Dunning found that those with less competence in this area were likely to not recognise this and, *relative to their peers*, over-estimate their own ability and accuracy. Likewise, Ehrlinger et al., (2008) asked students about their own performance in exams and found that those who had not performed well had the expectation that they had, *relative to others in their class*. Conversely, for tasks or domains thought to be difficult a below-average effect can be evidenced (Ehrlinger et al., 2008; Kruger & Dunning, 1990, 2009). Based on this, it may be that findings in this study are not surprising and to be expected in a domain considered easy or commonplace. Importantly, however, the findings in this study do suggest that particular characteristics of the domain of EUC may set occurrences of this bias in this context apart from those found in other domains considered routine. These characteristics, it is argued, provide a useful context to test and extend theory on the AAE.

Evidence of the AAE in areas such as driving a car or using a computer mouse typically are explained by the perceived easiness of a domain leading to this effect (Brown, 2012; Kidd & Monk, 2009; Sundstrom, 2008; Williams & Golivich, 2008). In a computing context, operating a computer mouse is likely to be considered 'easy' by regular computer users and an area where most people may consider themselves 'above-average', even though it is unlikely that mouse using skills are in fact measured. Likewise, for most people, once a driver's licence has been granted they are never again measured for driving ability. Nevertheless, studies have shown that it is common for a person to believe that, *relative to other road users*, their driving is better than average (Kidd & Monk, 2009; Sundstrom, 2008). Studies have also found that occurrences of the AAE are less evident in domains that are perceived as more complicated or 'hard' such as computer programming (Brown, 2012; Ehrlinger et al., 2008). While EUC in the workplace may not appear to be measured, in fact when a person uses their computer to perform tasks implicit measures may be occurring. These may be the time taken to complete tasks, or the accuracy of a model created. For example, Tubinis (2015) noted that lawyers bill their clients for the time taken to prepare documentation which suggests that inefficient skills will mean that clients are being charged for time that may not be necessary if the user had a better grasp of efficient EUC.

The domain of EUC was used in this study because it was considered an ideal environment in which this effect could be tested. EUC is used in most types of employment, schools and tertiary study as well as for general use (Gibbs et al., 2010; Murray & Perez, 2014; Murray et al., 2007). One disadvantage of such ubiquity is that the intricacies of the domain can be overlooked, underrated or misunderstood and therefore considered to be easier than it is (Sundstrom, 2008).

More specifically, there are three main characteristics which set EUC apart from other domains in which this effect is routinely found: (1) the lack of opportunity for end-users to directly observe others; (2) the fast pace at which this domain is changing; and, (3) the diverse nature of the skills expected in a wide range of occupations. These specific differences shift EUC from a domain that could be labelled as 'easy' to one that is far more sophisticated than many users may appreciate. While applications such as word-processors or even spreadsheets are relatively simple to use at a basic level to the point that a person may have no trouble "knowing enough to get by", this does not necessarily equate to having mastery or even expertise with the software (Tubinis, 2015). This type of software is used in many occupations where the skills that are core to that occupation are considered of utmost importance. However, some who have enough computing skill to 'get by' consider that their skill is far more advanced than the reality. For example, Tubinis (2015), when looking at the technology use of lawyers said

*"Some lawyers will consider their skills to be far more advanced than they actually are. By the criteria they see before them, gainful employment and successful application of technology to daily tasks, they evaluate themselves as being competent with the technology."* (Tubinis, pg 2 (2015))

By way of comparison, in domains such as driving, drivers have the opportunity to observe other drivers in what is a near-continuous setting and use these observations to base their self-assessment on. In the domain of EUC, however, there is often little opportunity to observe other users, aside perhaps from a few colleagues in the immediate workplace setting. Further, the nature of the EUC domain has changed remarkably in the three or so decades that it has been part of typical workplaces (Birch, 2007; Eschenbrenner & Nah, 2014; Govindarajulu & Arinze, 2008). These changes have altered the functionality of the software that is typically used in workplaces, changing applications from ones that were only used for entering text or simple data entry to ones where more advanced document editing, data visualisation and data analysis is possible (Baker et al., 2008; Panko & Port, 2013). Such rapid and continuous change may mean that end-users, unaware of the level of functionality available, may not be assessing their skill based on the set of skills required for full use of current software.

Certainly, it is interesting to note that a third of the participants in this study correctly completed less than a third of the spreadsheet tasks. Despite this, two thirds of this group believed their EUC computing knowledge to exceed that of an AEU. Yet, while all of these participants were required to use EUC software for their employment their performance on task assessments rated as 'basic' by panels of experts was less than such ratings would suggest it should be. This result is similar in some respects to that found by Pavel et al., (2012). They found that aviation students over estimated, *relative to their peers*, their knowledge of basic aviation skills and regulations that professionals in this field would be expected to know.

The variety of occupational roles that involve EUC skills also means that there is a diversity in the range of skill level and focus needed. In EUC, many workers in many roles and in many types of organisation are responsible for their own computing and the use made of software. This use can range from the basic task of opening a document to the sophisticated use of data analysis tools (Baker et al., 2008; Lawson et al., 2009; Panko & Port, 2013). Due to the varied range of use and need for different levels of skill, some users will be unaware that what they do does not require as high a skill level as they may believe it does, based on what they have observed in the domain. The participants in this study with the highest overall demonstrated skill (eighty percent or greater) represented a range of roles; however, the largest group in the study (administrators) was not included. The type of roles represented, perhaps unsurprisingly, included business and account analysts, an accountant, a manager and a researcher. Interestingly, and in line with expectations based on the DKE, with the exception of one participant in this group, all others had conservative estimates (14 pages on average) of the difference between their knowledge and that of the average person.

From what is currently understood about the AAE and the observed perception that EUC is easy, it is perhaps not surprising that this phenomenon occurred in this study. However, this lack of surprise is tempered by what is known about the domain of EUC, compared with domains this effect is typically found in. Domains which are considered routine or easy and often where there may be opportunity to observe others there is no opportunity to measure skill often are affected by the AAE (Ehrlinger et al., 2008; Kruger & Dunning, 1999; Pavel et al., 2012). The first hypothesis used in this study to test for this effect confirmed that a person's self-perception of knowledge in EUC is greater than their estimation of the knowledge of an average computer end-user (AEU). In this study, on average, participants believed their knowledge to be 13% greater than that of the AEU ( $H_1$  – Section 4.4.1.1). This finding is in line with previous work that found people would be inclined to see themselves in

the best light when comparing themselves to a group or individual about which they have limited information (Alicke et al., 2005; Huang, 2013; Pavel et al., 2012; Sundstrom, 2008). While EUC is commonplace, end-users are often in workplaces where they have little opportunity to observe the computing of others.

When participants were grouped, for purposes of analysis, by perceived difference between themselves and an average computer end-user the largest group was the group whose members, on average, believed they knew between 0 and 5% more than the average user (see Section 4.4, Table 21). This was also the group with the lowest perception of their skill and knowledge level. This suggests that while there is evidence of an AAE in this study the effect is not marked. Nevertheless, the group with the largest positive gap between ratings of themselves and ratings of an average computer end-user also had the highest self-ratings, in keeping with the DKE. One explanation for this type of over-estimation bias is egocentrism (see Section 2.1.3.3), which involves placing more emphasis on your skill or knowledge in the domain being assessed rather than on others' skills in a comparison situation (Greenwald, 1980; Windschitl et al., 2008).

Some studies suggest that it is possible that using an average person comparison has negative connotations because people may deem the 'average person' as not being something to aspire to, which encourages people to consider themselves to be 'above average' in their self-reporting (Sundstrom, 2008). To understand better how participants in this study perceived the "average person" in the context of EUC, a manipulation check was undertaken (see section 3.5). This check confirmed that the participants believed the average person to be someone who uses computers in a similar way to them. This suggests, but does not completely confirm, that in this study the "average computer end-user" label was not regarded negatively. This may be due in part to an appreciation of the breadth and depth of a domain that makes an average user seem more competent, as they have mastered a broad domain to an average level.

Occurrences of the AAE are said to be either direct or indirect (Zell & Alicke, 2011; Krizan & Suls, 2008; Moore, 2007). As discussed in the literature review, occurrences of the AAE have been found to be weaker in indirect comparisons than in direct comparisons situations where people have been found to inflate self-evaluations when asked to compare themselves directly to a referent group (Zell & Alicke, 2011; Krizan & Suls, 2008; Moore, 2007). In this regard, the nature of the comparison used in this study could be described as hybrid, which is to say neither direct nor indirect. In an indirect comparison participants made an independent self-report of EUC knowledge before being asked to



rate this same knowledge for an average person. Although the self-assessment in this study was not made as a direct comparison, the estimation of the AEU occurred directly in light of the former. Although self-reports in this study were indirect in relation to estimations of an AEU, estimations of the AEU were not. The hybrid nature of the comparison may have had some effect on the outcomes from this measure with the explanation of egocentrism being more likely than focalism. As mentioned earlier, egocentrism has been used to explain instances of the AAE in indirect situations; however, some caution should be taken in attributing all occurrences of the AAE to egocentrism, or the motivational factor of self-enhancement. For this reason, a focus of this study was on the association of personal factors, such as age, sex, expertise and personality, with occurrence of the AAE in the context of end-user computing.

Previous studies have also found that an above-average effect may be influenced by individual differences, demographic factors or expertise (Gravill et al., 2006; Schaeffer et al., 2004; Zell & Alicke, 2011). By contrast, findings in this study did not produce a statistically significant association between a *combination* of demographic, expertise and personality variables and the AAE ( $H_2$  – Section 4.4.1.2). The following considers why this apparent difference in findings might have occurred.

To take specific examples of findings in previous studies, a link has been found between overconfidence and both extraversion (Schaefer et al., 2004) and sex (Burnett et al., 2011) while other studies have found links between experience and accurate self-assessment (Gravill et al., 2006). However, findings in this study suggest either that the presence of previously unidentified interactions between this combination of variables lessens the strength of the AAE or that this effect is purely situational. In studies which have found associations between the AAE and individual factors, the effects that were found seem explicable in terms of the characteristics of the situation. For example, Zell & Alicke found that age was positively associated with the AAE in situations where a participant's age was not seen to be a factor in performing a particular task but declined in situations, such as physical activity, where age is seen to be a factor. In their study investigating the links between personality and over-confidence Schaefer et al. (2004) found in general knowledge tests using a student population that extraversion was associated with over-confidence but not with accuracy. Differences between self-reports and demonstrated skill in this study may be due, simply, to the ubiquity of workplace computing. EUC is a domain which is entrenched in many workplaces and something that is non-negotiable as far as many jobs go. Without the opportunity to actively observe others in similar roles it may be that people come to believe that their skills are better than

they actually are, even relative to others. That is they may have made a cognitive error by misinterpreting basic skills as expert skills. This explanation is similar to that observed by Tubinis (2015) in his study of the workplace computing skills lawyers have. He said that some equated having a basic set of skills that allowed a lawyer to “get the job done” as being a good lawyer who was good with technology.

Along with evidence of an AAE in comparison with an average computer end-user, Chi-squared analysis revealed an association between self-reported EUC knowledge and demonstrated EUC skill as tested by  $H_3$  (Section 4.4.1.3). The values of the contingency table (Table 24) suggest a significant difference between expected and observed frequencies in one or more of the categories. Findings show more than a third of study participants have a self-assessment greater than their estimation of the AEU but returned a lower than the study average score for demonstrated skill. While the self-assessment measure used in this study did not ask about specific tasks this is similar to measures used in other studies. For example, Kidd and Monk (2009) found inconsistencies between driving tests and the predictions people made about their driving ability, relative to an average driver, prior to the testing of specific driving skills. The results from this study do indicate that the self-assessments of EUC knowledge for study participants suggest a moderate level of confidence in their ability in EUC relative to the perceived ability of an AEU (someone who performs similar end-user computing).

As already noted, one possible interpretation is that participants in this study were ‘self-selecting’ and therefore likely to have above-average knowledge and skills in EUC. That is, it could be argued that there is no above-average effect only a realistic reporting of above-average skills and knowledge. There are, however, several arguments that mitigate against that interpretation. These include that participants, while seeming to be above average, were comparing their skills and knowledge with those who use computers in a similar manner to how they do (Section 3.3). This suggests that rather than comparing themselves to people who may only use computers for activities such as Web search or social networking, they are including those who need - as they do - computer skills for employment. Given this is a domain where observations of others in similar positions may be limited, coupled with the fast changing nature of the domain, it is difficult to know how a user can be confident that their skill and knowledge in EUC is better than that of an AEU.

However, it is also interesting to consider the findings outlined in Table 25 that show comparisons between study participants and the expectations of the panels involved in instrument development

(Section 3.8). These findings show that, on average, participant's EUC demonstrated ability was lower than expected. It is acknowledged that different skill sets will be required in different occupations, but nevertheless, difficulty in completing tasks judged by expert panels as basic - such as adding up a column of values in a spreadsheet, or creating a numbered list in a word-processed document - appears inconsistent with perceptions of above-average EUC knowledge. Similarly, in a study situated in the aviation field, Pavel et al., (2012) found that students studying to be aeronautical engineers or pilots over-estimated their knowledge *relative to their peers* on tasks and specific knowledge necessary for their field of employment.

Findings in this study may be attributable to the complexity of the domain making EUC skill level difficult for many participants to judge. Reasons for an overestimation of knowledge in the area of end-user computing include the ubiquity of the domain coupled with the vast differences found in need and ability within the domain. When employers are searching for new staff members it seems they themselves are not sure how to describe the required EUC skill. Samples of wording used in recent job recruitment material include "solid IT skills"; "competent knowledge of Microsoft Word and Excel" and "A high degree of computer literacy across the Microsoft Office suite". These descriptions were used in jobs ranging from administration to managerial roles. The other side to this is that EUC skill is, in most cases, not the core skill set required for a job, but a complementary one. Therefore, because a person completes a EUC task in an inefficient manner the outcome may be desirable, meaning that the inefficient practices may be acceptable in the light of the overall job objectives. However, unwarranted perceptions by employees of technological competency that may result can create broader business inefficiencies. The 2010 report commissioned by the NZCS(ITTP), for example, warned that businesses risk huge fiscal losses due to inefficient and inaccurate use of technology (Bunker, 2010).

Further, the moderate AAE found in this study may itself be a result of the study sample being broadly representative of the population to which participants are comparing themselves. That is, the still significant but relatively moderate effect suggests that the sample is not strongly biased towards end-users who are above average and who are simply reporting this above average ability. This moderate effect is comparable to the results from the study carried out by Grant et al. (2009) who also found that a person's self-perception of ability, relative to their peers, was higher than their actual ability. In this current study all participants were employed in roles where they are required to use EUC software. Similarly, in Grant et al's. (2009) study all participants were undergraduate students who all used the same software. Grant et al. (2009) were concerned that the discrepancy

between self-perceptions and actual skill has an effect on a person's confidence levels. They claimed that when people found their skill level was not at the level they had believed their confidence was affected and that further skill improvement may therefore be impeded. They suggested that a desire to learn and improve skills is driven by the confidence one already possesses. This may occur because a person, while being confident using software for the purposes that they need to, does not always have the skill or knowledge to extend their use to complete tasks outside their normal usage. To some extent this may be explained by differences in demonstrated ability between the word-processing and spreadsheet domains. These same people also are unlikely, at the time of self-assessment, to recognise their own limited skill-set.

Given the rejection of  $H_2$ , it was then surprising to find significant support for the acceptance of  $H_4$  (Section 4.4.1.4). This hypothesis tested the association between the combination of personal factors and estimations of an average person's knowledge. This finding suggests that, unlike self-assessment, participants' estimation of an AEU were associated with the combination of personal, expertise and personality factors. Given that age was the sole individually significantly variable, it is interesting to consider its impact on the overall result. Participants in this study were what is considered to be in an age range representative of a typical workforce (Section 3.3). Zell & Alicke (2011), found that egocentrism accounted for age differences in comparative evaluations when people are comparing themselves to others. This may be due, in part, to middle-aged and older adults having had more time to learn about their relative strengths and weaknesses. This finding suggests that, given the average age of participants of 42 years, most participants had grown up in an era when computer technology was not commonplace, but instead have had to learn technology within the workplace. This may mean that, as Zell & Alicke (2011) found, egocentrism accounting for age had a moderating effect on participant's perceptions of the AEU. Zell & Alicke (2011) say that egocentrism predicts that an AAE will decline with age for things like physical ability, attractiveness and health but the AAE does not decline across age groups for things such as intelligence, sociability or honesty. They say that age differences in comparative situations are consistent with egocentrism, in that people will rate themselves as better (or worse) than average because they place more weight on their own characteristics than those of others.

In summary, support for the hypotheses that tested for the presence of the above-average effect in the context of end-user computing was mixed. Three of the four hypotheses ( $H_1$ ,  $H_3$ , and  $H_4$ ) were supported. This support shows an association between the AAE personal differences and estimations of the average computer end-user and differences between self-assessment and demonstrated skill

in an EUC context. However, the hypothesis ( $H_2$ ) testing variables that, separately, had been found to be associated with the AAE in previous studies were not significantly associated with the AAE when analysed in combination. The implications of these results are discussed in more detail in the following chapter. The following section will discuss the findings in relation to the four hypotheses used to test for the Dunning-Kruger effect as an explanation of the AAE.

### 5.3 The Dunning-Kruger effect

Support for the four hypotheses that tested the DKE as an explanation for the AAE was mixed. There was support for  $H_5$  (Section 4.4.2.1). This finding indicates some association between a person's awareness of the breadth of the domain of EUC and their self-assessment. However, there was no support for  $H_6$ ,  $H_7$  or  $H_8$ . The latter hypotheses were formulated to test for an association between the DKE and a combination of personal, personality, and demonstrated computing ability and expertise variables and for an association between the DKE and the AAE.

The Dunning–Kruger Effect indicates that individuals with lower skill or knowledge levels have overly positive perceptions of their capabilities when they compare themselves to their peers due to a lack of information they possess about a domain. Those with lower competence in a domain are also unlikely to recognise competence in others (Gross & Latham, 2012; Kruger & Dunning, 2009, 1999; Pavel, 2012). Just as unskilled individuals are likely to over-state their knowledge or ability; skilled individuals are likely to underestimate theirs and believe that others possess the same knowledge they do (Kruger & Dunning, 2009, 1999). The theory expects that as competence and experience increase, so will domain information and self-reports will become less exaggerated as competence is developed (Gross & Latham, 2012). Findings related to the DKE indicate a necessity for further understanding of how to overcome any miscalibration between self-report and domain proficiency.

The attempt, in this study, to measure participants' estimations of the breadth of the EUC domain within computing as a whole was not an attempt to determine perceptions of computing. It was an attempt in understanding if people who estimated EUC to be a high proportion of the domain of computing, would be more inclined to over-estimate their knowledge of EUC. Conversely, it was assumed that those with more awareness of the breadth of the domain of computing would believe that EUC occupies a relatively smaller part of the overall domain of computing. Findings, as illustrated in Section 4.4.2, indicate that those with a greater estimate of the  $EoD_{EUC}$  relative to computing as a whole also had higher expectations of their own ability in this domain than those with lower estimations of  $EoD_{EUC}$ . The assumption made in this study, and aligned with the DKE, is

that those people with a lower estimation for  $EoD_{EUC}$  are likely to be people with a greater appreciation of how varied and complicated the domain of computing is. Conversely, it is assumed that those with higher estimations of  $EoD_{EUC}$  will likely have less appreciation of the different areas within, and breadth of, the domain of computing. Although it may be unreasonable to say that a knowledgeable end-user needs to know about the extent of computing as a domain, it is reasonable to believe that the more a person knows about, or is aware of a domain, the more they are likely to believe that there is more to know than they currently know.

Acceptance of  $H_5$  (Section 4.4.2.1) provides some evidence of an association between expertise, self-assessment and  $EoD_{EUC}$ . These results are in-line with those found in previous studies investigating the DKE (Carter & Dunning, 2008; Dunning, 2011; Kruger, 1999; Kruger & Dunning, 1999, 2009).

Using the analogy of a book about computing, participants estimated how many pages of this book pertained to EUC. The findings, depicted in Figure 27, show that estimations of the breadth of the domain of EUC were, overall, reasonably modest with only a few predicting that EUC made up half or more of all computing. The findings from this perception measure show that ten percent of participants, who are regular computer users and who live in a world dominated by computing technology, appear to have no appreciation for the size of the domain of computing. Although this result is low, it is none the less of interest. All participants use and interact with technology on a regular basis in their employment, yet some estimated that more than half of all computing could be described as EUC. It should also be noted that this same small sample, had on average, lower demonstrated EUC skills and knowledge than the study average. However, on average the gap between their self-reports and their estimations of an AEU, at forty-five equivalent pages, was greater than the study average of thirty pages. Interestingly, the group with lower expectations of the breadth of the domain had demonstrated ability ranging from quite low to the highest achieved in the study. According to Kruger and Dunning (1999, 2009) there are different reason why top and bottom performers provide inaccurate self-reports and perceptions. They argue that for the bottom performers the problems relate to meta-cognition (how they perceive the domain) and self-perception. By contrast, they say that top performers are more able to assess their own knowledge but struggle to assess that of others. In sum, they say that top-performers are inaccurate because they are wrong about others, whereas bottom performers are inaccurate because they are wrong about themselves.

One probable reason why expertise is related to self-assessments and comparison with an average person is that those with more experience and knowledge in a domain which, as with end-user computing, has different levels of complexity are less likely to over-estimate their ability, but have confidence regarding what they know. Experience in an area provides people with feedback about skill sets and levels and this can help in becoming more accurate in self-report situations. Kruger & Dunning(1999, 2009) claimed that the less competent are less aware of the amount of knowledge there is in a domain, so will likely believe that what they know is close to the sum of knowledge in that domain. The dual burden of the DKE is that those who do not recognise their own lack of knowledge in a domain also are unable to recognise competence in others. Kruger and Dunning (1999, p. 1121) state, “incompetent individuals lack the ability to know how well one is performing, when one is likely to be accurate in judgment, and when one is likely to be in error.” This lack of knowledge has been variously labelled as a lack of metacognition; metamemory; metacomprehension; or self-monitoring (Kruger & Dunning, 1999, 2009). A lack of metacognitive skills is often expressed through overly positive, inaccurate assessments of ability. Experts in a domain are likely to have better metacognitive skills than domain novices (Kruger & Dunning, 1999, 2009; Ericsson & Smith, 1991; Chi et al., 1981).

There are other cognitive biases that could also be used to describe parts or all of the phenomena of illusory superiority. Certainly, there are links between cognitive biases that concern over-confidence and the work on judgements under uncertainty. Examples include the anchoring effect, identified as a bias that occurs when a person is required to make a judgment under uncertainty (Tversky & Kahneman, 1974). Anchoring is the tendency to be influenced by something we know about when making judgments about something we know little about (Kahneman, 2011; Tversky & Kahneman, 1974). Daniel Kahneman coined the acronym WYSIATI (what you see is all there is) to explain over-confidence. He said that when the mind makes a decision it is dealing with what is known and seldom considers unknowns (Kahneman, 2011). Kahneman (2011, p20) argues that humans have two systems for decision-making. System 1 is a ‘quick & dirty’, and often, automatic approach whereas System 2, is an approach which involves conscious engagement. He contends that, when considering one’s self, System 2 is likely to be employed, whereas System 1 describes the originating impressions and feelings that become the main source for clear beliefs and choices. WYSIATI is associated with System 1. When considering the Dunning-Kruger effect, where it is said that the less competent are unaware of their incompetence, it could be as Kahneman describes, “What you see is all there is”, in your mind anyway. Panko (2014) says that over-confidence or risk blindness in using and then assessing the accuracy of end-user applications, could also be explained by what

Kahneman (2011) describes as System 1 decision-making - the 'fast' approach where automatic judgements take over. Therefore, while a person may be capable of creating a complex spreadsheet model, either they do not have the skills to realise the risk of errors or their overconfidence prevents them from seeing the possibility of errors in their work.

In this current study there was a significant association between participants awareness of the domain of EUC as it fits in the wider domain of computing and the above-average effect in EUC. Findings for the test of  $H_6$  revealed no direct association between a participant's estimation of the breadth of the domain and the difference between their self-assessment and their estimation of the knowledge of an AEU. Nor was there any significant associations in situations where experience was compared in combination with expertise and individual difference variables ( $H_7$  and  $H_8$ ). The finding ( $H_5$ ) that more competent individuals viewed EUC as a small part of all computing - therefore moderating the effects of the AAE - suggests the perception (i.e., estimations) of domain are related to self-assessments. Those who appear to have a more conservative view of how much of the domain of computing is occupied by EUC were more likely to be more accurate in their assessment of themselves. However it does not follow that there is any association between self-assessment, estimation of an AEU and the breadth of the domain. It appears that estimations made between self and peers are made based on what a person believes they know about the domain rather than what they believe there is to know. Twenty-four percent of participants estimated that EUC occupied ten percent or less of the domain of computing, these same participants believed, on average that they knew around a third of what there was to know about EUC and that the AEU knew around 81 % of what they knew. This group had an average demonstrated score of sixty-one percent, slightly greater than the study average of fifty-eight percent. However the thirty percent of participants, with a less conservative view of the breadth of EUC, believing that EUC occupies a third or more of all computing, estimated that on average they knew about half of all there is to know about EUC which tied with their average demonstrated result of just on fifty percent. This group believed that an AEU would know about seventy percent of what they do about EUC. It is interesting to consider that this last group, with what seems like a less conservative view of the breadth of the domain, did appear to have a reasonably accurate assessment of their knowledge of that domain.

The importance of the non-significant relationship between the AAE and experience and individual differences is important to note. Poor performers, those with less domain knowledge than others, are poor at judging their own ability or knowledge (Kruger & Dunning, 1999, 2009). However, while some studies have found that experience moderates the DKE (Kruger & Dunning, 1999, 2009) other



studies have found that experience is not necessarily a moderator of this effect (Schlösser et al., 2013). For example, Schlösser et al.(2013) say, generally, that it was those with less information in an area, who were more likely to over-estimate their knowledge or skill, than were those with more information. However, they found no difference in the accuracy of self-reports for poor performers in experiments where experience was a factor. In their study participants took two exams and prior to each estimated their performance relative to others in the study. Schlösser et al., (2013) were surprised that, given the feedback from the first exam, there was no improvement in accuracy of self-assessments for the second exam from the group who had the poorest performance. That is, the experience of having made inaccurate self-assessments for the first exam did not appear to have any impact on self-reports for the second exam. They concluded that experience does not appear to improve self-assessments, although they do note that in studies where incentives are offered (e.g. Miller & Geraci, 2011), self-report accuracy has been seen to improve. In this study, those with the greatest demonstrated ability had reasonably modest expectations of the extent of the EUC domain. With the exception of one participant, those correctly completing more than eighty percent of tasks estimated that, on average, only ten percent of computing could be described as EUC.

Demonstrated ability was measured using assessments of tasks considered commonplace word-processing and spreadsheet tasks an end-user would encounter in a workplace situation. In a somewhat surprising result, no association was found between a person's demonstrated skill and their expectation of  $EoD_{EUC}$ . However, as evidenced in Figure 31, there is a negative significant association between estimation of breadth of domain and spreadsheet skills but not word-processing. This is an interesting finding, as these two software applications are the top two applications used in workplaces. Given that the study result for the Word-processing assessment was higher than the spreadsheet assessment, it seems that the Word score may be moderating the association between breadth of domain and spreadsheet skill in the regression analysis. The level of functionality provided in a spreadsheet tool is vast compared with that of a word-processing application. However, the level of use people make of that functionality ranges from simple data entry to use of the analysis tools or automating worksheet formulae and features. On the other hand, word-processing tools are relatively simple to use and while there are several inbuilt features intended to be used to make documents reusable - such as styles, templates etc. - much of the time these features are underutilised. For example, Tubinis ( 2015, p. 2), claimed that "there are so many functions and tools built into Microsoft Word alone that no mortal being could ever know all of them." He went on to say, in his paper reporting on the use of EUC technology made by lawyers, that clients are interested in the law skills of a lawyer not if they are a Microsoft certified guru. However,

he also emphasised that it is important that lawyers do have the necessary level of technical skills to create and transmit documents quickly, accurately and efficiently, and that not having the right skill level can hinder this. In this study, findings suggest achieving a high score in the word-processing assessment does not guarantee a high score in the spreadsheet assessment. Although the converse was true, those who were proficient at using spreadsheets were also proficient with advanced Word features. It was also found that those who have a high level of spreadsheet skill are likely to have a more conservative view of the extent of the domain of EUC than those with lesser ability.

As with the study reported by Schlösser et al.(2013) , Gravill et al. (2006) also found that those with more years of experience in workplace computing were no more accurate in their self-assessments than those with fewer years' experience. However, that is not to say that experience is only measured by time served. In this study the measures used to assess experience included occupation, the number of applications used and the hours involved in an average week involving the use of computers, as well as computing education. These variables all work together to enhance ones experience. A tenet of the DKE is the notion that, as competence increases self-assessments become more accurate. While there was no suggestion that expertise or experience in this study moderated the AAE, there is some suggestion that studies where this moderation has been found have offered some kind of incentive to people to improve their knowledge or to provide more accurate (or conservative) self-reports (Schlösser et al., 2013).

Further, while previous studies in the area of the AAE have found links between over-estimation, overconfidence , extraversion, conscientiousness, lack of expertise, age and sex, most studies examining the DKE have not explored factors other than experience and feedback (Huang, 2013; Schlösser et al., 2013, Pavel et al., 2012). Given this and the results of this study, perhaps then, the findings relating directly to the DKE as conclusive explanation in this study are not as surprising as first thought. Experience or expertise did manifest in perceptions of the breadth of the domain, but not when combined with individual differences or when relative to another end-user . This suggests, to a point, that experience does seem to modify social bias but as no feedback was available to participants it is unclear if this also would help to improve accuracy of self-perceptions and those relative to other end-users.

This study was undertaken as a means to extend understanding of the above-average effect as it pertains to the domain of end-user computing. The section that follows will provide a discussion of the implications of this effect in the context of end-user computing in the workplace.

## 5.4 End-user Computing

The context chosen for this study was end-user computing in the workplace, with participants recruited on the basis that they were current users of the two most common end-user applications: spreadsheets and word-processor software.

End-user computing is a branch of computing which has been described as the kind of computing that non-computing professionals do (Yoon, 2009; Panko, 2013, 1989). This domain has undergone rapid growth and penetration into most modern workplaces. Due to the common need for this type of computing, people in many different jobs are now responsible for their own computing (Gupta & Anson, 2014; Barker & Fielder, 2010; Holtzman & Kraft, 2010; Hansen & Hansen, 2010; Murray et al., 2007; Panko & Port, 2013; Stoner, 2009). It is common for employers to rely on candidates' self-assessment of their skills and yet these are frequently flawed by self-evaluation biases such as the above-average effect (Brown, 2012; Kidd & Monk, 2009; Sundstrom, 2008; Williams & Golivich, 2008). Previous studies have found differences between self-assessed computing skill and demonstrated skill (Grant et al., 2009; Gravill et al., 2006). In contrast to this study, previous work has compared perceptions of skill with demonstrated skill but has not specifically investigated occurrences of the above-average effect in this domain. That is, this study provides a substantive original contribution because previous work has not focused on what (social) cognitive mechanisms may underpin differences between perceived and demonstrated skill.

It is clear that end-user computing practices vary substantially, not only between users or job type but also between organisations, as does the level of training offered and the level of application auditing which occurs (Panko & Port, 2013; Lawson, et al., 2009). These differences mean that, despite variations in the use of end-user applications and the level of use, this type of computing is seen as unimportant to some, including the IT group and some management, although the wide use shows how important to organisations, EUC is (Panko & Port, 2013). In fact, the disregard with which some view end-user computing may well be signified in the term end-user itself. This generic and imprecise term is used to refer to workers in a variety of roles who use technology in a variety of different ways. In some respects the term end-user highlights the lack of nuance in how this domain is often viewed (Panko, 2014). By contrast, findings from this study reflect the heterogeneity in the end-user computing practices over a number of occupations and workplaces. Although participants in this study were recruited on the basis that they used both spreadsheet and word-processing applications for their employment, the results for correct completion of spreadsheet tasks

considered to be common workplace tasks were low, with the average for the study being just 47% correct. However, results for the use of word-processing software were, perhaps predictably, better. The findings for demonstrated skill may mean that, for some people, “using a spreadsheet” may mean updating values rather than performing calculations. In this study, only 34% of participants scored more than the study average. It is not surprising then, that the two most basic tasks were those with the highest rate of correctness. These basic tasks involved adding up a column of values and changing the formatting of a cell. However, it is a little more surprising that other tasks, considered basic by the development panel, did not have high rates of correct responses. Examples of this included sorting a data range by more than one sort category. These findings complement those found by Baker et al. (2008) and Lawson et al. (2009) who found large differences in skill among spreadsheet users and also those found by Berezina et al., 2011 where actual demonstrated computing did not match industry expectations. For example, spreadsheet skills were one of the areas identified as essential for graduates entering the Hotel Industry. However, Berezina et al. (2011) found these skills to be lacking in their study. They indicated that there was a definite need by training organisations to ensure that graduates skill level was at the necessary level identified by industry. For users currently in the workforce, Baker et al. (2008) suggest that a lack of skill may be attributable, in part, to organisational policy with users not being encouraged or given the opportunity to increase knowledge using spreadsheets in the workplace. Alternatively, it may be that particular roles within an organisation do not have the need for workers with high levels of spreadsheet or other end-user skills and this result was acceptable. It may also mean that those whose use of end-use applications is only at a basic level may not themselves be aware of this. As pointed out by Lawson et al. (2009), there can be a difference between users who have expertise using a particular spreadsheet model and users who have expertise using many different spreadsheet models. However, the implication from this study, with respect to occurrences of the above-average effect, is that low-level use may not be recognised by some as that; i.e., they believe what they are doing in an end-user computing sense is at a higher level than it is. This in turn can lead to judgments of skill that are greater than justified. This summary is in line with that found by others, for example Turbinis (2015) said that lawyers in their study may not be aware of the need to update their skills or even be willing to do so if they believe that their knowledge of the legal domain is good then may also think this skill flows over into their use of technology. Turbinis (2015) did say that an unwillingness to update may come from the fact that lawyers charge by the hour, and, therefore, any inefficiencies in their use of technology may not, indeed, hamper them financially. It may also be that participants are anchoring their judgements about their ability relative to others’

proficiency at completing required tasks for their job. In their study of skills in the financial section, Kyng et al., (2013) found both graduates and employers agreed that spreadsheet skills were important, with new-graduates spending 60% of their time using them. However, they disagreed as to where those skills should be obtained. Graduates believed that employers should offer workplace learning, whereas employers thought that new graduates should already have these skills. This is in line with the findings of Gibbs & McKinnon (2009), regarding the skills of graduate accountants, in which the skill set of new graduates did not match that required by employers, or indeed that expected by employers.

Although this study did not specifically seek to look at individual occupations, it should be noted that those who completed the most of both the Word-processing and Spreadsheet assessment tasks were in occupations where a high level of computing ability could be expected, such as accountants and business analysts. However, the largest occupational group represented in this study (administrative staff) is a group where spreadsheet use should be expected, yet this group returned a poor completion rate of what could be described as basic spreadsheet tasks – although they did well in word-processing. These results appear to show that while expectations of some groups are as expected, this can't be said for all such workers. It may be, as Turbinis (2015) said of lawyers in his study, that people expect that because they have knowledge in their core domain, this knowledge flows over into their use of technology. Findings certainly do suggest that there are, indeed, technological inefficiencies present in workplace computing that employers should be taking notice of.

As well as calculating the number of correctly completed tasks as a measure of demonstrated skill, a time was also recorded for each task from each of the two skill assessments. Participants were unaware of this recording occurring. While there was no relationship between time taken and the outcome of the word-processing assessment, there was a significant relationship between time taken and result for the spreadsheet assessment. These findings show taking a longer time to complete a task did not lead to higher scores for these tasks. Those who received the highest scores generally did so in the shortest times. This shows that the participants who knew how to complete a task did so efficiently. Time should be considered an important indicator of skill level in areas that are more complex, such as the spreadsheet assessment compared with the word-processing assessment, but it should be noted that time taken is not necessarily an indicator of success (Schout et al., 2010).

The modes of learning EUC that participants used help to make sense of the variations of demonstrated skill level shown in this study. The findings show that the most common modes of learning were the informal approaches such as being self-taught or learning from a peer. This result was similar to that found by Lawson et al. (2009) who also found that the most common method of learning was being self-taught and that those who had been offered formal training in spreadsheets had more expertise than those who had not had the same opportunities. Lawson et al. (2009) argued that more experienced users were more likely to employ best practice in their spreadsheet use including being well-trained and working closely with colleagues in the planning and designing of spreadsheet models. Findings in this study showed that the approach taken by participants in learning end-user computing skills was significantly associated with occupation, demonstrated spreadsheet ability, assessment of the average computer end-user and estimation of the breadth of the domain of end-user computing. These associations may mean that, in general, informal learning methods are not the best approach to gain a broad range of skills suitable for a workplace setting. A risk of not providing formal targeted end-user computing training for staff is that skill level will not improve, bad habits will be allowed to continue, and users may remain unaware of their skill deficiencies (Lawson et al., 2009). Because end-user skill is often a product of self-learning it is difficult for some to correctly assess their own ability and difficult to recognise skill deficiency. It then follows that, when one is self-taught and does not have the skill to recognise deficiencies in one's knowledge or training, one is more likely to be overly optimistic in self-report situations than those who have had formal training (Baker et al., 2008).

This point relates to a broader issue concerning the way in which technology often develops. As a particular technology evolves and as uses for it have become more commonplace, it often becomes deliberately designed for ease of use. Interfaces are created using simple, repeatable patterns to which users become accustomed. The level of expertise required to use it has become lower than it was previously, when not as many functions were available via the interface. Regular use of a software application can lead to a level of familiarity with the application, and to others with similar types of interface. This familiarity may mean that users have confidence in their ability with this software even if their use of the application is limited to a small number of tasks. This is no different for common software applications that are used in the workplace, with the level of expertise required to use having decreased. What this may do, however, is send contradictory messages to users. On the one hand, a user who is confronted with an easy to use application has little trouble performing simple tasks, but on the other hand, the need for expertise has been undermined due to

the occurrences of the above-average effect. That is, signals that the use of the software requires expertise have been reduced through evolving design and task familiarity.

## 5.5 Summary of discussion

To summarise this discussion, an above-average effect in the self and comparison assessments of EUC has been identified. Three of the four hypotheses testing this effect were supported, with evidence of this effect in both comparisons between self-assessments and an AEU, between self-assessments, demonstrated skill level and occurrences of the AAE. These associations indicate that further investigation of the factors affecting self-assessment in an end-user computing context are warranted.

Surprisingly, a combination of expertise, demographic and personality traits were not identified as predictors of this bias in the domain of EUC. Previous studies have found that the individual factors of sex, age, expertise and extraversion have all had positive associations with the AAE. When combined, as in this study, there was no association with the AAE. Perhaps it should not have been surprising since the model used addressed a different question to the individual regression models. Certainly future research is required to investigate these relationships (or lack of) further.

Likewise, evidence of the Dunning-Kruger effect was also mixed with only one of the four hypotheses testing this effect being supported. Evidence was found to support the DKE as an explanation of differences between self-assessment and a person's awareness of the breadth of the domain of EUC, offering some support for the notion that expertise in a domain will moderate the DKE. However, there was no support for the combination of personal factors, expertise and personality being associated with this effect. As with the AAE, further research is required to investigate this effect further and in particular in context such as the one used in this study.

Technology is advancing at a fast rate and end-user computing applications are not immune to this change. Although a person may learn some type of computing at school or university, applications change at a faster rate than some users update their skills (Grant et al., 2009; Gravill et al., 2006). Even though rapid change is occurring this domain is not immune to occurrences of the above-average effect. In fact, it would seem, this is a rapidly evolving domain that is susceptible to occurrences of this bias.

The following and final chapter in this thesis provides a conclusion to this discussion, implications, both theoretical and methodical, and recommendations for end-users and those employing them.

Suggestions are made for future research, which could extend this study further and improve knowledge and understanding of the social bias, the above-average effect.



## Chapter 6 Conclusion, Implications and Future work

### 6.1 Introduction

This study was undertaken to explore the relationship between self-assessment and demonstrated skills in the domain of end-user computing. Eight hypotheses were developed to test the overarching research question: *“What individual differences are critical in instances of the above-average effect in the context of end-user computing?”* The hypotheses, (Section 1.3) separated into two groups, tested evidence of the above-average effect and evidence of the Dunning-Kruger effect as a mechanism for this bias.

An above-average effect was evident in comparisons between participant’s self-assessment of end-user computing and that of the average computer end-user. Probable explanations for this include the cognitive mechanism of egocentrism or the motivational need to self-enhance. It can be assumed from this finding that some of the self-assessments given would be inaccurate, given the majority of participants rated themselves as being above average. Evidence of an above-average effect (AAE) was confirmed after the participant’s skill assessment results were added to the analysis. An above-average effect was also found in comparisons between self-assessment and estimations of  $EoD_{EUC}$ . A possible explanation of this was the Dunning-Kruger effect (DKE). This suggests that self-assessments would become more accurate as a person’s knowledge in the domain increases. Also evident was an above-average effect evident in self-reports related to an average end-user and also relative to estimations of the breadth of the domain of end-user computing. This result suggests evidence of the DKE, that a person’s perception of their own knowledge and that of an average end-user is related to what they understand there is to know about end-user computing. Those with a larger estimation of the domain breadth are more likely to perceive a larger gap in knowledge between themselves and an AEU than those with more modest estimations of domain breadth.

This chapter is presented in seven sections including this introduction section.

Section 2 discusses the theoretical implications of the study in relation to the above-average effect. Section 3 provides discussion relating to methodological implications of the measures used in this study. Section 4 discusses the implications of this study that are directly related to the context of end-user computing, and the computer end-user. In Section 5, recommendations are made for employers and, in Section 6, recommendations are made for future research. Finally, Section 7 provides an overall summary of this chapter and this thesis.

## 6.2 Contribution of research

The novelty of this research can be found in several different areas. Firstly, this research is the first of its kind in the combination of domains explored. Evidence for and explanations of evidence of the social bias, the above-average effect, were found in the domain of end-user computing. This is significant because, although studies have both domains have been undertaken, never have they been combined.

Secondly, research novelty is evidenced in the combination of individual differences used and the fact that the combination of these was not found to be an explanation of the Dunning-Kruger effect, in particular, when studies of individual differences suggest this combination should have been significant. These findings suggest that more work is needed in identifying the influences of each of the individual differences and if this is, indeed important in allowing for accurate self-reporting.

The third area where novelty is a factor is that of the domain and its interaction with the social bias, the above-average effect. The majority of the studies under taken to explore this bias do so in either controlled situations where a domain is stable and/or where it is easy to observe others. The domain of end-user computing is neither stable nor is it one where observations of others are easy to achieve. For this reason alone this makes this study different to all others which explore the bias and important for those interested in the pervasiveness of end-user computing.

The fourth area where this study provides a valuable future contribution are the questions that have been raised by this study, leading to a number of possibilities for further study. Indeed the data collected from this study can and will be examined in ways outside the bounds of this research. These areas may be to look more closely at the influence of personality and occupation on the findings. Alternatively it may be that workplace training is examined in greater detail in order to understand the diverse interactions presented in this study.

## 6.3 Theoretical implications of an above-average effect

The main findings of this study indicate that the social bias called the above-average effect is present in situations of self-assessment and estimations of the average computer end-user in a workplace-computing situation. Although many studies have investigated the above average effect in different domains (Alicke et al., 2005; ; Dunning et al., 1989; Kruger & Dunning, 1999,2009; Larrick et al., 2007; Mattern et al., 2010; Pavel et al., 2012) and likewise, many studies have investigated end-user

computing skill level (Birch, 2007; Eschenbrenner & Nah, 2014; Govindarajulu & Arinze, 2008; Grant et al., Gravill et al., 2006, 2001) this study is original in taking a combined focus on these two areas.

One potential concern about this study's findings is that rather than there being evidence of an above-average effect it may be that participants were, indeed, above-average computer end-users. While this is logically possible, it has been argued that the sample used does approximate randomness, as can be seen in findings reporting bootstrapping values and explained in Section 3.3. Further, the recruitment method used in this study is similar to other studies investigating this effect, and in some respects more representative of the actual population given that only people in workplaces who used EUC software took part.

Although the above-average effect is regularly found in areas considered easy or ill defined, a difference between this current context and others is the fast changing nature of the domain. From a theoretical perspective, the ways in which the fast changing nature of a domain moderates or exacerbates this effect has not previously been considered. End-user computing is a readily available example of such dynamic domains. Other domains in which this effect is found are established and are not subject to the rapidity of change experienced in computing. When knowledge within a domain changes rapidly, awareness of new knowledge will be harder to maintain. That applies not only to difficulties in knowing how to use new functionality (e.g., in software applications) but also to the knowledge that such functionality even exists. Therefore, it is likely that self-reports of knowledge and skills would be less accurate in fast changing domains than in those that are less dynamic. It may also be that the rapidity of change increases the levels of ambiguity associated with a domain due to people being unable to keep up with the changes or being unaware of them. Ambiguity of a domain can be explained by the broadness of a domain. For example, participants in this study used spreadsheets for their work. Use of a spreadsheet can range from simple data entry to the sophisticated use of functions and inbuilt features. Therefore, due to domain broadness, one person's understanding of the use of a spreadsheet will differ from another person's understanding. Workplace use of computers and computing applications varies widely and is often linked to the type of business being undertaken. As previously noted, it can be difficult for an end-user to witness similar use of the applications to that of themselves. This lack of opportunity for observation may lead a person to have inflated views of their own use and knowledge of those tools. So when asked, they may, incorrectly, believe their skills to be better than their peers in similar roles in different workplaces.

Social comparison biases are found in many differing domains and explained by cognitive or motivational mechanisms (Sedikides & Strube, 1997). Self-enhancement is a motivational mechanism that drives the need to feel good about one's self (Brown, 2012; Moore, 2007; Chambers & Windschitl, 2004; Sedikides & Strube, 1997; Alicke, 1985). Egocentrism, a special case of focalism, is a cognitive mechanism, found in either direct or indirect comparison situations, where a person places more importance on self-relevant information than information about a referent person or group (Alicke, 2005; Krizan & Suls, 2008; Windschitl et al., 2007). The DKE is a cognitive mechanism used to explain instances of the AAE. The main tenet of this explanation is that those with little knowledge of a domain lack the knowledge to realise this and to recognise knowledge in others. This study found that the DKE is at least a partial explanation for the AAE in the current context when self-reports of knowledge and skills were entered into the relationship with estimations of the breadth of the domain. However, no association was found between what a person believes they know about the domain of EUC and what they believe there is to know about EUC when they were rating an AEU. That is, their ratings of an AEU seemed to be based on what they believe they knew and not what they believed there was to know. Also, and as with the findings for the AAE, no differences were found to suggest that experience alone sufficiently moderated instances of the AAE. The findings do suggest that those with greater overall EUC skill and knowledge may moderate their estimations of the breadth of the domain, self-assessments and estimations of the knowledge and skill of an AEU. Pavel et al. (2012) declared that the DKE was prevalent in the aviation industry based on overly optimistic self-reports made by poorly performing aviation students made in relation to peers. They found a disconnect between the perception and reality in relation to how well a student believed they would answer domain specific questions in relation to their peers.

A focus of this study was on the factors at a personal level (e.g., personality traits, learning modes, etc.) that may influence the occurrence of the AAE in EUC. The AAE has been found in both direct and in-direct experimental settings and has been found to be associated with individual differences including age, self-esteem, and experience (Zell & Alicke, 2011). Although originally thought to be motivated solely by a need for individuals to self-enhance (Markus & Wurf, 1987), cognitive mechanisms have also been suggested as explanations of this type of bias (Alicke et al., 2005). Similarly, the personality traits of extraversion and conscientiousness have been found to be significant factors in studies investigating over-confidence (Schaefer, et al., 2004). Over-confidence is, in turn, aligned to social biases such as the AAE (Larrick et al., 2007; Moore & Healy, 2008). Therefore, it was surprising that, in this study, the combination of personality, expertise and demographic factors were not significantly associated with the AAE. One possible interpretation of

this finding could be that the instruments used were not sensitive enough to measure the effect of interest. That is, it could be argued that the measures of perception used were measuring ‘different things’ than the skill assessment instruments. However, many studies focussing on the above-average effect use a similar approach, usually with some type of discrete measure and a skill test or examination (Mattern et al., 2010; Kruger & Dunning, 1999, 2009). A difference in this study to others examining this social bias was the use of the VAS for measuring perceptions. Intensive pilot testing (Section 3.5.1) allowed for the creation of an instrument that provides a more accurate measure of perceptions than discrete scales do. This finding does, however, raise a number of questions about how each of the variables may interact to moderate the overall effect and how this affects our understanding of this bias. For example, is conscientiousness inversely related to expertise (i.e., experts may have less need to be conscientious to solve problems) or, alternatively, does age moderate over-confidence and the effects of the other variables (e.g., older people may be more conservative in their self-assessments than younger people)?

Explanations for the AAE range from the need to self-enhance to cognitive mechanisms which place more emphasis on self-information than information about others. The DKE explanation for the AAE attests that experience in a domain will moderate this effect (Pavel et al., 2012). In this study, there was evidence to suggest that an awareness of the breadth of a domain may moderate the AAE; however, findings, which specifically tested experience, personality and demographic variables with this bias, were not significantly associated. In previous studies, findings have suggested that immediate feedback, training or the offering of incentives can modify inaccurate self-reports. For example, Miller and Geraci (2011) examined whether providing concrete feedback and incentives (i.e., extra credit) for accuracy would improve predictions by improving students awareness of their own knowledge because predictions had almost always been higher than the actual grade earned, especially for the poorly performing students. After the feedback (and offer of extra credit) predictions made by the more poorly performing students improved, however examination results did not. Conversely other studies have found feedback about ability did not improve self assessments for the less competent (Gravill et al; 2006; Schlösser et al., 2013). These conflicting results are interesting to consider in the context of this study. Those studies where improvement was found were those where immediate feedback and some type of incentive was offered, whereas the studies where no change was found were similar to this one in that they were measuring experience in a domain and not offering immediate feedback.

### **6.3.1 Theoretical implications of an above-average effect in an EUC context**

There is no doubt, based on findings from this study, that an above-average effect is found in end-user computing, with the plausible explanation being that this effect is found in end-user computing for the same reason it is found in areas that are considered easy, ubiquitous or routine, such as driving.

Although end-user computing is now commonplace it is interesting to consider why this area might be considered easy by some, given the varying levels of expertise required (Lawson et al., 2009). Just as having some appreciation of how a car's engine works may help someone drive better, some understanding about the functionality of a particular application could make end-users more effective. While many end-users are able to perform tasks once shown how to, they do not necessarily understand enough about the task they are performing and its relationship to the software's capability and structure to be able to extend their knowledge further. In addition, the field of computing has evolved from one where interaction between computers and users consisted of command line requests or punch cards and moved to the graphical user interfaces with which users have now become familiar (Baecker, 2008). Some users may fail to understand or appreciate the intricacies of end-user applications beyond what they believe there is to know nor do they understand what is happening behind the interface. Therefore, they could mistake their level of skill in the area and thus believe it to be better than the average computer end-user. Alternatively, some users may not believe they are better than the average user but, because of the ubiquity of computing and the implication that it is therefore a skill that all should possess, they do not want to appear to lack knowledge in a domain they believe should be easy for all to master. This explanation is associated with what Paulhus & Reid (1991) describe as "impression management". Impression management, in social psychology, is an objective-driven process undertaken either consciously or unconsciously, where a person attempts to control other people's perceptions of them by regulating information in a social context (Paulhus & Reid, 1991).

The implications that follow from identifying an above-average effect in end-user computing are various. Due to the ubiquity of computing in modern lives, end-user computing appears to fit into the same category as other areas that are considered easy, such as driving, or hard to define, such as happiness. However, the suggestion of it being 'easy' may be misleading. It is perhaps better to say that the intricacies of the domain are relatively unknown to many users (compared with other domains). Thus, such users can be mistaken in their belief that what they know is all there is to know.

Moore (2007, p. 54) suggested that if people self-selected for domains in which they believed themselves to be better than others then the above-average effect would dominate. However, given its ubiquity, end-user computing is often obligatory as it increasingly forms part of standard employment skills. While it might be reasonable to assume that a constraint such as this may temper social biases such as the AAE the findings in this study suggest that, in end-user computing at least, this is not the case.

## 6.4 Methodological implications

Evidence of the above-average effect was found in comparisons between self-assessed knowledge of end-user computing and estimations of the average computer end-user. However, in line with previous studies (Moore, 2007; Pedregon et al., 2012), the results from subjective self-report measures need to be interpreted with caution. For any individual, it is entirely possible that either indirect or direct comparisons do not always lead to absolute evaluations of themselves, or indeed of others (Moore, 2007). This is why this study employed both subjective and objective measures and why the subjective measure used a visual analogue scale rather than a more traditional measure.

As previously noted, one concern about the validity of findings in this study may be that the instruments used were not sensitive or fine-grained enough to measure perceptions against ability. That is they may not be measuring the same thing. However, the approach used in this study replicates that used in many studies of the AAE (Ehrlinger et al., 2008; Kidd & Monk, 2009; Kruger & Dunning, 1990, 2009; Mattern et al., 2010), with the exception of trying to mitigate effects of the perception measure by using a visual analogue scale. The use of the visual analogue scales as the subjective response measure for the perception measurements allowed users the freedom to mark the line without feeling constrained by categories of response. A continuous measure scale, such as the VAS, allows for finer grained responses than does a discrete scale. This means there is a possibility for responses to be marginally more moderate (or more extreme) than when using a discrete scale. More generally, continuous scales have been claimed to provide greater levels of sensitivity and to provide for responses that may fall between discrete categories (Funke & Reips, 2006; Marsh-Richard, et al., 2009; Parkin & Devlin, 2004). Importantly, the VAS is thought, in some cases, to mitigate instances of the above average effect and provides fine grained measurements that can easily be quantified and analysed against each other (Marsh-Richards et al., 2009; Parkin & Devlin, 2004).

An important reason for choosing the VAS was to limit the 'looseness of definition' inherent in discrete scale instruments. A problem with discrete categories, that are too 'loose' as measures is that they may not be tied precisely to the granularity of the perceptions they hope to measure. One of the things about the AAE is that it is often exacerbated by the ambiguity of the question or domain being assessed (Dunning et al., 1989). Often, an aspect of ambiguity that is not reported is that provided by the instrument itself by way of the descriptor categories provided. Typically, studies assessing self-perceptions use discrete measures with labelled descriptors. These descriptors used when assessing skill may include labels such as 'Below Average', 'Average' or 'Above Average'. Using a VAS presented as a line with end-points goes some way to mitigate the imprecision encouraged by the more common discrete scales. The pilot studies used in this study at the instrument development stage (Section 3.6) aided in developing versions of the instrument that, amongst other improvements, increasingly moderated this imprecision. While it might be argued that since each version reduced the apparent occurrence of the AAE further development could potentially have eliminated all such apparent evidence this reasoning is flawed. Empirically established biases such as the AAE are theoretically explained by motivational or cognitive mechanisms and as such it is unlikely they can be completely removed. It is also difficult to see how even greater response precision could be achieved by either visual or linguistic measures. There is also likely to be perceptual and cognitive limits to the precision of the actual perceptions.

In conclusion, the benefits of using such continuous measures of perceptions related to the AAE are currently under-tested. Such measures are currently used in domains such as health care studies where participants are asked to measure levels of pain but not in social psychological research on the AAE. Use of this instrument in this study shows how successfully a VAS can be utilised for social science research and amounts to a substantive and original contribution to methodological development in this area.

Finally, while subjective measures have their place, and in some cases are accurate, in situations where skill can be demonstrated then objective measures should also be used (Moore, 2007). The objective measure used in this study was a bespoke application developed to test common-place EUC tasks required in workplaces. Panels involves in the content development part of instrument development highlighted a number of basic and advanced tasks considered appropriate to test workplace computing over a number of occupations. A bespoke application was used as the proprietary ones available are often difficult to customise for a particular purpose. Added to this the instrument created was able to be piloted and fully validated, for both internal reliability and



consistency prior to use. The detailed and extensive development and testing process undertaken gave confidence that both the instrument and the content were fit for purpose (Appendix 4).

Findings in this study, using both the subjective and objective measures, showed evidence of the above-average effect. Participants believed that their knowledge was greater than an average computer end-user and that their estimations were at a higher level than they were able to demonstrate in targeted assessment tasks.

## 6.5 Implications for computer end-users

In the context used in this study (EUC), unwarranted, positive self-assessments have consequences in an employment situation. Inaccurate self-assessments may mean that people find themselves in roles where the computing required of them is outside their realm of knowledge (Gravill et al., 2006). This can lead to mistakes being made and possibly not being detected (Panko & Port, 2013). In extreme cases, it may also mean that a person loses his or her job. Less dramatically but still of importance, inaccurate knowledge about one's own ability may result in one using inefficient methods to complete computing tasks. Because end-user computing is a vital component of many jobs, overconfidence leading to overly optimistic self-assessments can and does lead to mistakes and inefficient use of time (Panko & Port, 2013). While end-user computing is perhaps not viewed by many as being as specialised as computer programming and other computing skills, the extent of the domain and the degree to which inefficient users can potentially cause problems should prompt concern about occurrences of this effect.

As highlighted in this study, occurrences of this bias may be due to the perception by many that this domain is easy, when in fact there are high-level skills achievable. That is, users who are unaware of the breadth of the domain may see little need to extend their skill. Perceptions about whether a domain is easy or difficult, when presented in a comparative situation, are based primarily on the judgments that a person makes about their own skill or knowledge in that domain (Brown, 2012). For example, this may be riding a bicycle, something a person may have done since childhood and find easy. When asked about cycling ability a person does not necessarily take into consideration that many other people have also ridden a bicycle since childhood so will also find it easy. While it is difficult to verify exactly how or why some domains have become known as 'easy' or 'difficult', this may be a consequence of the extent to which a domain, task or activity is, has become, routine.

Another risk that arises from inaccurate self-assessment applies to those who incorrectly consider themselves expert in end-user computing. Such a person may be seen incorrectly by his or her workmates as the person from whom to seek end-user computing help. This may result in the propagation of incorrect and inefficient knowledge. This may also be a problem for employers if people who do not recognise the constraints of their own skill and knowledge pass on their inefficient practices to workmates. These risks are reasonable to consider given the relatively high rates of 'self-taught' end users found both in this and other studies (Korpelainen & Kira, 2010; Lawson et al., 2009).

Self-assessments of any type are difficult to make, especially when a person does not have a reasonable grasp of the breadth of the domain being assessed or how other people rank in that domain (Kruger & Dunning, 1999; 2009). Because of this, people may not be comfortable seeking retraining or, indeed, they may not realise that more training would be useful. End-users may find that having further training or seeking formal validation of their current knowledge by way of some type of industry standard will increase the information that they have about their own ability. This may also increase the information they have about the depth of end-user computing skill that can be potentially realised. The challenge is for employers to offer this type of professional development as a matter of course so that employees will have the opportunity to be exposed to different skills and different features available in the software they are using.

## 6.6 Recommendations for employers

As just argued, overestimation by end-users of their computing ability can lead to employers engaging staff who do not have the skill level they attest to having. This may lead to people being employed in roles outside their demonstrated level of competence. These mistakes can occur because both employers and (prospective) employees do not have enough information about required end-user computing skills. An assessment tool, such as the one created for this study, could be used in a workplace to train as well as test end-users. Any information that more precisely characterises the tasks required is likely to reduce the occurrence of the AAE and, therefore, the likelihood that people without the skills for a particular role will be chosen, or apply, for such positions.

While in this study information was not directly sought from employers, previous research has found that often employers are unsure of the computing requirement of a particular role within an organisation (Gibbs et al., 2010). One issue, especially regarding self-perceptions, is that it is difficult

to quantify a person's perception of their ability against the expectation of another party. In other words, above average ability to one may be average ability to another. This can cause problems for organisations, especially given that many rely on the use of applications such as spreadsheet software to produce documentation vital for the organisation's operation.

Findings from this study suggest that the level of EUC skill of many participants was a level lower than they believed it was, and in some cases lower than was expected they would be by panels of experts. It is difficult for employers to know the level of skill that employees have, given that self-assessments are known to be flawed, and that evidence of the AAE in EUC was found in this study. In an attempt to moderate instances of this bias and to improve employee EUC skill, there is a need for continued professional development in the area of end-user computing. Targeted training would help employers to know the skill level of employees, and the employees to learn and improve their skill and be better positioned to make more accurate self-assessments. To be of the most benefit to end-users training could be designed to incorporate elements beyond the routine tasks of a person's job. This approach would go some way to increase people's awareness of the breadth of the skill domain and potentially improve performances in routine areas. This type of training, however, may not always be aimed at the people who would benefit the most and training may not be targeted at the skills most needed (Gupta et al., 2010; Lawson et al., 2009; Berezina et al., 2011; Rondeau et al., 2006).

The most prevalent methods of learning EUC skill in this study were being self-taught and learning from a colleague. While each of these methods has the benefit of not involving any outside financial cost and being timely, they both have disadvantages. There is a great amount of information freely available via Internet sources which people can easily access to learn any number of EUC skills. However, much of this information is not moderated and the skills learned may not be the best ones for the problem or task someone is trying to complete. Learning from a colleague has merit from two points of view. It can be a cheaper option for an employer since they do not need to involve a third party in training. It can also mean that the person giving the mentoring may extend their own skills, because of helping others. A disadvantage of this method, like that of being self-taught, is the lack of control by organisations of the correctness and effectiveness of the skills being passed between colleagues (Gravill et al., 2006, 2001).

Another issue involves convincing people, whose skills are lower than they believe them to be, that they require training. One approach may be to increase the opportunities that people have to

observe others using the relevant software tools, as observations are a method of providing feedback to others, given that providing appropriate feedback has been found to help people make better decisions (Eberlein et al., 2005).

## 6.7 Future research

This study has confirmed that social biases are evident in the self-assessments of end-users in computing, and that there are differences between this domain and others where this effect is routinely found. For this reason, there is scope for more investigation into occurrences of the above-average effect in a broader computing context in order to see if this problem is as prevalent as it is in end-user computing. Several suggestions are made in three areas: Study of the AAE in general; occurrences of the AAE in EUC; understanding EUC skills.

Given the rejection of the omnibus test of the hypothesis regarding the influence of personal, expertise and personality traits on occurrences of the AAE in EUC, further investigation into the influence of each of these variables is recommended. The findings in this study suggest the presence of previously unidentified interactions between the personal factors that are moderating the strength of the AAE in the context of EUC. While the context of EUC may be pivotal in understanding such apparent interactions further research should consider the possible influence of such interactions more broadly.

More specifically, previous studies have found significant associations between the AAE and these factors individually so in order to deepen understanding of their role in generating the AAE it is important to understand how these factors might interact. Although the findings of this study do not supply definitive reasons as to why this combination was not associated with the AAE or the DKE, it is interesting to consider associations that may give possible explanations. For example, both the personality traits, extraversion and conscientiousness were positively associated with age (See Table 27, Section 4.4.6). Although the traits of the FFM are considered stable measures of personality over reasonable periods, studies have found that age can affect some of the five traits (Specht, Egloff & Schmukle, 2011). In particular, Specht et al. (2011), in their discussion of the stability of traits over five year periods, found that age had a complex influence on conscientiousness. Younger people (under 30 years) were less conscientious than those considered middle-aged, but the stability of conscientiousness then decreased in the oldest age group. This variation may explain the positive influence of this trait in this study, given that the majority of participants could be considered middle-aged. Higher levels of conscientiousness may work to moderate biases such as the AAE, with

people acknowledging that they need to work to learn new skills. Specht et al. (2011) also found that extraversion differed across age groups, although it should be noted that their study focussed on extraversion for the dimension of social vitality, which itself is seen to decrease over one's life span. However, their analysis showed a strong association between extraversion and age, with extraversion seeming to decline for older people. In terms of this study, it would seem, that higher levels of extraversion are associated with the AAE for the age groups generally found in a working population. In relation to this study, it may be that these traits are moderating each other resulting in a moderation of both the AAE and DKE. Future work could include longitudinal studies to investigate the effects of age on these personality traits with respect to occurrences of the AAE.

A difference between EUC and other domains in which the AAE is routinely found is the rapid rate at which changes occur. Longitudinal studies could be undertaken to track any relationships between the rapidity of change in the functionality of the domain and occurrences of the AAE. Comparative studies, for example, of the use of software applications that have undergone considerable and substantive rapid development and applications that have developed more slowly could be carried out.

It is also suggested that future research could explore the ways in which the DKE is manifest in end-user computing. This research would help in identifying the basis for the lack of knowledge about the domain that seems to exist currently, evidenced by, amongst other things, a lack of training, a lack of understanding that there might be more to know, and a lack of motivation to learn.

Another area in need of further investigation is that of computer skills training. The most prevalent method of training reported in this study was the informal method of self-learning with the online method being used by far fewer participants. This result was surprising given the amount of information available in an online environment. Therefore, it is suggested that further research could help to identify what people mean by "self-taught", and how they see this as being different from using online resources.

A prominent model in Information Systems research, the Technology Acceptance Model, explains how users accept and use technology (Davis, 1985). This theory suggests that a user's intention to use new technology is influenced by a number of factors. These factors include the perceived usefulness and the perceived ease of use of technology, as well as the intention to use, attitude toward use and actual use. Since it was first introduced by Davis (1985), several attempts have been made to extend this theory to account for the changing nature of information technology

(Venkatesh, 2012). Although this model was not considered appropriate to use in the context of this study given that participants in this study had no choice over the use of spreadsheets or word-processing in their employment. However, given that the findings suggest many users may consider EUC computing 'easy', it would be interesting to explore possible relationships between the TAM construct of "ease of use" and the AAE in an EUC context. It may be possible, for example, that there is a trade-off between the benefits of making a technology acceptable and the costs of increasing the likelihood of occurrences of the AAE in EUC jobs. In particular, increased ease of use may not only increase acceptance of the software technology but also increase the AAE in the domain.

One potential influence on the above-average effect that may require further investigation is the possibility that self-assessment situations that occur in a workplace may be affected not only by the biases and assumptions of an individual, but also by the biases of an organisation or of colleagues. This type of bias may be because of company culture, which promotes the idea of doing things better or faster than other organisations and only hiring the best people (Biswas & Chalil, 2013). A company or organisation's culture is the behaviour of people within that organisation and the meanings that people attach to that behaviour (Needle, 2010). An organisation's culture includes the collective beliefs, principles and values of the organisation and members of it. It also includes the patterns of behaviour, which are passed on to all new employees as the way of organisational thinking and behaving. Given that one of the five concepts of company culture mentioned in the literature is the 'self-in-organisation concept' (Harris, 1994), it is interesting to consider the idea that individual occurrences of the AAE in a workplace situation could be linked to company culture. The self-in organisation concept is described as a person's concept of oneself within an organisational context. This includes personality, role and behaviour. It is also interesting to consider that if an association between organisational culture and the AAE was found, would it be more likely to occur in large corporations as opposed to small-medium enterprises, or if the inverse would be true. In this type of context it is plausible that an individual may 'buy into' that line of thinking and believe that they, on an individual level, are better than average because of where they work. Investigation into the existence of links between instances of the AAE and company culture is therefore also recommended. Additionally, it is also interesting to consider, if such a link was found, whether organisational characteristics such as size and type of organisation, were correlated with the AAE.

One final area that should be considered for future investigation is the possibility that occurrences of an AAE in a workplace setting are the result of people anchoring their judgments about their ability *relative to others* on their proficiency at work tasks. That is, a person's perception of their own

ability may relate directly to how they perceive their job performance relative to others they observe rather than directly with their facility in using a software application.

Each of the suggestions for future research are anchored in the concept of understanding occurrences of the AAE, both in general terms and in settings such as EUC, in an attempt to further understand the implications of social biases in everyday situations.

## 6.8 Concluding remarks

This study has emphasized an area which has not been previously highlighted in research. The demands of the modern workplace require most employees to have highly effective computing skills. It is also necessary that computer end-users are able to recognise deficiencies in their own end-user skill and make an effort, in partnership with their place of employment, to keep skills up to date as technology advances.

Currently the most common method of assessing workplace end-user skill is by way of self-report. However, self-reports are potentially inaccurate given biases such as the above-average effect, evidence of which was found in this study. Participants' self-reported end-user computing skill did not match demonstrated skill. One of the issues found in the NZCS report of workplace digital literacy was the lack of a mechanism by which people can benchmark their own skill level (Bunker, 2010). The results based testing system created for this study provides a mechanism by which bespoke testing and learning environments can easily be customised for different uses in different workplaces.

Past studies have highlighted the above-average effect in areas that are deemed easy or ambiguous. It is not clear if EUC as a domain is considered easy by some users, or if the breadth of the domain makes it difficult for one to make an accurate self-assessment. It may be that users, with less experience in the domain, do not realise a domain has greater breadth and depth than they are familiar with. This ambiguity is also a product of a domain that is ever changing. The implications of this effect being present in this type of domain are far reaching and may have repercussions for both users and those who employ them, if they do not have an accurate perception of their skill. Findings of the above-average effect in this domain raise questions about understanding this effect in situations where there is little opportunity to directly observe those one is comparing oneself to. It is also interesting to consider instances of the AAE in domains in which participation is not the main context for a participant, but a consequence of it. For example, EUC is required in many occupations,

but often may not be the core competence of the role, but used as a tool to complete required components of a job. An accountant uses technology to perform accounting functions, just as a lawyer needs to use technology to prepare legal documentation. In each of these examples EUC is not the core of the role but complementary to the role.

The risk to the user of being unaware of their skill level is that they may overlook or even avoid opportunities to update their skills because they are unaware they need to do so. While this may mean an ineffective workplace, which at the very least may threaten productivity levels, even worse for organisations, and end-users, is the risk of financial losses and missed opportunities due to mistakes being made by end-users who do not have the skill required to recognise mistakes when they occur.

In sum, this study has confirmed that the AAE is evident in the context of end-user computing. Importantly, however, combinations of variables that had been found in previous research to influence instances of this effect did not appear to do so when analysed in combination. The results of this study, as well as answering several of the questions asked about the AAE, have also raised several questions which, when answered, will aid further in understanding social biases and the cognitive or motivational mechanisms used to explain them. This should improve understanding of how differences between domains affect the occurrence of these biases. In particular, this study has highlighted the complex nature of the domain of EUC, the apparent under performance of regular end-users and their lack of accuracy in their judgments of their skill level. The prevalence of workplace computing is likely to increase, as is the functionality of the software available. It is therefore important that users, and those employing them, have an awareness of the skill-set available and that the biases that affect self-assessments of knowledge and skill are given the attention they deserve.



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## Appendices

Supplementary material is presented in the following sections divided into to five appendices.

### Appendix 1: Participant recruitment

This section requires material used during the participant recruitment process. This material includes the invitation to participate, the study consent form and the study information sheet.

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#### Invitation to participate

My name is Shirley Gibbs, I am a Lecturer in the Department of Applied Computing at Lincoln University and completing my PhD. My research project involves trying to understand the range of computing skills that are required in a workplace and the level of computing skill that people in different jobs have.

In order to establish these things I am planning to conduct a study of people in the workplace who use Word Processing and Spreadsheet software.

I would appreciate your help in recruiting participants in Christchurch for my study. If you think people in your organisation would be willing to help, I would appreciate the opportunity of contacting them. This contact could be made in a variety of different ways:

- I could post a message on your staff intranet site inviting people to partake.
- I could compose an email to be circulated around staff.
- I could come into the workplace, explain my study, and ask for participants.

The study will require participants to be available for around an hour to complete a questionnaire followed by a Word-processing and Spreadsheet skill assessment. The study can be conducted at a time and place to suit participants. This may be in your workplace, at Lincoln University or alternatively some other venue that is convenient for the participant. I plan to start my study in October of this year and will work with participants to organise a suitable location and time.

The aim of this study is, not to individually rate people, but rather, to gain an overview of skill level. While I am aware that this is a major time commitment for busy people, the results of this research will help to identify ways that businesses can improve productivity levels and increase awareness of computer literacy.

I would appreciate hearing back from you as to your willingness to support this research or if you have any questions about the study.

My supervisor, Gary Steel ([gary.steel@lincoln.ac.nz](mailto:gary.steel@lincoln.ac.nz)), is also available to answer any questions you may have about the study.

Regards

## Research consent form

***Name of Project: An investigation of workplace end-user computing.***\_\_\_\_\_

I have read and understood the description of the above-named project. On this basis I agree to participate as a subject in the project, and I consent to publication of the results of the project with the understanding that anonymity will be preserved I understand also that I may withdraw from the project, including withdrawal of any information I have provided any time prior to completion of data analysis (December 2013).

Name: \_\_\_\_\_

Signed: \_\_\_\_\_ Date: \_\_\_\_\_

## **Research information sheet**

**Lincoln University**

***Faculty of Environment, Society and Design***

### **Research Information Sheet**

You are invited to participate as a subject in a project entitled: An investigation of workplace end-user computing.

The aim of this study is to gain an understanding of the types of end-user computing tasks that are required in a workplace and to gauge the level of skill necessary for the average person to satisfactorily carry out these tasks.

Your participation in this project will involve completing a two-part written questionnaire.

Part one of this questionnaire will involve answering some questions relating to the type of computing you do in the workplace. You will also be asked to provide some demographic information

Part two of this questionnaire involves you completing a short personality test

You will then be asked to complete a number of common tasks using both a Word-Processing application and a Spreadsheet application.

In total, the complete survey should take you around an hour to complete.

The results of the project may be published, but you are assured of complete anonymity in this investigation: the identity of participants will not, under any circumstances be made public. You should also be aware that your individual results will not be made available to your employer. To ensure anonymity and confidentiality no names or other identifying information will be collected on the questionnaire.

If you agree to participate, you will be asked to sign a consent form. This form will be kept securely away from the collected data.

Participation in this project is on a voluntary basis You may withdraw from the project, including withdrawal of any information I have provided any time prior to completion of data analysis (December 2013).

The project is being carried out by:

*Shirley Gibbs ([Shirley.gibbs@lincoln.ac.nz](mailto:Shirley.gibbs@lincoln.ac.nz))*

She will be pleased to discuss any concerns you have about participation in the project.

*Shirley's supervisor is Dr Gary Steel ( [gary.steel@lincoln.ac.nz](mailto:gary.steel@lincoln.ac.nz)).*

The project has been reviewed and approved by Lincoln University Human Ethics Committee.



## Appendix 2 – Combined Instrument

This section presents the combined demographic, perception measures and personality instrument as it was given to study participants.

---

1. What is your age?

\_\_\_\_\_

2. What is your sex?

Male ☐

Female ☐

3. What is your occupation? \_\_\_\_\_

4. Please indicate which, if any, of the office type software applications listed below you would routinely use.

Word Processor (e.g. Word) ☐

Spreadsheet (e.g. Excel) ☐

Presentation software (e.g. PowerPoint) ☐

Database (e.g. Access) ☐

Other (explain below) ☐

\_\_\_\_\_

5. Please indicate approximately how many hours on average per week you use a computer: \_\_\_\_\_

We would like your estimate of everything that there is to know about using common office type software in comparison to everything you think there is to know about computing overall. This type of software would commonly be used in a business situation for creating word documents, spreadsheets, presentations and databases.

6. Suppose that the line below represents all the pages in a thousand-page book, and that this book contains all that is known about computing. If the section on office type software began on the first page, please indicate (by marking a **T** on the line below) how many pages in this book you believe would be this type of computing.



1 Page

1000 Pages

7. The line below is the expanded section between one and T that you just indicated on the first line. Please indicate (by marking an **I** on the line below) how many pages you think you know about common office type software.



0

T

8. Also on the second line (above) please indicate using an **X**, how much you believe the average person knows about common office type software.

9. Please indicate which of the following best describes the computer education you have had.  
Tick as many boxes as are relevant.

- ☐ Community based computer training (High School Night class, etc.)
- ☐ High School Computing (NCEA, NZQA or similar)
- ☐ ICDL
- ☐ MOS (Microsoft Office Specialist)
- ☐ Tertiary qualification in ICT/Computing
- ☐ Workplace computer training– (please specify)

---

- ☐ Other – (please specify)

---

- ☐ Online tutorials
- ☐ Self-taught
- ☐ Taught by workmates, family, friends etc.
- ☐ Other – Please specify

---

Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who *likes to spend time with others*? Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement.

| 1                    | 2                 | 3                             | 4              | 5              |
|----------------------|-------------------|-------------------------------|----------------|----------------|
| Disagree<br>strongly | Disagree a little | Neither agree<br>nor disagree | Agree a little | Agree strongly |

*I see myself as someone who...*

|    |  |                                      |
|----|--|--------------------------------------|
| 1. |  | Is talkative                         |
| 2. |  | Tends to find fault with others      |
| 3. |  | Does a thorough job                  |
| 4. |  | Is depressed, blue                   |
| 5. |  | Is original, comes up with new ideas |
| 6. |  | Is reserved                          |

|     |  |   |
|-----|--|---|
| 23. |  | Tends to be lazy                        |
| 24. |  | Is emotionally stable, not easily upset |
| 25. |  | Is inventive                            |
| 26. |  | Has an assertive personality            |
| 27. |  | Can be cold and aloof                   |
| 28. |  | Perseveres until the task is finished   |

|     |  |  |
|-----|--|--|
| 7.  |  | Is helpful and unselfish with others   |
| 8.  |  | Can be somewhat careless               |
| 9.  |  | Is relaxed, handles stress well        |
| 10. |  | Is curious about many different things |
| 11. |  | Is full of energy                      |
| 12. |  | Starts quarrels with others            |
| 13. |  | Is a reliable worker                   |
| 14. |  | Can be tense                           |
| 15. |  | Is ingenious, a deep thinker           |
| 16. |  | Generates a lot of enthusiasm          |
| 17. |  | Has a forgiving nature                 |

|     |  |  |
|-----|--|--|
| 29. |  | Can be moody                               |
| 30. |  | Values artistic, aesthetic experiences     |
| 31. |  | Is sometimes shy, inhibited                |
| 32. |  | Is considerate and kind to almost everyone |
| 33. |  | Does things efficiently                    |
| 34. |  | Remains calm in tense situations           |
| 35. |  | Prefers work that is routine               |
| 36. |  | Is outgoing, sociable                      |
| 37. |  | Is sometimes rude to others                |
| 38. |  | Makes plans and follows through with them  |
| 39. |  | Gets nervous easily                        |

|     |  |                           |
|-----|--|---------------------------|
| 18. |  | Tends to be disorganized  |
| 19. |  | Worries a lot             |
| 20. |  | Has an active imagination |
| 21. |  | Tends to be quiet         |
| 22. |  | Is generally trusting     |

|     |  |  |
|-----|--|--|
| 40. |  | Likes to reflect, play with ideas            |
| 41. |  | Has a few artistic interests                 |
| 42. |  | Likes to cooperate with others               |
| 43. |  | Is easily distracted                         |
| 44. |  | Is sophisticated in art, music or literature |

**Please check:** Did you write a number in front of each statement?

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## Appendix 3: Result data

In this section, results are presented for the skills assessment and include the raw predictor correlations for the DKE and AAE hypotheses.

Table 33 displays and describes each of the spreadsheet tasks along with its difficulty rating.

Table 33 - Spreadsheet tasks and difficulty ratings

| Spreadsheet task  | Difficulty rating   |
|---|---------------------|
| 1. Basic Cell formatting.   | Basic               |
| 2. Using a simple Sum function.   | Basic               |
| 3. Using a Count function.  | Basic               |
| 4. Using a conditional function to count values meeting a criteria.       | Moderately Advanced |
| 5. Using Text Functions.  | Moderately Advanced |
| 6. Using a fixed cell reference in a formula.                             | Basic               |
| 7. Create a pivot table with one summary value                            | Basic               |
| 8. Using a conditional function to return value.                          | Moderately Advanced |
| 9. Naming a Cell.   | Moderately Advanced |
| 10. Creating a simple Column chart using adjacent ranges                  | Basic               |
| 11. Creating a one series column chart with numeric values as the x axis. | Moderately Advanced |
| 12. Sorting multi column data.  | Basic               |
| 13. Using a Lookup function in a formula.                                 | Moderately Advanced |

|                              |                     |
|------------------------------|---------------------|
| 14. Using a simple filter.   | Moderately Advanced |
| 15. Create a validation rule | Basic               |

Table 34 presents the average times taken to complete each of the spreadsheet tasks by both the participants and the experts involved in the pilot study.

**Table 34 - SS assessment task times (hh:mm:ss)**

|                   | Expert times    | Participant times | Participant times for correct tasks | Number correct |
|-------------------|-----------------|-------------------|-------------------------------------|----------------|
|                   | $\bar{x}$       | $\bar{x}$         | $\bar{x}$                           |                |
| <b>Total Time</b> | <b>00:15:03</b> | <b>00:20:18</b>   |                                     |                |
| Task 1            | 0:00:16         | 0:00:31           | 0:00:30                             | 87             |
| Task 2            | 0:00:21         | 0:00:25           | 0:00:25                             | 88             |
| Task 3            | 0:00:26         | 0:00:50           | 0:00:49                             | 44             |
| Task 4            | 0:00:47         | 0:01:21           | 0:01:26                             | 24             |
| Task 5            | 0:01:04         | 0:00:50           | 0:01:05                             | 16             |
| Task 6            | 0:01:02         | 0:01:30           | 0:01:11                             | 33             |
| Task 7            | 0:01:06         | 0:02:12           | 0:02:25                             | 38             |
| Task 8            | 0:01:03         | 0:01:50           | 0:02:28                             | 32             |
| Task 9            | 0:00:25         | 0:00:46           | 0:00:30                             | 11             |
| Task 10           | 0:00:55         | 0:01:22           | 0:01:22                             | 71             |
| Task 11           | 0:02:43         | 0:02:50           | 0:01:22                             | 31             |
| Task 12           | 0:01:03         | 0:01:46           | 0:01:34                             | 54             |
| Task 13           | 0:01:41         | 0:02:10           | 0:03:33                             | 18             |
| Task 14           | 0:01:06         | 0:00:56           | 0:00:56                             | 71             |
| Task 15           | 0:01:07         | 0:01:00           | 0:01:40                             | 17             |



Table 35 displays and describes each of the word-processing tasks along with its difficulty rating.

Table 35 - Word processing tasks and difficulty level

| Word processing tasks                              | Difficulty<br>1: everyone; 2: expert |
|--|--------------------------------------|
| 1. Applying basic paragraph formatting.            | 1                                    |
| 2. Changing a paragraph's alignment                | 1                                    |
| 3. Copying formatting between paragraphs.          | 1                                    |
| 4. Indent a paragraph.                             | 1                                    |
| 5. Creating multi-level lists.                     | 2                                    |
| 6. Applying pre-set styles to text.                | 1                                    |
| 7. Modifying a pre-set style.                      | 2                                    |
| 8. Inserting text and page number into page footer | 1                                    |
| 9. Updating a table                                | 1                                    |
| 10. Positioning an image within a block of text.   | 2                                    |
| 11. Working with sections within a document.       | 2                                    |

Table 36 presents the average times taken to complete each of the spreadsheet tasks by both the participants and the experts involved in the pilot study

Table 36- Summary of times for Word tasks (hh:mm:ss)

| <b>Task</b> | <b>Expert Time (<math>\bar{x}</math>)</b> | <b>Participant time (<math>\bar{x}</math>)</b> | <b>Participant times for correct attempts only (<math>\bar{x}</math>)</b> |
|-------------|---|--|---|
| 1           | 0:00:12                                   | 0:00:32  | 0:00:31   |
| 2           | 0:00:15                                   | 0:00:26  | 0:00:22   |
| 3           | 0:00:24                                   | 0:00:56  | 0:00:46   |
| 4           | 0:00:21                                   | 0:00:23  | 0:00:23   |
| 5           | 0:01:31                                   | 0:02:51  | 0:02:31   |
| 6           | 0:00:31                                   | 0:00:26  | 0:00:21   |
| 7           | 0:00:40                                   | 0:00:55  | 0:01:07   |
| 8           | 0:01:28                                   | 0:01:28  | 0:01:21   |
| 9           | 0:00:10                                   | 0:00:25  | 0:00:25   |
| 10          | 0:00:46                                   | 0:01:17  | 0:01:07   |
| 11          | 0:01:25                                   | 0:01:40  | 0:02:26   |

Table 37 presents the average results for each skill assessment by each of the occupation groups. This table also includes the average age by occupation.

Table 37 Assessment results by occupation

|                                | <b>N=91</b> | <b>Spreadsheet<br/>Assessment <math>\bar{x}</math></b> | <b>Word Assessment <math>\bar{x}</math></b> | <b>Age<br/><math>\bar{x}</math></b> |
|--------------------------------|-------------|--|---|-------------------------------------|
| Academic                       | 3           | 0.49 (SD 0.21)   | 0.79 (SD 0.10)                              | 46.6                                |
| Accounting and Finance         | 9           | 0.62 (SD 0.25)   | 0.64 (SD 0.19)                              | 45.22                               |
| Analyst                        | 4           | 0.78 (SD 0.310)  | 0.91 (SD 0.07)                              | 38.7                                |
| Environmental Planning         | 2           | 0.42(SD 0.33)  | 0.91 (SD 0.13)                              | 33.5                                |
| HR & Recruitment               | 4           | 0.33 (SD 0.05)   | 0.64 (SD 0.13)                              | 34.25                               |
| ICT                            | 3           | 0.87 (SD 0.18)   | 0.73 (0.31)                                 | 37                                  |
| Library                        | 4           | 0.33 (SD 0.21)   | 0.75 (SD 0.09)                              | 44.5                                |
| Management                     | 7           | 0.45 (SD 0.24)   | 0.65 (SD 0.23)                              | 51.1                                |
| Marketing                      | 2           | 0.56 (SD 0.14)   | 0.79 (SD 0.06)                              | 30.5                                |
| Project Role                   | 4           | 0.48(SD 0.13)  | 0.77 (SD 0.12)                              | 36.5                                |
| Researcher                     | 17          | 0.51 (SD 0.23)   | 0.75 (SD 0.17)                              | 39.76                               |
| Scientist                      | 7           | 0.54 (SD 0.19)   | 0.84 (SD 0.13)                              | 45.85                               |
| Secretary or<br>Administration | 19          | 0.32 (SD 0.13)   | 0.74 (SD 0.17)                              | 46                                  |
| Self-employed                  | 2           | 0.30 (SD 0.05)   | 0.55 (SD 0.13)                              | 58                                  |
| Misc.*                         | 4           | 0.45 (SD 0.28)   | 0.75 (SD 0.20)                              | 37.75                               |

*\*Participants in the four occupations represented by only one person were grouped together in the miscellaneous category*

Table 38 shows the full results for the bivariate correlations between the predictor variables used in the MLR analysis of the AAE and DKE hypotheses.

Table 38 - Bivariate correlations for AAE and DKE predictor Variables

|                        |                     | Age   | SEX  | Number SW applications | Hours computer use | SS result | Word result | Extraversion | Conscientiousness | Learning Approach | Occupation |
|------------------------|---------------------|-------|------|------------------------|--------------------|-----------|-------------|--------------|-------------------|-------------------|------------|
| Age                    | Pearson Correlation | 1     | .129 | .218*                  | -.124              | -.217*    | -.185       | -.086        | .291**            | .059              | .085       |
|                        | Sig. (2-tailed)     |       | .221 | .038                   | .241               | .039      | .079        | .419         | .005              | .576              | .425       |
|                        | N                   | 91    | 91   | 91                     | 91                 | 91        | 91          | 91           | 91                | 91                | 91         |
| SEX                    | Pearson Correlation | .129  | 1    | .078                   | .086               | -.337**   | -.104       | .212*        | .262*             | -.098             | .108       |
|                        | Sig. (2-tailed)     | .221  |      | .465                   | .417               | .001      | .325        | .043         | .012              | .357              | .306       |
|                        | N                   | 91    | 91   | 91                     | 91                 | 91        | 91          | 91           | 91                | 91                | 91         |
| Number SW applications | Pearson Correlation | .218* | .078 | 1                      | .058               | .118      | .183        | -.067        | -.032             | .034              | .151       |
|                        | Sig. (2-tailed)     | .038  | .465 |                        | .584               | .267      | .083        | .530         | .764              | .748              | .152       |
|                        | N                   | 91    | 91   | 91                     | 91                 | 91        | 91          | 91           | 91                | 91                | 91         |

|                       |                     |        |         |       |        |         |        |         |       |       |         |
|-----------------------|---------------------|--------|---------|-------|--------|---------|--------|---------|-------|-------|---------|
| Hours of computer use | Pearson Correlation | -.124  | .086    | .058  | 1      | .233*   | .337** | -.080   | .019  | .086  | -.312** |
|                       | Sig. (2-tailed)     | .241   | .417    | .584  |        | .026    | .001   | .449    | .862  | .415  | .003    |
|                       | N                   | 91     | 91      | 91    | 91     | 91      | 91     | 91      | 91    | 91    | 91      |
|                       | N                   | 91     | 91      | 91    | 91     | 91      | 91     | 91      | 91    | 91    | 91      |
| SS result             | Pearson Correlation | -.217* | -.337** | .118  | .233*  | 1       | .437** | -.309** | -.028 | .128  | -.317** |
|                       | Sig. (2-tailed)     | .039   | .001    | .267  | .026   |         | .000   | .003    | .789  | .225  | .002    |
|                       | N                   | 91     | 91      | 91    | 91     | 91      | 91     | 91      | 91    | 91    | 91      |
| Word result           | Pearson Correlation | -.185  | -.104   | .183  | .337** | .437**  | 1      | -.255*  | -.035 | .192  | .046    |
|                       | Sig. (2-tailed)     | .079   | .325    | .083  | .001   | .000    |        | .015    | .740  | .069  | .668    |
|                       | N                   | 91     | 91      | 91    | 91     | 91      | 91     | 91      | 91    | 91    | 91      |
| Extraversion          | Pearson Correlation | -.086  | .212*   | -.067 | -.080  | -.309** | -.255* | 1       | .072  | -.030 | -.055   |
|                       | Sig. (2-tailed)     | .419   | .043    | .530  | .449   | .003    | .015   |         | .499  | .780  | .606    |
|                       | N                   | 91     | 91      | 91    | 91     | 91      | 91     | 91      | 91    | 91    | 91      |
| Conscientiousness     | Pearson Correlation | .291** | .262*   | -.032 | .019   | -.028   | -.035  | .072    | 1     | .119  | -.143   |

|                   |                     |      |       |      |         |         |      |       |       |        |        |
|-------------------|---------------------|------|-------|------|---------|---------|------|-------|-------|--------|--------|
|                   | Sig. (2-tailed)     | .005 | .012  | .764 | .862    | .789    | .740 | .499  |       | .261   | .178   |
|                   | N                   | 91   | 91    | 91   | 91      | 91      | 91   | 91    | 91    | 91     | 91     |
| Learning Approach | Pearson Correlation | .059 | -.098 | .034 | .086    | .128    | .192 | -.030 | .119  | 1      | -.224* |
|                   | Sig. (2-tailed)     | .576 | .357  | .748 | .415    | .225    | .069 | .780  | .261  |        | .033   |
|                   | N                   | 91   | 91    | 91   | 91      | 91      | 91   | 91    | 91    | 91     | 91     |
| Occupation        | Pearson Correlation | .085 | .108  | .151 | -.312** | -.317** | .046 | -.055 | -.143 | -.224* | 1      |
|                   | Sig. (2-tailed)     | .425 | .306  | .152 | .003    | .002    | .668 | .606  | .178  | .033   |        |
|                   | N                   | 91   | 91    | 91   | 91      | 91      | 91   | 91    | 91    | 91     | 91     |

## **Appendix 4: Design and implementation of skill assessment instruments**

### **Introduction**

To assess the skill level of study participants' two automated test instruments were created. The content for each of the assessment instruments was created using a thorough and rigorous content validity test as outlined in the Method chapter. The instruments were developed using a Research Design Approach (Wang& Hannifin, 2005). This approach typically consists of five steps that are:

1. Problem identification
2. Solution development proposal
3. Outline of potential implementation of the proposed approach
4. Evaluation of the approach
5. Conclusions as to effectiveness of the approach

The process of developing these instruments is described in the following sections and technical specifications are available.

### **Problem Identification**

The instrument used in this study was created for assessment of commonplace workplace tasks using spreadsheets and word processors. As discussed in the Literature review for this study, there are propriety tests available using similar software applications. However, we were unable to find statistical evidence of internal and convergent validity. Therefore, it is difficult for us to say these instruments would serve the purpose we require of them.

The problems associated with using proprietary software include:

- The inability to include tasks as identified by our content validity analysis
- The difficulty in tailoring an assessment for a particular group of users
- The inability to ensure consistency between users
- The difficulty to collect measures such as time
- The difficulty collecting information by way of screen recording.

In an attempt to solve the identified issues a two-pronged approach was proposed. The first stage was to develop and validate content that was suitable for testing workplace end-user computing skills. The development of the content is described in Section 3.8. The second stage was to develop automated test instruments.

### **Solution development proposal**

The instruments necessary for this study required the following features:

- The instrument should be consistent over currently available versions of the software
- Each participant should have an individual spreadsheet or document which can be checked for correctness after the trial
- The participant needs to be able to determine when they are ready to start and stop each task to enable accurate automated recording of times
- The timing data needs to be recorded on the individual worksheets and then summarised and transferred to a master workbook
- The participant should not feel under time pressure so no time limits should be imposed
- To ensure consistency over all participants, the test should be fully automated once the trial has begun.
- The correctness of the participants' work needs to be checked and results summarised in the master workbook
- The participants' methods of completing each task need to be recorded with screen capture software.

### **Instrument development**

Two instruments were created: one a word-processing assessment and the second a spreadsheet assessment. These were created in MSWord and MS Excel. The automation involved using visual basic for applications (VBA) to provide an automated standalone assessment environment.

### **Software Versions**

It was necessary to create two versions of the applications. This requirement was necessary due to the fundamental change to the user interface of Microsoft Office Products during the upgrade from Office 2003 to Office 2007 & 2010.



The cost for a business to change software versions can be considerable, and has meant that there many organisations that have not upgraded. Consequently some users are not familiar with the “new look” ribbon based interface in Office 2010. It was important that participants were able to carry out the test using the interface with which they were most familiar.

The underlying features of the different versions were the same for the tasks we were testing. It was merely the interface that had changed. We are confident that the different versions would not affect a participants’ ability to complete a task, however the different interfaces may have some impact on the times.

### **Evaluation of approach**

Pilot studies were undertaken to test the content but also to test the applications. Prior to piloting, the instruments underwent significant testing by the developer. This testing included such things as:

- Checking the accuracy of the time recording
- Ensuring that the movement between tasks was seamless and accurate.
- Ensuring that that the task results were recorded in the correct place for each task
- Ensuring that the finishing and starting times could be distinguished.
- Ensuring that the user could not click the buttons more than once for a task.
- Incorporating the necessary VBA features to ensure that users were unaware that the time recording required the movement between sheets.
- Researching and writing the necessary functions to use to check answers
- Transferring the conditionally formatted results between Excel workbooks.

### **Effectiveness of solution**

The use of the finished product was effective. This effectiveness was evident through the following:

- Users completed the assessment without any issues.
- Little or no instruction was required for the users to use the instruments.
- Multiple users could be tested at one time on separate machines
- All times were recorded accurately
- Correctness of spreadsheet tasks were recorded accurately
- Minimal checking of answers required due to the use of functions and automation.

In summary, these instruments, proved to be reliable and consistent for each of the ninety-one participants used in this study. This gives confidence that the data collected under similar conditions each time and was sound in nature.

There is potential to develop further these applications for use with employer's assessment of job.

Technical specifications are available on request.

## Appendix 5: Perception measure development and pilot studies

In order to develop a reliable instrument that can be used to test a person's perception of computing knowledge, and to test the existence of the social biases such as the above-average effect and the Dunning Kruger effects, three pilot studies were undertaken.

### Pilot study one

The purpose of this pilot is to design an instrument that can be used to gauge how much information about a subject that a person believes there to be. In particular, it will be used to test a person's perception of their knowledge with particular computing tasks. The participants in the first pilot were shown a diagram of a horizontal line drawn to represent the sum of knowledge available about a common every day task or subject. Examples of the perception measures shown to participants are shown in Figure 32 and Figure 33.

|            |       |
|------------|-------|
| Driving:   | _____ |
| Computing: |       |

Figure 32 - Version One comparison

|            |       |
|------------|-------|
| Nature:    | _____ |
| Computing: |       |

Figure 33 - Version Two comparison

Pilot One consisted of two versions of the instrument. Version 1 used a line to represent the total knowledge available on driving while version two's line represented the total knowledge available about nature. These two examples, driving and nature were chosen as they were considered things that all people would be familiar with. It was decided to use two versions with one example, nature, being much broader than the other, driving is.

For each version, there were six participants. Each participant was invited to draw a horizontal line as their representation of the sum of knowledge available about the subject of computing, using the line they had been given as a comparison. Participants were then asked to indicate by placing marks on their line what they considered their level of knowledge about computing and what they considered the level of knowledge about computing of most other people. Participants were also asked to indicate their occupational use of computers and to estimate how much time, during the working week, they spent using computers.

The results of this pilot revealed an obvious above-average effect for both of the versions trialled. The versions using Nature as the comparison line were the most challenging for participants. Most of the six had some difficulty conceptualizing what nature meant and therefore what all knowledge about nature could mean. The results for this pilot are outlined in table one and shown graphically in figures 9 and 10.

On average participants in the driving guide version considered that there was 250% more to know about computing than there was about everyday driving. At the extremes for this version, one participant considered that there was approximately 20% less to know about computing than driving, while another considered there five times more to know about computing than driving. In the nature, the mean for the amount participants considered there is to know about computing was practically the same as what there is to know about nature. At the extremes for this version, one participant considered that there was 1 ½ times as much to know about computing than nature while another participant considered that there was ten times more to know about nature than computing. The results from both versions show that the mean for self-rated knowledge as a proportion of all computing knowledge was identical at 39%. This translates for both versions, that on average, participants believe they know 39% of all there is to know about computing, while they believe that the average population knows around 27% of all there is to know about computing.

Of the twelve participants, only three rated their own knowledge of computing as lower than what they perceived an average person would have. One person thought that their rating was the same as the average. All of these four participants were female.

It was interesting to note that results for the two quite different versions were very similar in many aspects. The results from the first pilot identified a very strong above-average effect from both of two very different versions. It was considered that given the domain of computing is indeed very broad it would be beneficial to run a second pilot, this time making the target domain more specific.

Table 39 provides a summary of data collected from all participants in Pilot 1.

Table 39 - Pilot one summary of results

| Participants  | Driving    | Nature     |
|---|------------|------------|
| Male  | 2          | 3          |
| Female  | 4          | 3          |
| Range of Total Comp Knowledge                                   | 24 - 148   | 10 - 108   |
| Range in Comp Line length compared to sample line               | 80% - 483% | 16% - 174% |
| Ratio of SR to Total Comp knowledge                             | 30%        | 37%        |
| Range of self-rated knowledge                                   | 5% - 68%   | 23% - 50%  |
| Range of rating of other peoples computing knowledge            | 6% - 58%   | 12% - 56%  |
| Ratio of "All Others" to "All Knowledge"                        | 21%        | 25%        |
| Usage Hours   |            |            |
| Mean  | 38         | 31         |
| Range   | 3 - 70     | 11 -60     |
| Occupation  |            |            |
| Information Technology (IT) worker                              | 1          | 2          |
| Non-IT professional who uses computers for a majority of my job | 2          | 2          |

|   |   |   |
|---|---|---|
| Non-IT professional who uses computers for a minority of my job |   | 1 |
| Student (in a computing degree)                                 | 2 | 1 |
| Student (not in a computing degree)                             | 1 |   |

A summary of pilot one participants who completed the “Driving” version perception ratings is shown in Figure 34.

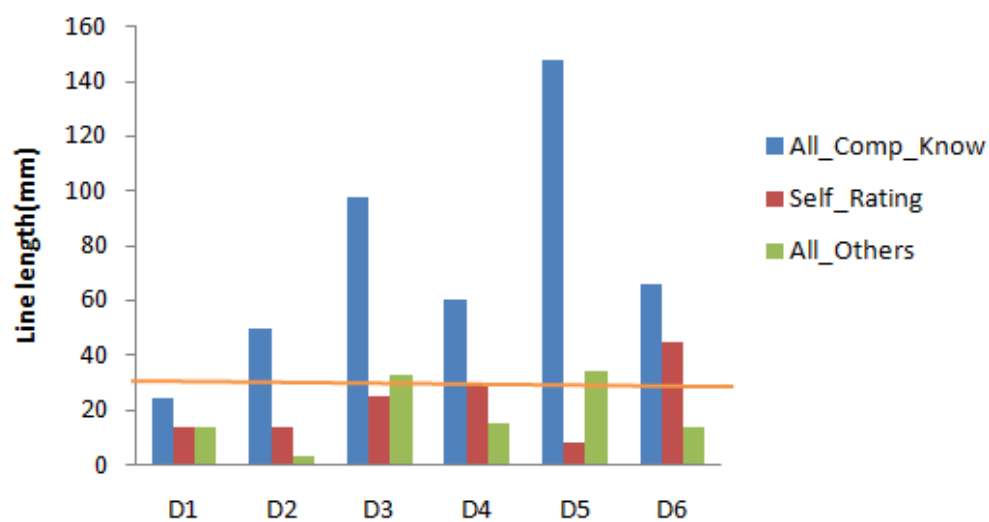


Figure 34 - Computing Knowledge (Driving as guide)

A summary of pilot one participants who completed the “Nature” version perception ratings is shown in Figure 35.

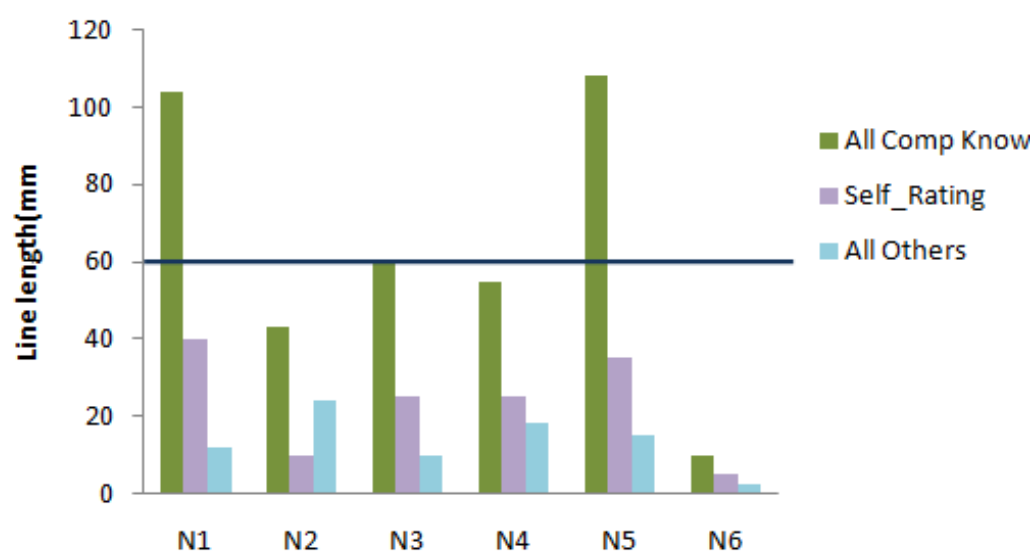


Figure 35 - Computing Knowledge (Nature as guide)

A summary of results for participants who completed the “Nature” version of the pilot is displayed is shown in Table 40.

Table 40 - Pilot one Self-rating and hours by occupation

| <b>Occupation</b> | <b>Self-assessment compared with<br/>All Comp Knowledge</b> | <b>Average of<br/>hours use</b> |
|-------------------|---|---------------------------------|
| Non-IT role       | 38%   | 25.2                            |
| IT role           | 40%   | 44.2                            |

### **Pilot study two**

The purpose of the second pilot study was to test an instrument similar to that used in pilot one except this time the example would be more specific. Participants were again given a reference line to use as a guide. For this pilot they were asked to assume that the given line represented all there was to know about computing.

Participants were asked to place a mark on this line to indicate how much they considered the knowledge about computing was specifically related to productivity software such as MS Office. Once they had made this mark, they were then asked to make two further marks on the line, one to represent their own knowledge of this type of software and a second representing how much they thought all other people knew about this type of software. A summary of the data collected from Pilot 2 participants is shown in Table 41.



Table 41 - Pilot Study 2 summary of results

|   |                                 |                   |
|---|---------------------------------|-------------------|
| Number of participants                              |                                 | 10                |
| Occupation  | Male                            | 5                 |
|   | Female                          | 5                 |
|   | IT Worker                       | 2                 |
|   | Non-IT worker-<br>Majority Comp | 3                 |
|   | Non-IT worker-<br>Minority Comp | 1                 |
|   | IT Student                      | 2                 |
|   | Non IT student                  | 2                 |
|   |                                 |                   |
|   |                                 |                   |
| Weekly Comp Usage (Hrs)                             |                                 |                   |
|   | Average                         | 36.3              |
|   | Range                           | 10 - 60           |
| Productivity Software (PS) Knowledge                |                                 |                   |
|   | Mean                            | 58% (of all Comp) |
|   | Range                           | 27% - 98%         |
| Self-Rating of PS knowledge                         |                                 |                   |
|   | Mean                            | 56% (of PS Know)  |
|   | Range                           | 22% - 72%         |
| Rating of all others' knowledge                     |                                 |                   |
|   | Mean                            | 52% (or PS Know)  |
|   | Range                           | 33% - 71%         |
| Ratio of perceived "all others" to all PS Knowledge |                                 |                   |
| Self compared to "all Others"                       | Mean                            | 21%               |

Participant's perceptions of the contribution of productivity SW to all computing, self-rating of productivity SW and estimations of the average person are shown in Figure 36.

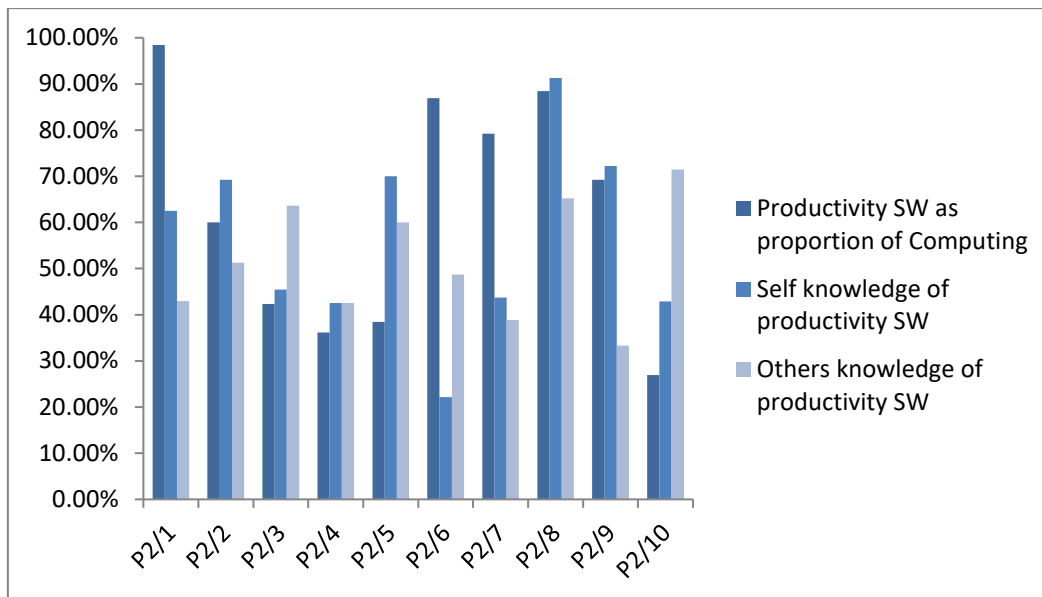


Figure 36 - Pilot Study 2 rating results

#### What has pilot 2 told us that pilot 1 did not?

Although the comparison in pilot two was more specific than in pilot, one there was still a marked above-average effect present. Again, three people believed they were below what they perceived to be the average and one person believed they were at that average. The three who rated their ability as lower than what they perceived to be the average for everyone else were female, as was the case in pilot 1. What was a little different in this study was that the one person who considered himself or herself to be at the average level was male and a computing student.

It is interesting to examine how much of the total knowledge about computing each of the participants considered there to be about just productivity software. It is also interesting to note, although not significant given the low number of participants, that six of the ten participants consider that knowledge about productivity software is equivalent to more than half of all there is to know about computing. Pilot two findings for knowledge of productivity software are display in Figure 37.

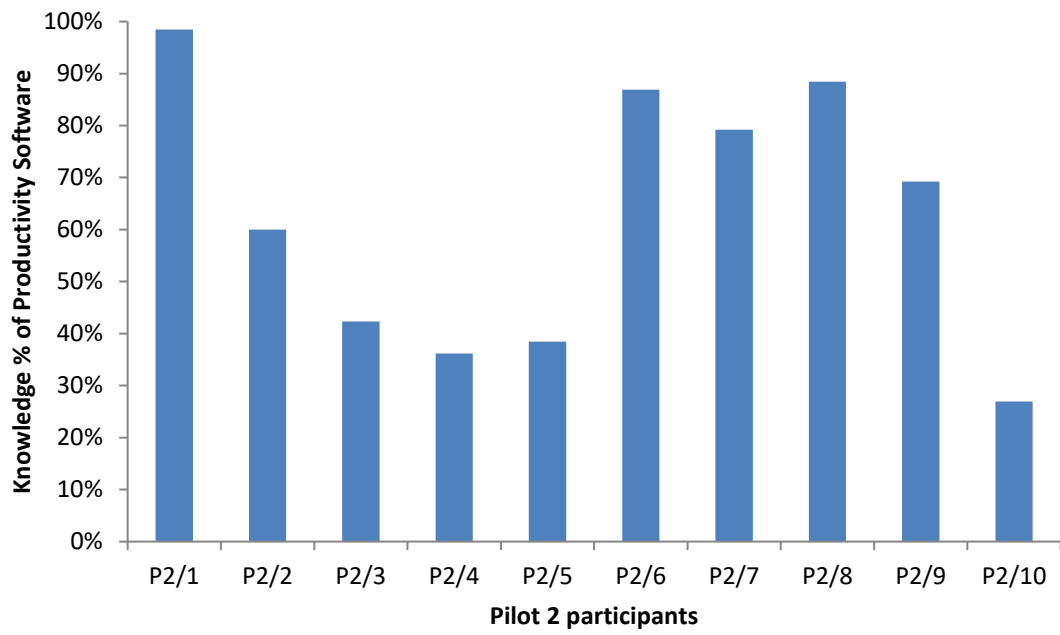


Figure 37 - Percentage of computing each participant considered productivity software

A summary of the data collected from Pilot 2 participants is shown in Table 42.

Table 42 - Participants by occupation and weekly computer usage

| Occupations<br>And Weekly Computer<br>Use (hours) | Self-Rate of PS<br>knowledge | Self-rating<br>compared to<br>Others knowledge<br>of PS |
|---|------------------------------|---|
| IT Worker   | 58%                          | 105%  |
| 40  | 43%                          | 71%   |
| 50  | 72%                          | 33%   |
| Non-IT worker-Majority Comp                       | 43%                          | 130%  |
| 30  | 44%                          | 39%   |
| 37  | 63%                          | 43%   |
| 40  | 22%                          | 49%   |
| Non-IT worker-Minority Comp                       | 45%                          | 64%   |
| 10  | 45%                          | 64%   |
| IT Student  | 81%                          | 125%  |
| 20  | 70%                          | 60%   |
| 40  | 91%                          | 65%   |
| Non IT student                                    | 56%                          | 94%   |
| 36  | 69%                          | 51%   |
| 60  | 43%                          | 43%   |

A summary of participant self-rating and weekly computer use are shown by sex in Table 43.

Table 43 - Participants self-assessment and weekly computer usage by sex

| Sex | Weekly Comp Usage (hrs) | Mean SR of PS Knowledge | Self compared to others (Mean) |
|-----|-------------------------|-------------------------|--------------------------------|
| f   | 157                     | 43%                     | 87%                            |
| m   | 206                     | 69%                     | 142%                           |

### Limitations of Pilot 2

Due to some of the unexpected results returned in this pilot it was thought that the instrument required further fine-tuning to make its intentions more understanding to users. One such finding was where six of the ten participants considered that at least 50% of all that was known about computing consisted of knowledge about productivity software. Even more concerning was that of those six participants two were either IT professionals or IT students. It should also be noted that while this pilot was more specific than pilot one there still appears to be a certain amount of ambiguity over the task concerned.

### Pilot study three

In an attempt to address some of the issues still present in the instrument, a slightly different approach was taken. The same approach of using the lines to represent the amount of knowledge available about computing was still used. However, in an attempt to reduce some of the ambiguity present in the previous version for this test the endpoints of the line were represented as being pages in a book. Participants were told that the line represented a 1000 page booking containing all there was to know about computing. They were asked to mark on the line how many pages, from page 1, they believed this book would have relating to all there is to know about personal productivity software. This line is displayed in Figure 38.

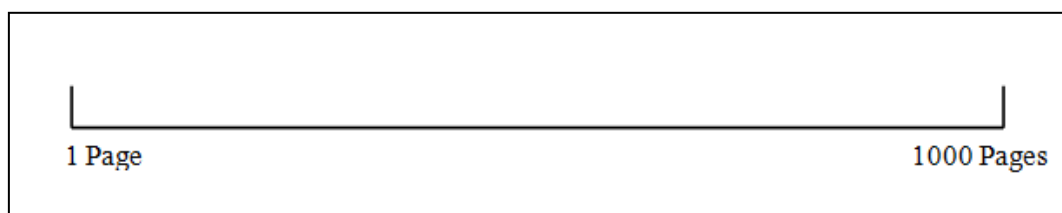


Figure 38 - Line representing a 1000 page book containing all there is to know about computing

The participants were then shown a second line (Figure 39). This line represented the expanded section between one and T on the first line. The participants were asked to mark, on the second line, what they believed to be their knowledge of personal productivity and what they believed to be the knowledge of the average person in New Zealand.

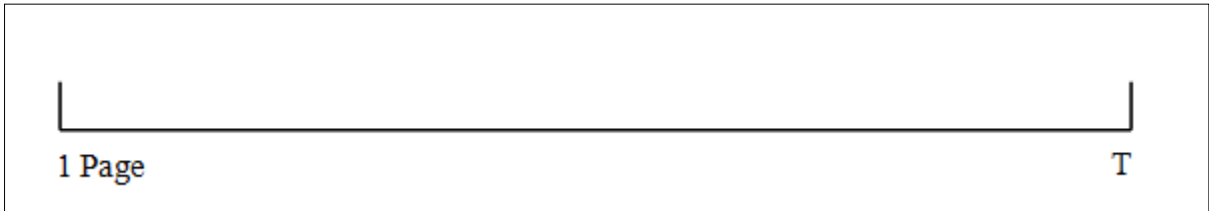


Figure 39 - Line representing expanded section of knowledge of personal productivity software

Participants were also asked to indicate what their occupation was and how much time they interacted with a computer on average over the course of a week. A summary of data collected from pilot three participants is in Table 44.

Table 44 - Summary of results for Pilot 3

|   |                |                   |
|---|----------------|-------------------|
| Number of participants                              |                | 8                 |
| Occupation  | Male           | 4                 |
|   | Female         | 4                 |
|   | IT Worker      | 2                 |
|   | Non-IT worker  | 2                 |
|   | IT Student     | 2                 |
|   | Non IT student | 2                 |
| Weekly Comp Usage (Hrs)                             |                |                   |
|   | Average        | 46                |
|   | Range          | 12 - 98           |
| Productivity Software (PS) Knowledge                |                |                   |
|   | Mean           | 36% (of all Comp) |
|   | Range          | 1% - 69%          |
| Self-assessment of PS knowledge                     |                |                   |
|   | Mean           | 37% (of PS Know)  |
|   | Range          | 4% - 79%          |
| Rating of all others' knowledge                     |                |                   |
|   | Mean           | 26% (or PS Know)  |
|   | Range          | 3% - 66%          |
| Ratio of perceived "all others" to all PS Knowledge |                |                   |
| Self-compared to "all Others"                       | Mean           | 21%               |

On average participants believed their own knowledge to be 200% greater than the average person in New Zealand did. These results are shown in Figure 40.

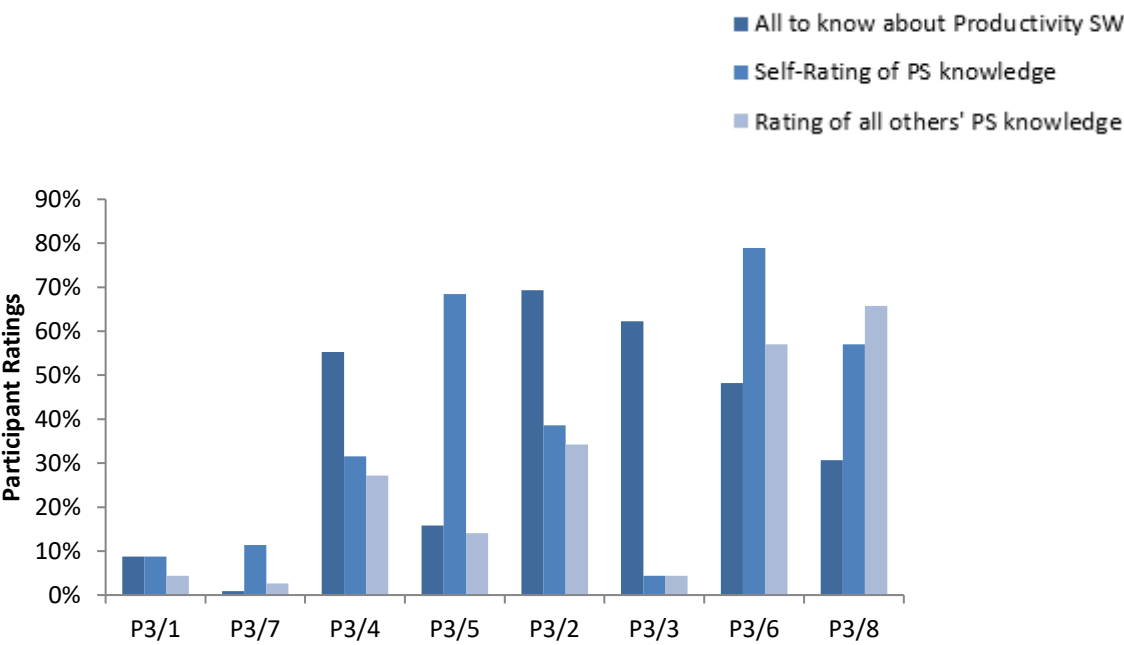


Figure 40 - Pilot study 3 rating graph

A summary of participant self-rating and estimation of the domain of EUC are shown by occupation type in Table 45.

Table 45 - Summary of Occupations by Self-Rating and EoDEUC

| Occupations         | Average of Hrs | Average of SR | Average of PPSW |
|---------------------|----------------|---------------|-----------------|
| IT Professional     | 47.5           | 10%           | 5%              |
| IT Student          | 61.5           | 50%           | 36%             |
| Non-IT Professional | 48.75          | 21%           | 66%             |
| Non-IT student      | 26.5           | 68%           | 39%             |



A summary of participant self-rating and weekly computer use are shown by sex in Table 46.

Table 46 - Participants self-assessment and weekly computer usage by sex

| Sex | Mean of Self<br>Rating | Mean of estimation of<br>average person | Average Hours |
|-----|------------------------|---|---------------|
| F   | 38%                    | 31%                                     | 40.875        |
| M   | 36%                    | 22%                                     | 51.25         |

### Summary of Pilot Study Three

The results from pilot three seems to more realistic that those from the previous two pilots. Participants appeared more comfortable with the analogy of the 1000 page book compared with being asked to mark a point on a line. While there was, still an above average effect this was not as pronounced as in the previous two pilots. The other marked difference in this study than there was only one person who believed their level of knowledge was lower than that of the average person in New Zealand. Overall, the differences between self-assessments and perceptions of others were smaller than in the previous studies. This result would suggest that given a more defined type of instrument the participants were more likely to make a more realistic judgment than when the boundaries were undefined to them.

It is interesting to note that using the version of the line with the book analogy the participants average rating of their knowledge of computing was a mere 14% compared with the average of the 39% result from pilot 1 and the 58% from pilot 2. This adds weight to the conclusion that as the test gets more specific then the ratings before more realistic.

## Appendix 6 – Regression analysis bootstrap data

This appendix contains the bootstrap regression data for all significant regression analysis.

Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples at a 95%v confidence level.

Table 47 - Bootstrap information for association between demonstrated spreadsheet ability and time taken

|                   |      | Bias | Std. Error | Sig. (2-tailed) | Lower | Upper |
|-------------------|------|------|------------|-----------------|-------|-------|
| Spreadsheet Score | .188 | .005 | .062       | .005            | .077  | .319  |

Table 48- Association between demonstrated spreadsheet ability and perception measures

|                                 |       |           |      |      | Lower    | Upper     |
|---------------------------------|-------|-----------|------|------|----------|-----------|
|                                 | .529  | .004      | .044 | .001 | .450     | .620      |
| Self-assessment                 | .001  | 9.530E-5  | .001 | .045 | 8.152E-5 | .002      |
| Estimation of AEU               | -.001 | -8.590E-5 | .001 | .146 | -.002    | .000      |
| Estimation of breadth of domain | .000  | -3.584E-5 | .000 | .077 | -.001    | -2.171E-5 |

Table 49- Bootstrap information for association between demonstrated word-processing ability and time taken

|            |       | Bias | Std. Error | Sig. (2-tailed) | Lower | Upper |
|------------|-------|------|------------|-----------------|-------|-------|
| Word Score | -.066 | .000 | .063       | .312            | -.186 | .052  |

Table 50 - Bootstrap information for associations between Word-processing ability and perception measures

|                                 |       | Bias      | Std. Error | Sig. (2-tailed) | Lower | Upper |
|---------------------------------|-------|-----------|------------|-----------------|-------|-------|
| Self-assessment                 | .001  | 4.940E-5  | .000       | .033            | .000  | .002  |
| Estimation of AEU               | -.001 | -4.163E-5 | .000       | .098            | -.002 | .000  |
| Estimation of breadth of domain | .000  | -1.559E-5 | .000       | .384            | -.001 | .000  |

Table 51 - Bootstrap information for association between self-assessment and estimation of AEU

|                   |        | Bias  | Std. Error | Sig. (2-tailed) | Lower  | Upper  |
|-------------------|--------|-------|------------|-----------------|--------|--------|
| Estimation of AEU | 28.659 | -.293 | 7.205      | .001            | 14.233 | 42.938 |
|                   | 1.019  | .008  | .118       | .001            | .821   | 1.278  |

Table 52 - Bootstrap information for associations between perception measures and demonstrated ability

|                   |       | Bias      | Std. Error | Sig. (2-tailed) | Lower    | Upper |
|-------------------|-------|-----------|------------|-----------------|----------|-------|
|                   | .569  | .001      | .026       | .001            | .520     | .622  |
| Self-Assessment   | .001  | 3.207E-5  | .000       | .051            | 6.285E-5 | .001  |
| Estimation of AEU | -.001 | -6.346E-5 | .000       | .010            | -.002    | .000  |

Table 53- Bootstrap information for associations between Estimation of the AUE and individual differences

|                   |        | Bias   | Std. Error | Sig. (2-tailed) | Lower   | Upper  |
|-------------------|--------|--------|------------|-----------------|---------|--------|
| Age               | -2.356 | .032   | .882       | .010            | -4.089  | -.604  |
| Sex               | 19.464 | 1.409  | 19.783     | .350            | -16.053 | 60.548 |
| Conscientiousness | 35.955 | -2.031 | 20.494     | .081            | -9.131  | 71.565 |
| Extraversion      | -5.170 | -1.143 | 14.449     | .722            | -36.286 | 22.274 |

|                                  |          |        |        |      |          |        |
|----------------------------------|----------|--------|--------|------|----------|--------|
| Learning Mode                    | -8.301   | .407   | 7.554  | .288 | -23.549  | 6.587  |
| Hours of computer used           | .197     | .003   | 1.178  | .887 | -2.179   | 2.407  |
| Number of software packages used | 2.693    | -.296  | 5.083  | .590 | -7.632   | 12.745 |
| Occupation                       | 4.870    | .173   | 3.395  | .168 | -1.852   | 11.392 |
| Demonstrated EUC                 | -114.089 | -1.106 | 62.757 | .066 | -246.476 | 3.866  |

Table 54 - Bootstrap information for associations between self-assessment and *estimations* of the domain of EUC

|                 |         | Bias   | Std. Error | Sig. (2-tailed) | Lower   | Upper   |
|-----------------|---------|--------|------------|-----------------|---------|---------|
| Self-assessment | 279.569 | -1.991 | 78.301     | .001            | 118.635 | 431.036 |