QUANTIFIED SELF-TRACKING, SELF-EFFICACY AND EMOTIONAL INTELLIGENCE

by

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Abstract

The quantified self has emerged as a new framework for self-improvement using personal data analytics and multiple forms of self-tracking. This project has examined the relationships between self-tracking for both mood and time expenditures with both emotional intelligence and emotional regulatory self-efficacy in a mixed methods experimental design. Through 14 days of time and mood tracking, 12 participant's emotional intelligence and emotional regulatory self-efficacy were examined in a pre- and post-test design; a significant ($p < 0.01$) relationship was observed for participants emotional regulatory self-efficacy in the domain of acting despite powerful emotions, while no other significant relationships were observed in this study. In multiple interviews, participants identified increased emotional understanding and reported some degree of behavioural change as a result. However, given the small sample size and multiple limitations, this study is only intended to serve as an exploratory framework for further research.

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Acknowledgments

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Chapter 1: Introduction

The concept of data has grown to have a larger impact in business, research, and health. Not only has the amount of data increased, but also the number of users and the accessibility of the data have also risen dramatically. While business information has focused on the advent of big data, small data, defined as individual and personalized datasets, also implicates a new type of data revolution. Within this data revolution, the quantified self-movement has emerged as a new grassroots-driven method of self-discovery. Quantified self is unique in that it is often pursued and analyzed by the participants themselves, rather than traditional researchers (Wolf, 2010). This process is fraught with potential difficulties, including lack of scientific rigour and insufficient quantification methods (Choe, Lee, Pratt & Kientz, 2014; Swan, 2009) as it is the domain of passionate amateurs rather than seasoned researchers. However, despite these difficulties, the quantified self-movement has provided individual insight to numerous participants, improving quality of life and increasing self-knowledge (Choe, Lee, Pratt & Kientz, 2014). This new method of self-tracking provides a unique opportunity for participants who might otherwise be unable or unwilling to investigate their own behaviours, thoughts, and feelings. In contemporary academics, some refer to this self-tracking method as *personal informatics* (Epstein, Cordeior, Bales, Fogarty, & Munson, 2014).

This data revolution represents a significant opportunity for the development of individual metrics designed to assist with personal goals, such as productivity, happiness, and the reduction of negative affective states, including depression and burnout. The quantified self-movement utilizes this emerging quantitative data through several different user-defined indicators to achieve a multitude of goals, including health and fitness, weight loss, learning new skills, and several unique user-created goals (Trickler, 2013).

This study is primarily exploratory in nature and seeks to understand the relationship between quantified self-techniques and self-improvement. Notably, several authors have indicated that the metrics used by the quantified self-movement increase self-awareness and understanding (Li, Medynskiy, Froehlich & Larsen, 2012). This creates a connection between quantitative self-tracking and numerous fields of self-awareness, but in the context of this study, two independent variables are assessed: the connection between self-tracking and emotional intelligence and the connection between self-tracking and self-efficacy.

Emotional intelligence has demonstrated a very strong and significant correlation with increased effectiveness in work performance (Dong, Seo, & Bartol, 2014; Drew, 2006; Goleman, 1998; Jha & Singh, 2012; Labby, Lunenberg, & Slate 2012; Penrose, Perry, & Ball, 2007; Rooy & Viswesvaran, 2003), leadership (Cho, Drasgow & Cao, 2015; Joseph, Jin, Newman & O'Boyle, 2015), and well-being (Cho et al., 2015; Goleman, 1998; Sánchez-Álvarez, Extremera, & Fernández-Berrocal, 2015) Emotional intelligence, defined as the ability to understand and manage one's own emotions and the emotions of those around one (Mayer & Geher, 1996; Salovey & Mayer, 1990) is a powerful tool for leaders and educators alike. As well, self-efficacy has been tied as a powerful predictor in the realm of behavioural change; it has been linked to reduced drug use, increase in physical activity (Ashford, Edmunds & French, 2010), increased weight loss (Olander et al., 2013), increased academic performance (Bandura, 2014), increased work ability, reduced depression, and has been highly predictive of employability (Weng et al., 2014).

Significance of the Research

This project is designed to provide an exploratory framework to assess the independent variables that allow quantified self and personal informatics techniques to influence our behaviours, thoughts and emotions. Given the tech-based dependency and recent emergence of many of these techniques, there is little research on the role that self-tracking has in this context, particularly for those outside Science, Technology, Engineering, and Mathematics (STEM), fields. For many, it is still strange to use quantified methods to improve their personal lives; tracking, measuring, and analyzing their own moods, spending habits, and lifestyles is still an extreme lifestyle, adopted primarily by those in quantitative fields, such as data analysts, programmers, or engineers (Choe et al., 2014). However, the potential impact and use of the quantified self-methodology indicates a powerful method for positive change, regardless of profession or inclination. Wolf (2010), the journalist who coined the term *quantified self*, wrote that the quantified is tolerated and embraced in business and research spheres because the results are powerful. The often-dry numbers indicate the growth, challenge, prospectives, and predictions and determine the direction business and research will take. The desire to quantify the minute in our own lives, such as our sleep, exercise, sex, food, mood, alertness, productivity, and well-being is not alien. It emerges from the clearly-defined power that quantitative information maintains: the power to compare, to test, to experiment, with "less emotional resonance but more tractable intellectually" (Wolf, 2010, para. 8). We use quantitative information to assist in research, to optimize an assembly line, to test the conclusions of educational policies; these are all reasons for extending data analytics into our personal lives to increase our self-awareness.

Additionally, the quantified self-methodology is similar to a journaling framework. The benefits of traditional journaling are derived from the articulation of connection between new and existing knowledge and writing about what has been learned (Kerka, 2002). This, as well as the task of physically writing something down, promotes reflection in the writer, allowing for the development of meaning in life experience and gains written about in journaling research (Kerka, 2002; Schuessler, Wilder, & Byrd, 2012). Reflection on data, trends, and relationship can potentially promote similar benefits, but has not yet been demonstrated. Journaling is often used for both growth and recovery (Lowe, Prout, & Murcia, 2013); however, the context and structure in which journaling and reflection take place are essential to the development of these goals. In a comprehensive literature review, Epp (2008) noted that there is limited evidence to suggest that journaling and reflective practice are effective measures to improve competency without the presence of a facilitated structured reflective journal tool. Given the parallels in reflection between journaling and quantified self-techniques, it is reasonable to assume that quantified self-metrics will also require a tool structured to provide effective reflection. Thus, the structure of quantified self will be investigated systematically to determine if and how quantified reflection serves as an effective tool.

In many quantified self-research tasks, the insights gained are developed through reflection and review. This underlying philosophy is closely related to principles seen in journaling methods to alleviate anxiety or stress or to facilitate growth and understanding. This is due to the emphasis on open-ended reflection inherent in the quantified-self movement. However, while the term quantified self originated with Wolf (2010), the methodology associated with it began earlier with the self-monitoring procedure within behavioural psychology in the early 1980s (Korotitsch & Nelson-Gray, 1999). Notable examples of the use of self-monitoring come from Agras and Apple (1997) in their work with tracking the eating, binging and purging habits of patients suffering from bulimia. Primarily, this was undertaken to find a quantitative way to measure and understand, through reflection, the triggers and habits that provide the basis for these behaviours. These principles can be adapted to serve behavioural change in more areas than eating disorders; they can be molded to address any undesired behaviour, chronic or acute.

Self-monitoring is not the goal, in and of itself, but it does provide the means to address and understand the underlying problems, rather than simply treating the symptoms that manifest. The goal of quantified self is to provide an understanding of our unconscious behaviours, emotions, or thoughts (Wolf, 2010), ultimately paralleling the goals of any reflective process. However, the quantified self movement has moved this self-investigation away from the traditional academic and clinical settings in which self-tracking would often occur, and the reduction of time-consuming data entry provided by modern technology has increased access to self-tracking.

What is truly distinct between quantifying our personal lives and the traditional aspects of journaling is the medium: quantified self lives in the domain of numbers, rather than words. The quantified journal allows the path to intricate and meaningful self-knowledge to be gained through a method other than language, which has traditionally dominated psychoanalytic discourse (Wolf, 2010). Self exploration from "the analyst's couch to the chatty inquisitiveness of a self-help questionnaire" (Wolf, 2010, para. 5) is dominantly found and created through words. Quantified tracking allows a shift of this paradigm, appealing to a demographic who would not normally choose journaling (Choe et al., 2014). If quantified self methods provide a similar benefit as journaling, such as increased self-awareness and emotional intelligence (Houghton, Wu, Godwin, Neck & Manz, 2012), it is of substantial benefit.

Importance of the Research

Much of the academic research related to quantified self tracking is related to personal informatics with regards to health management (Choe et al, 2014; Swan, 2009; Swan, 2012).

However, there are currently emerging trends, both in quantified self movement and in peer-reviewed research, to further examine self-tracking as it relates to behavioural traits and outcomes, primarily focused on mood management (Luxton, McCann, Bush, Mishkind, & Reger, 2011) or behavioural change (Aguilera & Muench, 2012; Michie, Abraham, Whittington, McAteer, & Gupta, 2009). Notably, these studies have discovered that the technology-based self-tracking applications have tendency to be more accurate than pen and paper and substantially less prone to error and misremembering (Aguliera & Muench, 2012). This identifies the application aspect of quantified self as a possible complement to many self tracking methods currently used in behavioural research.

Mood is one of the most-tracked outcomes in the quantified self movement, along with exercise, sleep, and diet (Choe et al, 2014). Given the difficulty associated with quantifying mood, as there are currently no wearable technologies that can accurately assess mood, and the user must track and categorize a mood outcome variable themselves, mood tracking methodologies are still highly associated with software rather than hardware (Trickler, 2013). However, many of the self-studies focused on mood management focus on only mood tracking, and do not establish trigger or context to explain the variability of the very subjective mood descriptors (Trickler, 2013). While there is a benefit to understanding the personal dataset of one's mood, a raw descriptive variable has substantial room for improvement.

Additionally, the growth of applications through both smartphones and wearables devices encourages continual research in this sector. The increased availability of advanced metrics designed to measure heart rate, diet, movement and its relationship to other variables, such as exercise or sleep, increase both the ease of use and the potential for in depth analysis (Trickler, 2013). As well, the grassroots nature of the quantified self has assisted in the creation of several new methods which bear investigation (Choe et al, 2014), as they are created quickly and for many different purposes by amateur researchers. Formal investigation into the effectiveness of these methods is constantly required for a better understanding of their efficacy.

The analytic components of the quantified self are still "surprisingly primitive" (Fawcett, 2015, p. 249). The data revolution has caused an increase in the methods to gather data but has not eased the difficulties associated with analytic techniques. Many of the informal experiments conducted by quantified self participants remain in the realm of descriptive statistics, such as the averages of steps taken, weight measured, or hours slept per day (Honan, 2014). This allows for summary statistics and personal key performance indicators, but does not provide insight into the relationship between data points. However, there is an increasingly large group of quantified self participants who have created a more holistic perspective framed in the language of "self-hacking" (Fawcett, 2015, p.250). This is the integration of numerous sources of data from several different applications into one coherent form. These integrations compile the data of one user, from applications such as RunKeeper, MyFitnessPal, and FitBit, into a dataset that can be viewed together (Fawcett, 2015); however, historically, these aggregated datasets have not provided analysis of the connection between these data points or a way to make sense of what becomes data clutter (Honan, 2014). In general, most quantified self apps do not provide more insight than the presence of trends in aggregated data points and visualizations (Fawcett, 2015). While there are several new and emerging technologies that demonstrate the relationship between these distinct data points in sophisticated analysis, little research has been directed their way. While newer apps have begun to aggregate and provide basic analysis, there is substantially more powerful results that can be gained through the application of advanced statistical rigor and understanding with the plethora of data that many quantified self-participants freely generate. If a participant's data can illuminate a negative relationship between, for example, caffeine and productivity, then this is a valuable insight for the individual participant (Fawcett, 2015). There is still substantial room for improvement in quantified self metrics.

The relationship between awareness and behavioural-change also needs substantial discussion. Kempen, Muller, Symington and Van Eeden (2012) discussed the implications of the awareness of nutritional information and relate it to the presence of healthy behaviours in the participants; in the context of this study defined as the avoidance of alcohol, actively exercising, and getting enough water. Kempen et al. (2012) identified a correlation between awareness and the presence of these behaviours. This study intends to investigate further the nature of the relationship between these two factors by actively increasing the awareness of participant's personal behaviours and investigating the impact this increased awareness will have.

There are four major variables considered for this study. The participant's daily time expenditure, measured in minutes, and the participant's mood, measured on a self-reported 1-10 Likert scale. Additionally, a measure of the participant's emotional intelligence and self-efficacy will be taken in a pre-and post-test method.

Purpose and Research Questions

There are two independent variables that will be considered in the context of this study. Specifically, the variables that will be measured will be emotional intelligence, with an emphasis on intrapersonal domain of emotional intelligence, and self-efficacy in the domain of self-regulatory behaviours. Given that this study is exploratory in nature, the two distinct independent variables provide a more robust basis for further research. As well, both emotional intelligence and self-efficacy have been highly associated with several positive outcomes, as emotional intelligence has been associated with increased performance (Rooy & Viswesvaran, 2003), teacher effectiveness (Jha & Singh, 2012), and self-efficacy has been associated with increased memory (Bandura, 1989), learning (Zimmerman & Martinez-Pons, 1990), physical activity (Olander et al., 2013), and other positive affective outcomes. If pursuing quantified self tracking techniques increases either of these independent outcomes, the research will demonstrate its positive effect on the participants and solidify the theoretical background for this technique.

The goal of this research is to provide an exploratory study into the relationship between the participant's increasing awareness of these trends and factors that implicate desired outcomes and mood, with the factors that can cause them, notably daily time expenditure. Specifically, this research seeks to test the idea that increased self-awareness of our behaviour, gained through quantitative measurement of our personal lives, will impact our behaviour, beliefs about ourselves, and our understanding about ourselves, tested in the context of self-efficacy and emotional intelligence. Mood management and productivity are strongly linked, as Mega, Ronconi and De Beni (2014) noted there is a demonstrated connection between emotions, self-regulation, and motivation, all of which ultimately impact achievement and productivity. This study should not be considered an exhaustive list of all potential variables that are captured in the quantified self community: the community measures a multitude of variables, dependent on the individual's goals, which include exercise, activity, idleness, medications, drugs, nutrition, and sleep, cognition, and blood pressure (Fawcett, 2015).

If this hypothesis is demonstrated through quantitative research, this would provide a framework to improve the quality of life and work performance that is highly adaptable and leverages the power of modern technology. This research intends to investigate the relationship between key personalized indicators and descriptive statistics or visualizations on behavioural change. Given that the independent variables tested in this study are highly associated with behavioural change, if an increase of either emotional intelligence or self-efficacy is noted, it can be theorized that quantified self techniques implicate behavioural changes.

It is hypothesized that this the identification of personalized relationships in these measures will increase emotional intelligence in the participant. This is due to the leveraging of increased self-knowledge and awareness gained through self-inquiry, as self-understanding is an essential aspect of emotional intelligence. As well, self-efficacy is defined as the perceived ability to execute action to attain goals (Bandura, 1977). This hypothesis assumes that objective updates on behaviour and mood can increase self-efficacy.

This study's primary hypotheses are:

H1: Emotional Intelligence will increase within a group given 14 days of quantified self-tracking methods.

H2: Self-efficacy will increase within a group given 14 days of quantified self-tracking methods.

In addition, participant responses will be solicited after the study in a mixed-methods format to further explain their relationship with the data, the emergent trends, and any potential implications of their exploration into the quantified self.

Researcher Context

This study's author has used quantified self methods for several years and currently works as a Data Scientist within education. It is likely that I have a strong bias towards using data analytics to further my own goals, both professional and personal, and this bias may be present in this study. I am strongly in favour of using quantitative key performance indicators to improve our lives, but will attempt to remove my bias from this project. The role of multiple survey instruments in this study with demonstrated validity should remove the potential for researcher bias to impact the study meaningfully.

Limitations and Delimiters

A limitation of this study will be its inability to generalize conclusions and correlations learned from individual quantified self experiments. Additionally, it may be difficult to obtain participants who are willing to share this data, as productivity and mood data can be considered highly sensitive information. Another limitation of this study is its use of manually-captured data for both mood and time spent; this increases the delays and opportunities for data misentry and increases errors and erroneous conclusions caused by incorrect data (Aguliera & Muench, 2012; Vawdrey et al., 2007) and does not leverage many of the strengths of the modern quantified self movement. This returns to the principle "garbage in, garbage out" (Vawdrey et al., 2007, p.296); there is a large burden placed on the participants to ensure accurate self-tracking if the results are to be considered valuable.

A delimitation of this study will be its sampling solely in Northern British Columbia. The limited geography considered will limit the generalizability of the conclusions. Further delimitations would be the 14-day nature of the study, the electronic nature of the productivity measures, the potential for data misentry when tabulating time expenditure, and the presence of the placebo effect, as there will not be a control group. Of note is the potential for missing or incorrect data in either the mood or time expenditure factors, but given that this is an investigation into the effectiveness of this method, and this method requires participants to gather their own data, it should be considered as an aspect inherent in quantified self techniques, rather than a feature to be controlled and avoided. Regardless, the data collection tool should be as simple as possible to reduce data entry errors.

Overview of the Proposal

The role of data in business, health, and education has grown substantially (Swan, 2012). This increase has data availability has provided the basis for a self-tracking revolution in which personal experiments and investigations have been undertaken not by scientists, academics or researchers, but by untrained laymen seeking to solve a personal problem or simply understand more of themselves. While this method has gained substantial popularity within a particular subgroup of participants, notably those in quantitative fields (Choe et al., 2014), there is more research required into the effectiveness of personal self-tracking. The contemporary research into quantified self techniques that has been accomplished focused on the self-reported evaluation of participants regarding the specific intervention (Müller, Divitini, Mora, Rivera-Pelayo, & Stork, 2012) which can provide best practices for quantified self techniques but does not provide a comprehensive analysis of the technique as it compares to other interventions. This study will provide an exploratory framework to begin assessing the relationship of quantified self techniques to traditional affective constructs.

Chapter 2: Literature Review

This literature review assessed the emerging self-tracking methodology known as the quantified self. While there are innumerable ways to use these new forms of data, education may benefit significantly from an investigation into the emotional health and intelligence of its leadership with the intention of understanding and improvement. If accurate and meaningful quantified self metrics are provided on a regular basis, this information may increase self-awareness of his or her emotional state, notably the ability to understand your own emotions (Goleman, 1998; Ybarra, Kross & Sanchez-Burks, 2014). In turn, this increase in emotional intelligence or self-efficacy will provide a subsequent increase in work effectiveness, as demonstrated in contemporary research literature (Dong et al., 2014; Drew, 2006; Goleman, 1998; Jha & Singh, 2012; Labby et al., 2012; Penrose et al., 2007; Rooy & Viswesvaran, 2003). This method was reflected in the practical and contemporary quantified self movement, which analyzes the self through the quantification of the everyday.

The use of the quantified self in rigorous research analysis came with substantial contention. The contemporary quantified self movement is designed to quantify traditionally-qualitative day-to-day experiences to inform and motivate action. This movement, as it is relatively new, originated only in 2007 (Lee, 2014), has substantial concerns about the validity and rigour of the process. Of importance is the identification of the connection between raw data and behavioural change: that individually interpreted data provided insight and the impetus to action. This claim remained to be substantiated in rigorous inquiry. Additionally, this individual self-collected data can be brought into the aggregate and analyzed as a very comprehensive dataset, a process deemed citizen science (Kido & Swan, 2013), but it used relatively rarely outside the medical and ecological disciplines. Finally, there are significant ethical and methodological concerns to be addressed for quantitative self-tracking. This literature review addressed the current research that has been done on the topic of the quantified self, as well as a general review of emotional intelligence and self-efficacy research that is relevant to this study.

The literature on emotional intelligence played a pivotal role in this discussion; there has been some contention in identifying the link between emotional intelligence and work effectiveness (Drew, 2006; Goleman, 1998; Jha & Singh, 2012; Labby et al., 2012; Penrose et al., 2007) and many scholars have correlated the two (Dong et al., 2014; Rooy & Viswesvaran, 2003). The connection between emotional intelligence and effectiveness was further strengthened by the relationship between emotional intelligence and turnover and work experience, emotional intelligence and physical health, as well as the relationship between emotional intelligence and work engagement that can range from burnout to thriving (Masten, 2001). However, there have been several major criticisms of the concept of emotional intelligence: notably assessing the accuracy of self-reported emotional intelligence as it related to medium and high emotional intelligence participants and the constructs predictive validity when distinguishing between those subgroups (Fiori, Antoniette, Mikolajczak, Luminet, Hansenne & Rossier, 2014). The connection between emotional intelligence and effectiveness provided the impetus for utilizing the contemporary quantified self methods to increase emotional intelligence.

As well, the literature surrounding self-efficacy demonstrated its validity as a construct in use in multiple disciplines for decades. Self-efficacy theory has been highly associated with numerous predictive measures, including memory (Bandura, 1989), learning (Zimmerman & Martinez-Pons, 1990; Bandura, 1993), behavioural change (Sherer et al., 1982), academic ability (Bandura, 2014), and work ability and depression (Weng et al., 2014). If quantified self techniques are associated with increased self-efficacy, it can be reasonably assumed that subsequent behavioural change will occur in the participant.

The Role of the Quantified Self

With the identification of a strong connection between emotional health and intelligence and workplace effectiveness in leaders, this project's goal was to provide a small-scale method for educational leaders that provides increased emotional intelligence or self-efficacy. This investigation reflected the principles of the contemporary quantified self movement. The term has been defined relatively recently by Kevin Kelly and Gary Wolf, editors of Wired magazine, in 2007 (Lee, 2014). The quantified self movement was designed to promote personal health through quantified metrics designed to represent different aspects of well-being (Beauchet et al., 2014). However, physical health was not the only concern of the quantified self; it also attempted to measure and analyze energy level, mood, cognitive performance, athletics, and learning strategies, as well as physical measures of health, such as blood pressure and sleep patterns (Swan, 2012). Currently, the tools used to measure data in the quantified self data streams are most often the self-reported data, but these tools also include device data, notably the wearable data devices such as heart rate monitors or the consumer-grade accelerometers, such as FitBit (Rivera-Pelayo, Zacharias, Muller, Braun, 2012) and mobile application data, collected autonomously but with permission from the user (Swan, 2012).

The average quantified self participant was not a typical researcher; though there were numerous participants with training in data analytics, most participants have developed their own sense of analytics (Nafus & Sherman, 2014). Though this presented several methodological problems in using the data generated by users who simultaneously act as "designers, data collectors, and critical sense makers who rapidly shift priorities" (Nafus & Sherman, p. 1784), it provided an avenue for the developmental of unique methodologies distinct from traditional academic discourse. Algorithms automatically investigated daily journal entries for information and trends on mood and mindset, interactive online dashboards related quality of sleep to exercise and diet, and informal investigated methods rule the day. While these informal methods may have created doubt of their rigour and reproducibility, the insights gained from this data should not be discounted.

These insights lead to numerous reasons for an individual to pursue the quantified tracking of any element in their life. Many have taken to the in-depth self-monitoring of physical health issues to provide this dataset to a physician (Swan, 2012; Wiederhold, 2012), but this information has been used to investigate sex, attention span, productivity, caffeine intake (Wiederhold, 2012), and even what time was most productive to answer emails (Ranck, 2012). In most cases, the purpose of the quantified self was to provide information to create informed action. However, a distinct inquiry must be investigated when examining the quantified self movement and its relationship to measuring and understanding data: the relationship between measurement and interpretation to behavioural change in the affected participant was the fundamental premise to quantified self.

The methods in quantified self were as numerous as the participants; while many of the methods used by most participants focused on the inputs of diet, weight, and footsteps, experimental methods in quantified self are being invented constantly. While many participants have developed their own sense of analytics, many more adopt methods from contemporary academics. For example, heart rate variability (HRV) has been noted by many in the medical field as an indicator of stress (Thayer, Ahs, Fredrikson, Sollers, Wager, 2012). As a result, an individual participant, Paul LaFontaine (2016), used his own HRV to analyze the level of stress and threats that he felt in meetings. His original hypothesis was designed to investigate a phenomenon he called "vapor lock" (LaFontaine, 2016, 0:30), described as the mental state in which one feels numb and unable to respond and defined as the period in which his HRV dropped consistently for 17 milliseconds and this phenomenon's relationship to his self-proscribed difficulty of each meeting. LaFontaine's definition of this phenomenon represented the experimental nature of quantified self. In standard academia, the term vapor lock was only used in relationship to pistons and mechanical engineering; however, the lack of consistent terms did lack rigor in both content and communication. LaFontaine's (2016) results indicated that the subjective difficulty of the meeting or conversation was unrelated to vapor lock ($r=0.17$) and that the greatest predictor of vapor lock was the number of people in the room ($r=0.73$). This result not only provided LaFontaine with actionable insight, but also increased his own self-awareness. However, this study and further post-experimentation noted that it did not decrease the frequency with which vapor lock would affect LaFontaine (2016).

However, examining quantified self studies that were self-published online contained a significant risk: the fundamental issue with the publishing of success stories of the quantified self movement was the issue of survivorship bias, as only the successful stories of personal data analytics were published. Survivorship bias is associated with a dataset that only includes survivors, often in a medical study, but is applicable to many fields. In the context of the publishing of quantified self techniques, which were published on informal internet forums, rather than academic journals, it was easily influenced by the self-selection of choosing to publish the results of a personal study. This self-selection method potentially suggested a higher success rate than is accurate, as individuals who are unsuccessful or do not find relevant information are less likely to publish. As well, given the social nature of these platforms, those studies which do not find relevant information but are published are further unlikely to gather attention, thus reducing their visibility. There was a distinct possibility that the success rate for quantified self techniques is lower than the would be suggested by the websites that are associated with them: those participants for whom this method fails to offer insight, incentive, or actionable change are unlikely to finish, catalog, and post about their experiences on the internet.

Data and Behavioural Change

Many have argued that data serving as a catalyst for behavioural change is the fundamental premise of the Quantified Self - all quantified self investigation was purposed to "allow the person to increase his/her 'awareness' by supporting the process of becoming conscious of his/her unconscious behaviour" (Kido & Swan, 2014, p. 2). Awareness, in the context of this movement, was particularly self-awareness. It was the basis for change in several psychological models – self-awareness is considered a fundamental characteristic of effective leaders when undergoing a change process (Higgs & Rowland, 2010) and even simple reminders, designed to increase short-term awareness of potential issues, can provide the basis for behavioural changes in a health context (Buis et al., 2013). It is reasonable to assume that the quantified self research methods can provide information that can increase awareness, and this awareness can serve as a catalyst for change.

However, the pragmatic relationship between collecting and developing a personalized dataset and creating actionable items was the most challenging aspect of quantified self (Swan, 2012). It required design-focused interpretation of large datasets; given that the vast majority of users of quantified self come from the STEM fields (Choe et al., 2014), this suggested that the data has not been interpreted and visualized in such a way as to create easily-identifiable action items to make sense of the data; many of the current quantified self tools were not designed with the average user in mind, for they often lacked components of both self-reflection and trending data (Li, Dey, Forlizzi, 2011). This lack of interpretability could be seen in even the most common of consumer-based quantified self tools, such as the FitBit pedometer. Without basic training in data analytics, a user could not investigate trends in their own steps over time (Bentley et al., 2013). This prevented the creation of actionable insight from trending data as it cannot be accessed and creates a lower chance of behavioural change taking place. This difficulty was compounded by the low rates of quantitative literacy in the general population: 41% of Americans have low graph literacy rates and difficulty understanding statistical data (Bentley et al., 2013). This implied that the potentially impacted population for any tool that relies on quantification is already much lower than traditional methods.

Quantified self metrics were often characterized as the setting, progress and measurement towards particular goals, and there was substantial literature supporting the relationship between goal-setting and increased self-efficacy. Schunk and Swartz (1993) investigated this phenomenon in the context of paragraph-writing skills in elementary students and found that those students who were regularly informed of their progress towards their goals scored higher, produced more, and maintained more skills and information than their peers who were told to work hard and maintain discipline. As well, Zimmerman, Bandura, and Martinez-Pons (1992) have attributed student goals to be a result of their self-efficacy related to academic achievement. A statistically significant correlation was identified at $r=0.30$ relating both goals and self-efficacy with a sample size of 102 (Zimmerman et al., 1992). However, Zimmerman et al.'s (1992) research has only demonstrated a predictive link between self-efficacy and goal and did not demonstrate a causal path. The identification of this relationship allowed for a thorough investigation into quantified self metrics, although these metrics often extended beyond simple goal setting and tracking; tracking reflected the persuasive side of quantified self metrics (Munson, 2012), which were designed to represent what should be happening given a specific goal, either defined by the participant or the developer. However, reflective learning (Munson, 2012; Consolvo, Landay & McDonald, 2009; Halko & Kientz, 2010) represented a unique part of quantified self methodology that allowed for deeper, yet more time-consuming, progress.

Li et al. (2011) have re-framed these two distinct phases into one cohesive framework in the adoption of behavioural change in the field of personal informatics - the phases of Maintenance and of Discovery. The maintenance aspect was defined as when the user is already familiar with the goal they wish to pursue, and whatever factors impacted that goal have been mostly identified (Li et al, 2011). For example, when a participant wished to know how much time at work he was wasting on surfing the internet, a simple app reminded him of when the participant spent more than a certain amount of time on a list of particular websites. In this case, the primary outcome variable designated was the participant's productivity, while the dependent variable was the minutes spent on the designated distracting websites list; a contemporary example of such an application is RescueTime, which provided a dashboard based on several user-defined productive and distracting categories. Maintenance quantified self tasks were often undertaken when a participant knows which action to take to fix a particular personal problem, but still failed at actualizing the actions required to finish this task (Li et al, 2011). The most important factors to a participant's success in this phase were the regular feedback about progress towards a goal (Li et al., 2011), which has been noted to increase both self-efficacy and achievement (Scunk & Swartz, 1993).

Li et al.'s (2011) other phase, Discovery, focused on a participant who is unsure of what variables impact a particular outcome variable, and the primary directive in this phase was to develop a large enough dataset that correlations are available to interpret and analyze. In this phase, the researcher must gather more variables and was substantially more time-consuming (Halko & Kientz, 2010; Munson, 2012). Examining a participant's productivity, an outcome variable must be designated, such as the total minutes spent on productive activities, easily measured for information workers with computer-based apps such as RescueTime, but several dependent variables, both quantitative and qualitative, must be set and tracked. These variables should be directed by a participant, as it is impossible to fully examine all possible variables. These may include quantitative variables, such as the number of cups of coffee, hours and minutes of sleep, or qualitative variables, such as mood and quality of sleep, or mixed variables, such as stress levels. However, there are several difficulties in the discovery phase. Considering the time constraints required in the creation of datasets that are so large, the best practices suggested indicated that a participant should move from this phase into a maintenance phase as soon as possible to encourage behavioural change (Li et al., 2011). As well, to mitigate the effects of this data collection, a number of automated tools have been used to help collect this large amount of data, but the greater the number of sources of data, the greater the difficulty in creating a coherent dataset that allows for correlation and analysis, particularly for participants without training in data analytics.

The action-taking layer of quantified self-tracking has been investigated in the realm of diet to powerful results – the self-tracking measurement of a daily food journal was the most significant positive predictor of future weight loss in multiple studies (Kong et al., 2012; VanWormer, French, Pereira & Welsh, 2008). While the impact of counting calories was not a particularly unknown phenomenon, the raw effect, a large 3.72% increase in weight loss (Kong et al., 2012), demonstrated the power of self-monitoring techniques. Of the most significance, however, was Kong et al.'s (2012) ranking of behaviours as they relate to ultimate weight loss – the inclusion of more data in the form of a food journal culminated in more substantial weight loss than cardiovascular training, assisted training, or strength training when controlled for all other features. While there was a strong relationship between diet and weight loss, and thus should also be understood in that context, the development of a personalized dataset was the most powerful method to create meaningful change in participants.

There was a strong relationship between the development of effective and persuasive personal informatics technology and the best practices of behavioural change techniques, hereafter BCTs, seen most often in health psychology (Kamal, Fels & Ho, 2010; Mercer, Li, Giangregorio, Burns, Grindod, 2016). Mercer et al. (2016) investigated this specific claim, examining the presence of BCTs in quantified self wearable technologies - specifically integrated pedometers, such as the Fitbit Flex or Spark Activity Tracker - in a meta-analysis. Notably, Mercer et al. (2016) found that while some products utilized a large amount of BCTs, many did not, though the commonly shared strand between these was the precept of self-tracking, which has been demonstrated to be effective in behavioural change in the context of personal exercise (Abraham & Mitchie, 2008). However, this was not necessarily a flaw of the system or developers, but may refer to the seminal author Fogg (2002), who had written about the interaction between humans and computers when machines act as motivating social agents. Fogg (2002) noted that "the more you increase your social capital, the more you increase your bet" (p. 114). In this, Fogg (2002) referred to the concept that attempting to utilize too many strategies to incentivize participation, cooperation, or adherence, may work against the product and cause potential participants to turn away from the overly-ambitious multiple BCTs. While Fogg (2002) was writing about incessant pop-ups regarding updating software, his words are perhaps more persuasive now; social media integration has become a prominent strategy of many, but can lead to data vulnerabilities and privacy concerns, as well as software selling personal data for financial gain ("Android Flashlight App", 2013). BCTs must be used strategically in self-tracking applications to actualize change in the participant: while any technique alone may have provided a incentive, motivation and the impetus to change, the incorporation of too many BCTs reduced the likelihood of success.

Reflective Learning in Quantified Self

Quantified self methods and the methods prescribed by theories of reflective learning parallel one another. Boud, Keogh and Walker (1985) defined reflective learning as the "intellectual and affective activities in which individuals engage to explore their experiences in order to lead to new understandings and appreciations". While quantified self was designed to be an intellectual, rather than affective, activity, contemporary research indicated that it is undertaken specifically for creating new understandings (Choe et al., 2014). Reflective Learning was the ability to learn by returning to our previous experiences, reflecting upon them, and creating actionable insight (Riphagen, 2014). The quantified self pragmatically-driven goal is "Self Knowledge through numbers", and the process of reflection was a central concept to the development of quantified self-driven self-knowledge (Pirzadeh, He & Stolterman, 2013). However, there were very few studies that have investigated the link between reflection and quantified self (Pirzadeh et al., 2013). In relationship to Li et al.'s (2011) theories relating to the distinct stage of quantified self goals - that of discovery and of maintenance - only discovery implied that understanding is created. In the maintenance phase only actionable insight was emphasized. Reflective Learning took place in the Discovery phase, but without a persuasive model to implement maintenance, behavioural change will not be actualized (Fogg, 2002).

Müller et al. (2012) have linked the impact of quantifying personal metrics to the theory of cognitive dissonance, referring to the rethinking and growth that occurs when behaviours and attitudes are mismatched. In this case, quantified self methods and applications served to provide the trigger for this reflective growth by inducing cognitive dissonance; for example, a participant may believe high productivity is related to multiple cups of coffee, but a basic analysis may show that excessive caffeine can drop his productivity rating. This represented only part of quantified self methods; specifically, this refers to what Li et al. (2011) refer to as the Discovery portion of quantified self. While it may not be considered likely that reflective learning will emerge naturally from the Maintenance (Li et al., 2011) phase of quantified self, it is certainly possible.

There was very little research that has been completed on the topic of the quantified self movement and its ability to foster learning in participants. Rivera-Pelayo et al. (2012) created a theoretical framework regarding the methods and advantages quantified self has in its relationship to reflective learning. Specifically, the authors mentioned quantified self supports learning through three main support dimensions: tracking cues, triggering, and recalling or revisiting. Tracking cues referred to the data entry, or quantifying a particular aspect of a participant's life. Triggering was the first stage of the reflective process, in which Rivera-Pelayo et al. (2012) distinguished between active and passive triggering: active triggering is a specific indication by the software or product, such as a push notification or an alert. This required the application to perform exploratory data analysis to identify tracked data that may be suitable for a reflective process. Passive triggering, however, simply displayed the data for the participant to analyze. Finally, the recalling or revisiting stage was not necessitated in the reflective learning process, but enriched learning by providing context, objective, or aggregated data (Rivera-Pelayo et al., 2012). However, while Rivera-Pelayo et al. (2012) defined a suitable framework that conceptualizes the process of quantified self reflective learning, their research did not contain any information regarding the effectiveness of quantification compared to traditional methods and required further research to indicate the best practices as they relate to learning and self-improvement.

This was not an uncommon theme: despite the analytical and numerical nature of quantified self, there was a dearth of literature that reviewed quantified self in a quantified experimental design (Pirzadeh et al., 2013), and thus it was difficult to accurately assess the impact of quantified self methods. Müller et al. (2012) have provided in-depth reviews of two separate quantified self methods in unique workplaces and are among the few to assess the effectiveness of quantified self-tracking methods. The app "CaReflect" (Müller et al., 2012) was designed to provide health care providers with regular, quantified feedback about the time they spend with individual patients. It required no input from the participant after logging on and only requires review of a graph at the end of the day, and most innovatively, used proximity sensors on the health care providers to scan for a short-range signal, which was emitted passively by the patient's badges. This allowed for an automatically-generated dataset which presented answers to important questions which may be inaccurately assessed by an individual, such as "Who needed the most time?" or "Who did I not see?" (Müller et al., 2012). Additionally, Müller et al. (2012) reviewed the emergency-preparedness Watch It. This was a highly-customizable piece of hardware that allowed emergency workers to unobtrusively self-report and track their own data based on personal design; this app was designed for personal self-reflection and assessment. In both contexts, participants reported that the application was highly beneficial, though the more customizable "Watch It" was found to be more beneficial to participants (Müller et al., 2012).

Notably, in both studies, participants with more experience found both applications more useful (Müller et al., 2012). Müller et al's (2012) studies reflected the dichotomy proposed by Munson (2012) and Consolvo et al. (2009) in which reflective learning is assisted by technology when the question asked is what is happening, rather than what should be happening. It was possible that the reflective nature of the personal informatics tools allowed for the more experienced staff members, both in healthcare and emergency settings, to better anticipate given the data and visualizations. This represented Boud and Walker's (1990) model of reflective learning, in that a learner is predisposed by their previous experience to more easily notice what is expected to occur. It was assumed that a greater wealth of experience provides more utility to these datasets, but more research was needed to confirm.

Müller et al.'s (2012) found several interesting conclusions. Most pivotally, collecting data did not imply reflective learning; it required concrete, usually pre-defined, methods of interpreting that data to provide the catalyst for reflective learning to occur. This requirement represented the shift to persuasive technology (Fogg, 2002). Many employees feared that this data will be used against, particularly in a healthcare context. This made employees much more likely to lie and neglect to fill in data when they fear for their employment. Privacy functionality must be a central tenet of any quantified self methods applied in the workplace. As well, simplicity in capturing data could facilitate adoption, but automatic and self-reporting tools should be combined to balance effort and control. And as with any good data method, visualization was key. Given the low quantitative literacy rates in the general population, the best visual graphs considered are statuses, comparison graphs, and timelines (Bentley et al., 2013).

Müller et al.'s (2012) conclusion that the collection of data did not necessitate reflective learning has strong implications for the research of Pirzadeh et al. (2013), who have proposed a framework for reflective learning in the context of personal informatics. Pirzadeh et al.'s (2013) research created three stages of learning that are implied in this context: awareness of an uncomfortable feeling, critical analysis of this feeling, and the development of a new perspective. Pirzadeh et al.'s (2013) research was particularly focused on the development of a journaling and informatics application, which used traditional journaling, combined with data analytics and social media integration to create data visualizations that explored journal entries through data analytics - the medium in which the second stage, critical analysis, was performed. Pirzadeh et al. (2013) noted that data visualization encouraged participants to reflect on their experiences more often and attempt to develop new perspectives and change their negative behaviours. From Pirzadeh et al.'s (2013) research, three significant insights were developed for effective quantified self experiments and methods: potential triggers for reflection must be addressed and examined in personal reflective research; users must be provided with enough information to analyze their data themselves; and time constraints are often the most cited reason for participants dropping out of an experiment or self-improvement activity. Despite the final product being quantified data, Pirzadeh's et al.'s (2013) research originated with qualitative journaling. This framework allowed for a unique brand of quantified self in different fields beyond the traditional health, finance, and productivity domains.

This parallels the motto of Quantified Self Labs, the largest community-driven quantified self company, "Self Knowledge Through Numbers". The methods were very similar; quantified self methods allowed for the greater identification of patterns through specific tools, and it often considered to be more pragmatic than the theory-driven reflective learning.

Citizen Science

The extraction of personal insights into practice on a larger-scale is called "collective intelligence" (Kido & Swan, 2013, p. 1) or "citizen science" (Kido, 2012, p. 1). Perhaps most notably, this technique was being used in the MyFinder genomic-behavioural project which used self-reported quantified information in conjunction with an individual's genotype to investigate possible genetic determinants of behavioural issues (Kido, 2012; Kido & Swan, 2013; Kido & Swan, 2014), but this technique has been used in a number of disciplines, including ecology (Dickinson et al., 2012) and medicine (Wick, Vaughan & Heywood, 2014). To date, MyFinder genomic study has identified a correlation between the quality of sleep and genomic profile (Kido & Swan, 2014), with potentially many more insights in the coming years. Citizen science operated on the premise that a large dispersed team of observers can provide significant data to be used for evaluation and analysis (Dickinson et al., 2012). It was not necessarily linked to the quantified self movement, but there was apparent synergy between the technique and the movement. Many researchers have noted that, while the data collected for each individual in a quantified self-tracking study does not approach "bigness" (Nafus & Sherman, 2014, p. 1790) as sample size is equal to only one, when this individual data is collected in the aggregate will have substantial implications in a number of industries (Nafus & Sherman, 2014). This exemplified the power of citizen science to provide a robust and complete database and may be used for generalizable analysis, when aggregated, effectively. Studying any large-scale pattern in nature required a large and vast dataset (Bonney et al., 2009), and in many cases, the use of citizen science was the only method available, when resources are considered, to achieve this.

There have been many counterpoints to the use of citizen science as a suitable for gathering evidence. Detractors have called it "poisonous" and "full of noise" (Lucian, Cumming, Wilkinson & Kahana, 2013, p. 5) and research studies that utilized citizen science were notably absent from many research publication (Silvertown, 2009). While it was the case that the self-reported observations inherent in both the quantified self and citizen science methods could not meet the standard of randomized clinical trials (Wicks et al., 2011), self-reported data can be useful in the context of observational studies and may be tremendously useful with coordinated efforts with traditional research methodologies, particularly when modern automatic data collection methods cannot be used (Dickson, Shirk, Bonter, Bonney, Crain, Martin, Phillips, Purcell, 2012; Wicks et al., 2011). Danielsen et al. (2014), in a large-scale study investigating the accuracy of community participants gathering data when compared with professional scientists, have illustrated that in many cases, the community participants had comparable levels of accuracy and can be used to accurately predict the observations of scientists; in this particular case, Danielsen et al. (2014) noted a correlation between scientists and community participants of R^2=0.81. However, in their study, Danielsen et al. (2014) noted that the learning curve for participants can negatively impact the quality of the data and should be addressed. All participants in Danielsen et al.'s (2014) study received 2-3 days of training and many participants had drastically low levels of literacy and formal education. Given that both the scientists and the community participants analyzed the same space and produced roughly equal results, Danielsen et al.'s (2014) conclusion that local communities can be equally good at monitoring and collecting data can be accepted. This conclusion creates the space for an investigation into the use of quantified self metrics collected by participants.

Additionally, citizen science promoted learning in participants as a form of experiential education (Brossard, Lewenstein & Bonney, 2005). For example, a medical investigation into the relationship between Gaucher's disease and Parkinson's disease underwent both traditional methods and online self-reported methods. While both methods provided similar results, the online self-reported method took only six months, while the traditional research method took six years (Luciano et al., 2013). In large part, this increased timeliness of this research study was due to the distribution of data gathering, colloquially known as crowdsourcing (Luciano et al., 2013). Bonney et al. (2009) designed a methodological framework for the use of citizen science in ornithological research, but their research regarding the best methods and placements for citizen science can be adapted to many disciplines. The authors noted that this method is best used when studying patterns occurrence of time or space. While this method was originally designed to track the movement and reaction of birds, it also fit the context of quantified self analysis. While citizen science did not have the robust nature to replace contemporary research, it did have the power to substantially augment. Of a more practical nature, citizens willing to invest time - and occasionally money - into research represented a source of free resources for researchers, which allowed for larger datasets, more in-depth investigations, and increased effectiveness (Silvertown, 2009).

The task of collecting data impacted the participant. Brossard et al. (2005) investigated this claim, examining the relationship between both the participant's attitude towards scientific methodology and contextual understanding. Most notably, Brossard et al. (2005) found no significant conclusions regarding an increase in either the participant's attitude towards science or their understanding of science, but there was a statistically significant, $p<0.001$, conclusion regarding an increase in the participant's contextual knowledge. This conclusion is of tremendous importance in the context of this study, as it was intended to investigate citizen science as a method for increasing scientific literacy as a form of experiential education, but found that there was no meaningful difference between these participants and a demographically-similar control group; however, the research identified that participants engaged with the context, rather than the method. Brossard et al. (2005) posited that this distinction may be due to errors in their own study, as the scientific methodology underlying the research study may not have been framed in a way that made it clear to the participants who were gathering this data. This conclusion was driven by Brossard et al.'s (2005) acceptance of their initial assumption that participants will engage meaningfully with the material regarding the study as the participants have volunteered, thus demonstrating their engagement with the material. However, this demonstrated only that the participants are engaged with the context. It did not demonstrate that participants are engaged with the methodological structure underlying the study, and the findings of this study supported this. Brossard et al.'s (2005) conclusions strongly implicated best design for quantified self studies: it should be assumed that participants are more likely to engage with context rather than structure when collecting data.

There are many potential problems within citizen science. Many authors have noted the need for a well-designed method for data validation before utilizing volunteer researchers (Bonney et al., 2009; Cohn, 2008; Silvertown, 2009). Volunteer researchers often required pairing with experienced researchers to mitigate data collection problems and increase understanding (Bonney et al., 2009; Cohn, 2008; Silvertown, 2009). Silvertown (2009) proposed several specific principles in which Citizen Science can be best completed, most notably he defined the necessity of data validation and standardized collection methods. These principles were in direct contrast with many other assertions that citizen science is a method that is learning by doing (Silvertown, 2009). This relationship between what was ideal for a systematic gathering of material, review and analysis suitable for publication and as what is practical, which was power users, often untrained in rigourous academic research, pursuing rapidly-advancing technologies, defined both modern citizen science movement and the current quantified self landscape. While there were numerous tool emerging to measure distinct variables regarding our own body, minds, and actions, there was very little systematic review on how these tools are used, how they are best used, or how participants reacted to these tools on an individual level.

Dickinson et al. (2012) have also noted that longer-term projects require a shift from traditional volunteer methods, and that it was better to focus on a niche group who are served by your research question. This adapts very well to quantified self methods, as the subject of analysis was the participant themselves and the question was designed by the participant, which may indicate it was easier to maintain engagement in quantified self than other disciplines which use citizen science methods. As well, several researchers have noted that participants may be unlikely to enter data, either based on unfavourable conditions or particular desires (Bonney et al., 2009; Danielson et al., 2014). Bonney et al. (2009) noted, in the context of ornithology, that quite often participants were unlikely to enter data if they reached an unfavourable conclusion: in this case, seeing only common birds or seeing no birds at all. Bonney et al.'s (2009) conclusion also applied in the context of quantified self; it was very likely that participants may be unwilling to enter data about themselves they find unfavourable. However, despite these flaws and methods required to circumvent these flaws, without fail the researchers reviewed here have written powerfully and positively about the effects of citizen science on their research.

Citizen science was yet in its infancy. With the advent of new methods used in the age of the Internet, the potential for integration with traditional research is intriguing, and many authors have used or noted its effectiveness in the augmentation of the data collection aspect of research (Brossard et al., 2005; Dickinson et al., 2012; Luciano et al., 2013; Newman et al., 2012; Wicks et al., 2011) and some authors believe it represented an evolution of the scientific method (Cohn, 2008). Currently, this method has been used more often in the ecological and medical disciplines, but the impact of regularly self-reported or automatically generated data to facilitate research and policy decisions could be tremendously useful in education. If the most optimistic projections are correct, citizen science has the opportunity to create global research projects, developing rich and diverse open-source datasets that may fundamentally change research (Newman et al., 2012). There are several technological start-ups that use this type of information in an educational setting, but it has not yet been incorporated on a large-scale. Many studies have used a similar method before the term citizen science originated; for example, the Christmas Bird Count in the USA has used professional scientists working with amateur birdwatchers to catalogue 63 million birds since 1900, with 60,000 to 80,000 annual volunteers (Cohn, 2008; Silvertown, 2009). This project has a strictly-defined methodology, with each citizen-researcher team given a 15-mile radius in a single day (Silvertown, 2009). This project would not have been possible without the citizen of volunteer researchers.

Most notably, citizen science was driven by the creation of new technologies and tools designed to reduce the competency requirement for participation, and there are "yet unimaginable devices to be created" (Newman et al., 2012, p. 300). Smartphone peripheral ports are often co-opted for sensor use, which can dramatically increase the requirement for manual data entry and removes the potential for transcription errors (Kuo, Verma, Schmid & Dutta, 2010). As well, modern machine learning interprets vast quantities of data and can improve data collection, control data quality and corroborate model results (Newman et al., 2012).

The potential impact quantified self may have extended beyond the personal health and wellness implications often cited. Of importance in the field of healthcare and community health, the impetus for developing large-scale self-reported methods revolved around the building of large datasets for analysis (Pickard & Swan, 2014). In a field with a multitude of complex interacting variables, such a database would be very powerful in predicting and preventing illness and improving patient care (Pickard & Swan, 2014). Further development of such a database would be useful in any context, provided that the analysis was done with competence and vision. In the context of education, such a developed database could drastically assist with improving the efficacy of any educational strategy that can be quantified. The issues investigated, such as identification of effective emotional health, serve as a preventative measure for several negative emotional health implications. This created the purpose for advancing the incorporation of these methods into the educational discipline and practice.

Conclusion

There was a substantial amount of research which supports the use of self-tracking as a tool for self-improvement. Given the use of quantified self metrics, the relationship between data and behavioral change techniques, as well as the research incorporating reflective learning, this tool has the potential for substantial benefit to a multitude of participants. As well, given the literature that supports that use of amateur researchers in the field of citizen science, the potential criticism of data quality when gathered by untrained researchers has been addressed. While several studies have noted a reduction in quality, the effect is slight and given the increase in the volume of data, it can be used safely and accurately.

However, though the use of quantified self techniques is quickly becoming widespread, there has been little research associating this technique with the well-researched and discriminant measures of psychological well-being. In this study, emotional intelligence and self-efficacy will be examined as they relate to technologically-driven self-tracking.

Emotional Intelligence

In assessing the impact of quantified self techniques, this study intends to investigate their relationship to contemporary measures in education. Assessing a life in a quantified fashion is highly related to the idea of self-awareness, which itself is tied to the concept of Emotional Intelligence, hereafter EI. Research has indicated that EI is one of the most significant predictors of workplace performance (Joseph et al., 2015). Originally synthesized and popularized by Goleman (1998), EI is the ability to understand your own emotions, as well as others around you (Ybarra et al., 2014). However, while there is a substantial amount of literature regarding the definition and effectiveness of emotional intelligence, there is very little literature about increasing EI in participants (Nelis, Quoidbach, Mikolajczak & Hansenne, 2009). EI is a very diverse subject, with several definitions spanning several domains, including conscientiousness, extraversion, ability EI, emotional stability, and cognitive ability, among others (Joseph et al., 2015). Current theoretical models of EI separate this into three domains - knowledge, abilities, and traits (Nelis et al., 2009). There were two major schools of thought regarding emotional intelligence, dependent on the definition of EI as an ability or as a trait (Benson et al., 2013). Fundamentally, trait EI was a representation of what can be determined through self- and peer-reported measurements, while ability EI was a representation of what can be determined through the quantification of the success rate of a task that utilizes EI (Benson et al, 2013; Rosete & Ciarrochi, 2005). Ability EI emerged as a measurement in response to criticisms of the trait EI scale and its self-reported nature (Mayer et al., 2014). While many authors used a mixed EI as a representation, ability and trait EI should be noted as distinct constructs (Benson et al., 2103).

This study and method emphasizes an increase in the conscientiousness domain of EI, the ability to manage and regulate ourselves, which has been demonstrated a highly predictive element of performance and efficacy (Dumfart & Neubauer, 2016), in a trait EI context. The role of quantified self in the domain of conscientiousness was designed to optimize our activities to more easily achieve self-regulation. This was achieved by quantifying numerous aspects in our lives to make our unconscious behaviours clearly identified and trackable (Kido & Swan, 2014).

Emotional Intelligence and Effectiveness

There have been several well-demonstrated connections between an employee's effectiveness and his emotional intelligence or their mental health. An employee's mental health, in the context of the work environment, is the result of several potential variables, including the employee's emotional intelligence, their ability to deal with stressful situations, and the net stressful events they experience. The potential of increasing the emotional intelligence of staff has been written about substantially. Labby et al., (2012) described EI as a fundamental aspect of organizational success.

Furthermore, the pursuit of emotional intelligence research in education demonstrated the effect it can have on both educators and administrators. In this context, some research has indicated that the increase of emotional wellbeing of teachers provides increases in teacher confidence, teacher performance, and decreases in student misbehaviour, alongside a host of other positive improvements (Weare & Gray, 2003). The relationship between emotional intelligence and effectiveness has been confirmed by several studies (Dong et al., 2014; Drew, 2006; Goleman, 1998; Jha & Singh, 2012; Labby et al., 2012; Penrose et al., 2007; Rooy & Viswesvaran, 2003).

In the context of educational administrators, emotional intelligence is a necessity. Emotional intelligence provided the fundamental skills required of the administrator to elicit the maximum potential of others (Benson et al., 2013; Labby et al, 2012). Using, maximizing and optimizing the use of human resources available in an under-performing school required excellent emotional intelligence, which consists of relational management, self-awareness, self-management, and social awareness (Labby et al, 2012; Goleman, 2002). Of importance is that these competencies were not necessarily innate, though many common perspectives contradict this, and can be learned through the development of emotional intelligence (Goleman, 1998). Leaders used this emotional intelligence to serve several goals, but regularly used it to manage successful relationships with faculty and staff (Benson et al., 2013).

However, despite the role that emotional health has on ultimate performance and achievement of schools, many schools did not develop a model that emphasizes healthy mental models for educators. Weare and Gray (2003) emphasized that little is attempted in the realm of effective emotional health in education, as they investigated the claim that many administrators want immediate solutions to immediate problems; this perspective diminished the role of emotional wellbeing substantially.

The impact of emotional health on learning, as well as other outcomes, such as productivity and efficiency, has been well demonstrated in the literature. Rooy and Viswesvaran (2003) analyzed the relationship EI, personality, and mental ability with performance and found a significant relationship between EI and efficacy. Jha and Singh (2012) identified relationships between a teacher's emotional health and teacher effectiveness, through both self-reported and student rated measures, and reported extremely strong correlations. Penrose et al. (2007) furthered the argument and posited that increasing emotional intelligence predicts an increase in student achievement through an increase in teacher's efficacy. Dong et al. (2014) investigated the mechanism of action that promotes effective choices when employees are faced with significant challenges, and the researchers found that emotional intelligence and emotional health are key aspects of performing above and beyond the limits of their cognitive ability or personality.

In a comprehensive meta-analysis of 69 studies investigating the relationship between emotional intelligence and performance measures, authors Rooy and Viswesvaran (2003) identified a high correlation between emotional intelligence with general mental ability when controlled for openness, conscientiousness, extraversion, agreeableness, and neuroticism. This meta-analysis was designed to create a unified body of knowledge to understand the predictive power of EI and performance in the domains of employment, academic, and general-life settings. Their research synthesized several differing instruments designed to measure EI in an effort to reduce the variability that is present in instrument choice to measure emotional intelligence (Rooy & Viswesvaran, 2003). The Bar-On test was most commonly used to measure EI, but several other instruments were also included in this study (Rooy & Viswesvaran, 2003). Rooy & Viswesvaran (2003) posited that the presence of so many instruments designed to measure EI indicated that no truly robust measurement of EI existed, and that the measurement was often conflated with personality measures not controlled for in studies. The aggregate data in these studies indicated that EI, when controlled for the various instruments and personality traits, is a valuable predictor of performance (Rooy & Viswevaran, 2003). This study was notable, as it synthesized multiple models of assessment to determine the predictive nature of the nebulous and difficult-to-define EI. While emotional intelligence is not the only predictor of organizational success, its significant impact cannot be easily dismissed. However, the criticism related to the robustness of the measurements should be highly considered.

Jha and Singh's (2012) research indicated that teacher effectiveness in highly-analytical university courses, such as engineering and medicine, was also predicted by the EI of the instructor. The researchers dismantled the concept EI into several subgroups, including self-awareness, empathy, motivation, emotional stability, and more, and correlated these subgroups with teacher effectiveness, measured by the Teacher Effectiveness Scale and the Teaching Rating Scale, which provided both self-reported and student-reported data (Jha & Singh, 2012). Self-awareness was identified as a key predictor in Jha and Singh's (2012) model. This indicated that the presence of self-awareness and the ability to understand one's own strengths and weaknesses assists in performance in the teaching profession. While the correlations identified in this study have high significance, the reliance on self-reported measures for both EI and teacher effectiveness in which both surveys are completed successively could confound this study. However, several studies have indicated that self-reported efficacy, using the Teacher Effectiveness Scale, is an excellent predictor of student success (Kogan & Vacha-Haase, 2001; Penrose et al, 2007).

Penrose et al. (2007) researched the effect of EI on teacher's efficacy. This study used a similar methodology to Jha and Singh (2012) by correlating teacher efficacy with EI. The Teacher Effectiveness Scale was also used to measure self-reported efficacy, though the researchers also use the Reacting to Teaching Situations to measure EI. The authors reported a similar conclusion, though with much higher degree of significance. However, as Penrose et al. (2007) did not distinguish between the subdomains of EI, and instead used it as a holistic predictive variable of self-reported efficacy, it is more significant, but contains less nuanced data than Jha and Singh's (2012) investigation. Notable is the distinction in R^2 values: Penrose et al.'s (2007) coefficient of determination was 0.14, while the blended model of Jha and Singh's (2012)

R^2 was 0.316 when using only the subdomains of EI self-awareness, empathy, self-development, and commitment. This suggested that the use of EI as a predictive model without dividing the concept into its subdomains did not create an ideal model.

Dong et al. (2014) investigated in a quantitative inquiry the implications of EI as a mediating agent between developmental job experience, turnover intention, and affective mindsets in MBA students. This study identified a relationship between the role of EI in reducing turnover intention when employees are faced with job tasks that are demanding and required significant growth in the employee to perform them with competence (Dong et al., 2014). The researchers believed that EI has the potential to influence affective processes, such as the classification of a demanding task as a challenge, exemplified by those with high levels of EI, or as a threat, exemplified by those with a low level of EI (Dong et al., 2014) This study did not link EI to performance, but an increase in turnover intention indicated a reduction in organizational effectiveness, as developed human resources are lost to other organizations and professions (Dong et al., 2014). This study faltered in its identification of ten unique hypotheses to be tested by measuring the p-value, with significance set at $p < 0.05$. Though it indicated a significant mediating relationship of EI between negative feelings and turnover intention, it did not indicate a significant relationship between any of the other hypotheses investigated. This study's multiple hypotheses inflate the alpha value without correction, indicating that the probability the relationship identified is due to random chance is substantially higher than 0.05. This, coupled with the low effect demonstrated in their research, indicates further study is needed to investigate the mediating relationship EI has on affective processes.

There are, however, counterpoints to this research. Some studies have demonstrated that emotional intelligence does not contribute to effectiveness throughout the major domains. Flores

(2009), in a study investigating the relationship between school principals' emotional intelligence and their effectiveness as indicated by the students' scores on standardized reading and mathematics tests, found no correlation between the two measurements. However, Flores' (2009) study investigated only five principals and their schools without controlling for the factors of personality, and Rooy and Viswesvaran's (2003) large-scale study did appear to be substantially more robust. Flores (2009) himself identified that the sample size of his study indicated a potential methodological problem. While Flores' (2009) conclusion may have been a result of the either the small sample size of principals investigated or the survey tool used to measure emotional intelligence, this did lend a valuable contrary opinion to the conventional literature that identified significant relationships between emotional intelligence and effectiveness in an educational administrator context. Feldman (2004) identified a weak correlation between emotional intelligence and outcomes in the context of undergraduate students; additionally, Ybarra et al. (2014) noted that much emotional intelligence research does not account for the distinction between unconscious and conscious emotional intelligence, and as such significantly reduced the predictive utility of the concept. Ybarra et al. (2014) also noted that emotional intelligence, when controlled for both IQ and personality measures, only explains 1-7% of the variance across work, academic, and life outcomes. Rosete and Ciarrochi (2005) discovered a significant relationship between self-reported EI and effectiveness, but found only 4% of the variance in their measures of effectiveness was predicted by changing self-reported EI; however, their model for ability EI was substantially more powerful, with an R^2 of 0.26 and 0.50 for their respective measures of effectiveness. There was substantial disagreement about the relationship and effect size of emotional intelligence as it relates to efficacy.

However, in many cases, particularly in highly-cognitively and creatively-demanding positions, emotional health and intelligence served as a predictor of successful outcomes; several authors have analyzed the relationship between emotional health of teachers and several positive outcomes: Jennings and Greenberg (2008) proposed that emotionally strong teachers are more likely to succeed and set the tone in their relationships with their students, and the authors further demonstrated that these behaviours exhibited by emotionally strong teachers are correlated with optimal classroom climate and student outcomes. Teachers who were not emotionally intelligent had lower rates of resilience and often suffered from burnout, and either left the workforce or continued to function in a suboptimal position (Jennings & Greenberg, 2008). This position is also clear in the literature regarding the burnout and emotional exhaustion (Leiter & Maslach, 2004; Vesel, Saklofske & Leschied, 2013). Emotional intelligence served as predictor of the either burnout or thriving conditions to a moderate degree.

When positive mental health, influenced by high rates of emotional intelligence, is maintained, turnover rates are lowered; this creates a more experienced staff, and a more experienced staff are more likely to achieve higher rates of student outcomes. The former claim is evidenced by the identification between turnover intention and burnout (Jung et al., 2012; Ploy & Roodt, 2010). The practical argument is also apparent: if an employee is miserable in his work, he is more likely to leave (Dong et al., 2014; Mohammed, Chai, Aun & Migin, 2014). While there are numerous potential indicators, predictors, and models of burnout development, it is always a state of mental and emotional exhaustion that is developed through stressful situations (Leiter & Maslach, 2004).

Emotional exhaustion can often be alleviated by the presence of EI; an employee with high EI reduces their own turnover intentions when faced with difficult or challenging work

(Dong et al., 2014), and a leader with high EI reduces the turnover intention of employees when controlled for the rate of emotional intelligence in the employee (Mohammed et al., 2014). As well, Mohammed et al. (2014) proposed a model which considers EI to have a profound indirect negative effect on turnover intention through the development of organizational culture. This optimal organizational culture consists of varying levels of challenge, communication, trust, innovation, and social cohesion (Mohammed et al., 2014). These aspects are fueled by the effective emotional intelligence of the general staff and leadership; high levels of emotional intelligence with either staff or leadership correlate negatively with the turnover intention of employees (Mohammed et al., 2014).

Emotional Intelligence Subdomains and Theory

The effects of strong emotional health are well documented. EI is positively associated with good general health, as well as many health-related behaviours, including exercise and proper diet (Tsaousis & Nikolau, 2005). However, emotional intelligence is a broad and diverse concept, consisting of several subgroups of domain mastery; for example, the distinction between stress management techniques and control over one's emotions is practical. It is worthwhile to investigate these subdomains of EI as they relate to particular behaviours and the instruments used to measure these subdomains, particularly the distinction between trait and ability EI.

Trait EI is the self-reported metric of EI provided by participants (Rosete & Ciarrochi, 2005). Trait EI was the original conception of EI and has been used in a multitude of studies to investigate the relationship between EI and efficacy (Jha & Singh, 2012; Penrose et al., 2007; Rooy and Viswesavaran, 2003; Rosete & Ciarrochi, 2005). However, recent studies have identified several problems with the use of trait EI as a predictor of efficacy (Mayer, Salovey &

Caruso, 2004; Rooy & Viswesavaran, 2003; Rosete & Ciarrochi, 2005) and have adapted Ability EI as a measure. Ability EI evaluates a participant's response according to a criterion of correctness. Ability EI has been noted to have more success as a predictor of workplace efficacy than trait EI (Mayer, Salovey & Caruso, 2004; Rosete & Ciarrochi, 2005). The instrument used to measure defines the distinction between trait and ability EI. The Mayer-Salovey-Caruso Emotional Intelligence Tests, or MSCEIT, was the most commonly used instrument to measure ability EI. The MSCEIT distinguished EI as four distinct subcategories, including perceiving emotions, emotions facilitating thought, understanding emotions, and managing emotions, often categorized as experiential EI, consisting of perceiving and using emotions, and strategic EI, consisting of understanding and managing emotions (Mayer et al., 2004). The measurement of ability EI emerged from the criticisms of trait EI, particularly that self-reported measures of EI were overly correlated with personality factors, often at a correlation of 0.52 to 0.75 (Mayer et al., 2004). These very high correlations indicated that self-reported EI was not a new or unique measurement, but reflected past research on personality domains (Mayer et al., 2004).

Ability EI emerged from Mayer at al.'s (2004) proposition that if EI is a valid construct of a unique type of intelligence, then an assessment must include correct or incorrect answers, similar to an IQ test. This additionally reflected the research indicating that self-reported measures of IQ were weakly correlated with ability measurements of IQ, similar to the IQ tests widely used contemporarily (Farrelly & Austin, 2007; Paulhus, Lysy, & Yik, 1998); Mayer et al.'s (2004) research confirmed a weak correlation between self-reported EI and ability EI, measured by the MSCEIT; the correlation measured was +/- 0.20-0.30 when the subdomains of ability EI were compared with the Bar-On EQ-I, the Scale of Emotional Intelligence, and the Occupational Personality Questionnaire Emotional Intelligence Scale (Mayer et al., 2004); this research was confirmed by Farrely and Austin (2007), investigating the correlations between the MSCEIT and Schutte's EI scale and found similar low yet statistically significant correlations.

Currently, the MSCEIT is still being test for validity; Fiori et al. (2014) explored this instrument. The researchers analyzed the incremental specificity and efficacy of trait EI, as measured by the MSCEIT, as a predictor of performance, intelligence, and personality traits (Fiori et al., 2014). Notably, the MSCEIT was identified as having low incremental validity to determine participants who were of either high-or medium-EI, and the tool was more suited to inquiry regarding low-EI participants (Fiori et al., 2014). As well, Fiori and Antonaki (2012) found ability EI to be a poor predictor of performance in a timed test to measure response and found significant correlations with the personality factors of openness, neuroticism, extraversion, conscientiousness and agreeableness, disputing the validity of both EI as a powerful predictor of workplace success and the validity of an instrument commonly used to measure this intrapersonal domain. The correlations with these personality factors were smaller than the correlations seen in trait EI measurement scales, such as Schutte's EI scale (Farrell & Austin, 2007; Mayer, Salovey & Caruso, 2004), but Fiori et al.'s (2014) work has indicated that a unifying measurement of EI is not apparent in the current literature.

Poor eating habits, smoking, or drinking are all behaviours which can cause several adverse health outcomes. Thus, the identification of the link between emotional intelligence and those behaviours is of the most importance. It is hypothesized that the lack of proper emotional intelligence promotes the need for the development of coping methods; in many cases, those coping methods are the unhealthy behaviours previously indicated (Salovey, 2001).

Burnout

These unhealthy behaviours and coping mechanisms can often lead to either adverse physical or mental health conditions, such as burnout or general disengagement. The effects of burnout are well-documented, and it is a well-known phenomenon within any human-service related field. The phenomenon has been broken down into three distinct dimensions: reduced self-efficacy, emotional exhaustion, and depersonalization (Leiter & Maslach, 2004). A high score on any of the elements of burnout, as indicated by the Maslach Burnout Inventory, can indicate the development of burnout. This is particularly dangerous, as Uchino (2006) has characterized burnout as a positive feedback loop; negative behaviours promote further negative environments, which further promote negative behaviours.

Burnout is a phenomenon traditionally considered to affect professionals working with service directed towards people-work (Maslach & Jackson, 1981). That traditional conceptualization of burnout has been expanded to include any occupational group (Bakker, Demerouti, and Schaufeli, 2002; Bakker, Demerouti, Verbeke, 2004; Schaufeli & Leiter, 1996). Burnout is a concept that can manifest as professional dissatisfaction, high rates of absenteeism, low professional involvement, emotional exhaustion, depression, depersonalization, anxiety, fatigue and culminate in a high desire to leave the profession. (Maslach & Jackson, 1981; Maslach, 2003; Sarros & Sarros, 1990; Schaufeli, Leiter & Maslach, 2009). It removes workers from their positions, or removes their motivation and passion for continuing to learn and improve.

The literature suggested a strong connection between burnout and a reduction in educational effectiveness. Much of this literature investigated self-reported measurements of efficacy, as it has been shown that self-reported efficacy is an accurate predictor of student success (Penrose et al, 2007). Educators became more effective in achieving educational outcomes with both experience and training (Klassen & Chiu, 2010). Burnout reduces the longevity of an educator's career by motivating them to leave the profession, or burnout reduces the passion for education, causing them to exhibit less work engagement.

Engagement, Resiliency and Emotional Intelligence

Work engagement and burnout were often written about as identical phenomenon, where burnout is the negative aspect of an engagement spectrum (Poulsen, Meredith, Khan, Henderson, Castrisos, Khan, 2014; Schaufeli & Leiter, 1996; Schaufeli & Bakker, 2006). While Burnout has primarily been designated as culmination of exhaustion, cynicism and low sense of personal efficacy (Leiter & Maslach, 2004), work engagement has been defined by vigor, dedication, and absorption (Poulsen et al., 2014). Maslach and Leiter (2010) have defined work engagement as the polar opposite of burnout and suggested that the positive characteristics of work engagement mirror the negative characteristics of burnout. Notably, Maslach and Leiter's (2010) definition does not include common third dimension of work engagement, absorption, but instead replaces it with efficacy to mirror the loss of self-efficacy felt in many burnout cases. However, Schaufeli et al. (2006) argued that the presence or absence of burnout does not imply the presence or absence of work engagement; they are related but distinct constructs. Specifically, Schaufeli et al. (2006) argued that work engagement is a positive state of mind that is both fulfilling and consistent. As mentioned previously, Schaufeli et al. (2006) includes the aspect of absorption in the characterization of work engagement, or the state of being fully engrossed in one's work.

Many of the studies reviewed did not conclusively identified whether or not burnout and work engagement are, as Maslach and Leiter (2010) have suggested, simply two ends of the same spectrum, or if they are distinct, according to Schaufeli et al. (2006). Poulsen et al. (2014) research indicated distinctly different predictive values for burnout-based models compared to work engagement models; Halbeslenben's (2010) meta-analysis indicated that while there is a negative correlation between the energy subdomains, exhaustion and vigor, the correlation was found to be an aggregate -0.37. This is in distinct contrast to the much stronger negative correlation of -0.65, found between the identification subdomains, cynicism and dedication. A longitudinal study enacted by Makikangas et al. (2012) indicated that while the relationship between cynicism and dedication was noted to be strongly negative, the relationship posited between exhaustion and vigor was not found in their study.

The literature suggested there was a degree of difference between burnout and work engagement. These findings indicated that the investigation of the subdomains of burnout was not enough to fully understand the multitude of factors that influence an employee's motivation, efficacy and sense of personal wellness. Thus, to prescribe effective treatment to not only address the negative implications, burnout, but to also foment positive and effective change beyond simply the removal of burnout, the vigor subdomain should also be addressed. The culmination of high engagement is highly associated with the resiliency construct.

Resiliency

Research has indicated a moderate link between the development of emotional intelligence and the development of resiliency (Armstrong, Galligan, Critchley, 2011). There is an identified correlation between high levels of emotional intelligence and high levels of resiliency (Grant & Kinman, 2012; Keshavarzi & Yousefi, 2012). Resiliency is the ability to recover from setbacks, serious or otherwise, effectively. Coutu (2002) defines resilience as "a staunch acceptance of reality; a deep belief... that life is meaningful, and an uncanny ability to improvise" (p. 6). Montpetit, Bergeman, Deboeck, Tiberio & Boker (2010) considered it both a set of characteristics and the process in which those characteristics affect individual response. In her seminal paper, Masten (2001) conveyed that resilience is a simple and common phenomenon that occurs when all the human systems are in good working order, which promotes development even in the face of severe adversity. The rise of positive psychology has placed resiliency at the forefront of many fields of research (Cooke, Doust, & Steele, 2013). Rather than a focus on the dysfunctional aspects of the workforce, positive psychology focused on the conditions that provide optimal performance and health. Resiliency was defined as the culmination of personal characteristics which support positive stress responses and protect an individual from personal adversity. It is the process of resisting against stress, which may be subset into both stress resilience and stress recovery (Montpetit et al., 2010).

Montpetit et al. (2010) categorized resilience as two dichotomous variables; specifically, the researchers referred to personal protective factors and community or social support factors. The former category involved personal characteristics, such as cognitive or social skills, which provided resistance or adaptability to stress in daily life (Montpetit et al., 2010). The dispositional characteristics of an individual were also included in the personal protective factors and can significantly impact a stress response. For example, how a stressful situation is mentally categorized by an individual significantly impacted their stress response. If a positive interpretation was maintained, it reduced the perceived stress from an event, while the inverse was true for a negative interpretation (Montpetit et al., 2010).

The connection between EI and resilience has been briefly established in the literature. Armstrong, Galligan & Critchley (2011) investigated the relationships between trait EI and resilience and found both statistically significant correlations and moderate predictive validity of EI and resilience; however, EI was postulated as an antecedent to resilience, rather than two terms for identical phenomena (Armstrong et al., 2011). Armstrong et al. (2011) found negative and significant relationships between EI and feelings of distress and negative life events in a large scale online study. Additionally, Montgomery et al. (2008) found a further correlation between resiliency and trait EI in a small-scale study investigating adult males diagnosed with Asperger's syndrome, and Liu, Wang and Lü (2012) identified the mediating role resiliency plays in managing trait EI.

Thriving was defined the culmination of high levels of resilience and expertise in a position, which was often conceptualized at the descriptive conclusion of higher emotional health in individuals (Carver, 1998; Porath, Spreitzer, Gibson & Garnett, 2012; Sarkar & Fletcher, 2013) which was categorized as both a high degree of individual vitality as well as continuous learning (Porath et al., 2012). Vitality was defined as the energy brought to a workplace situation, and learning was the thought and belief of continuous growth present in the position. These beliefs related directly to high degrees of emotional health, as emotional health was considered a necessary aspect to approach the workday with vigor and appraise personal learning (Porath et al., 2012). The thriving concepts also related directly to the negative aspects of poor emotional health: low self-esteem has been noted to overgeneralize negative outcomes as personal failings (Porath et al., 2012); this negativity was a potent environment for negative behaviours to form and burnout to manifest itself which was similar to the stress concepts of coping resources and coping strategies proposed in Thoits (1995). This low self-esteem and poor self-conceptualization lead directly into all three dimensions of burnout: low self-efficacy was a nearly identical personality trait (Leiter & Maslach, 2004), but emotional exhaustion and cynicism both emerged from negative mindsets. This demonstrated that strong emotional health in the workplace can provide the impetus to re-evaluate a negative outcome as something other than a personal failure, such as a challenge, an unavoidable consequence, a lesson learned. In long-term perspectives, the positive perception of challenge and failure was fundamental to continual success in the discipline of education.

Conclusion

EI suffered several criticisms regarding its validity as a psychological construct, but contemporary research suggested that as the understanding of this construct matures, the tools designed to assess discriminant and predictive validity also improve. There are many criticism associated with the multiple subdomains of EI, as well as its potential breadth of scope which implies low discriminant validity; however, despite these criticisms, this construct has been associated with several positive outcomes, particularly in disciplines associated with organizational effectiveness (Jha & Singh, 2012; Labby et al., 2012; Penrose et al., 2007; Rooy & Viswesvaran, 2003). Additionally, this construct has been demonstrated to have a mitigating effect on the development of burnout and a positive effect on the development of resiliency (Armstrong et al., 2011; Liu et al., 2012; Montgomery et al., 2008). If quantified self tracking can be associated with increased EI, it will provide a robust framework for further investigation into the positive effects of quantified self tracking.

Self-Efficacy

Bandura's (2004) Social Cognitive Theory is very relevant to the development of effective quantified self tools; social cognitive theory has been used successfully for many of the same goals that quantified self tools are often designed for, such as weight loss or reduced smoking (Kamal et al., 2010). Social Cognitive Theory investigated the role of personal agency as it related to personal efficacy. Bandura (2004) believed that personal efficacy was fundamental to creating any meaningful change. Therefore, if quantified self techniques can improve belief in self-efficacy, it can provide meaningful change to an individual. The two concepts appeared highly related, as the implementation of learned behaviours, investigated in quantified self-discovery, required improved self-efficacy to actualize (Bandura, 2004). Bandura's (2004) theory provided the framework for an investigation into the quantified self as an academically-rigourous method of self-improvement, specifically due to the Bandura's (2004) association that mastery experiences were the most effective way to create an improved sense of self-efficacy. Mastery experiences were defined as a challenging success in which a participant overcomes obstacles and succeeds; quantified self allowed for more effective growth in both of Bandura's (2004) necessary domains: success and mastery experiences in difficult tasks, such as changing eating habits, were displayed to the user in minutely quantified data (Aguilera & Muench, 2012) and this data allowed for greater assessment of the obstacles overcome, thus increasing resilience (Bandura, 2004). Self-efficacy was made more robust by the development of resiliency alongside self-efficacy, as it illustrated failure as instructive, rather than demoralizing (Bandura, 2004). However, there was no research examining the relationship between quantified self and the development of resiliency, which may have a strong mediating role in actualizing behavioural change in the participant.

Social Cognitive Theory also has implications for the further development of best practices of quantified self -related tools as they relate to the integration of social media. A fundamental tenet of Social Cognitive Theory was that observers learn when observing (Bandura, 2004). In addition to learning, observers also developed self-efficacy by seeing people succeed, and inversely, became apprehensive when viewing others fail (Bandura, 2004). This implicated the social media aspect many quantified self tools are integrating into their products to be more persuasive (Fogg, 2003). Instead, the ideal quantified self tool should allow for users to investigate role model datasets - people who have used this product and have changed their life as a result. Bandura (2004) has noted that even in television programs, when a character with whom the audience member empathizes changes their life, it improved self-efficacy in the audience member. It is reasonable to assume that this role model behaviour, when removed from a scripted story, will have an even greater effect on its participants; however, it also implicated that complete social integration can negatively effect the persuasiveness of a product by either displaying the failures, creating greater apprehension (Bandura, 2004) or by creating a measurement of success that is based on triumph over others, rather than by self-improvement (Bandura, 2004), which created a weaker self-efficacy devoid of resiliency. Social media has a very powerful potential in quantified self tools, but it also has the potential to be a negative influence, rather than a positive one.

Self-efficacy had a long tradition of empirical research that demonstrates its validity, uniqueness, and predictive power. Bandura (1977) constructed the theory built on the two-fold premise: self-efficacy could affect coping responses positively, and psychological intervention and procedures can alter self-efficacy. By the late 1980s, a large host of empirical research had been created supporting the theory: it was positively related to memory (Bandura, 1989), learning (Zimmerman & Martinez-Pons, 1990; Bandura, 1993), behavioural change (Sherer et al., 1982), as well as numerous coping strategies in areas such as stress reactions, reactions to failure, achievement striving and intrinsic interest (Bandura, 1982). While several criticisms of the theory did emerge (Biglan, 1987; Eastman & Marzillier, 1984), it was still used as a model in contemporary research, and no criticisms could be found today. While it may be argued that the numerous affective areas associated with self-efficacy theory will reduce its validity and sensitivity, Zimmerman (2000) has demonstrated both its discriminant validity, discrete nature from other psychometric tests, and its sensitivity to subtle changes.

Bandura (1977) originally created the idea when observing patients dealing with animal-related phobias: while all patients successfully handled the object of their fears, often a snake or a rat, at the end of the treatment, there was a distinct gradient between subjects perceived capabilities (Zimmerman, 2000). Bandura (1977) assigned this phenomenon the name self-efficacy, or the capabilities to organize and execute courses of action to attain goals. It should be noted that the assessment and measurement of self-efficacy is perceived self-efficacy and is a self-reported measurement: there was not an ability self-efficacy measurement scale (Zimmerman, 2000; Bandura, 2006). Self-efficacy theory has often been associated with the theory of locus of control, but was distinct from this theory primarily as self-efficacy necessitates sub-domains (Bandura, 2006), while locus of control is generalized (Zimmerman, 2000), demonstrated by Bandura's (2006) statement that "one cannot be all things, which would require mastery of every realm of human life" (p. 307); Bandura's (2006) previous statement is clearly evident, and thus demonstrated the rationale for his insistence that self-efficacy be measured within domains and not as a generalized personal attribute. This within subdomains measurements had also substantially increased the predictive accuracy of self-efficacy theory as it relates to desired outcomes, such as grades and career attainment (Zimmerman, 2000). Siegel, Galassi and Ware (1985) found an R^2 score of 0.13 as academic perceived self-efficacy related to final math grades, and Multon, Brown, and Lent (1991) found perceived self-efficacy related to 0.14 of the variance in student's grades. Though in many contexts, these coefficients of determination may be low, given the multitude of variables associated with producing student's grades and statistical significance found in these models, they are highly predictive and valuable variables.

Self Efficacy and Effectiveness

Self-efficacy is highly related to behavioural change in contemporary literature associated with increasing a desired activity in its participants. Ashford et al. (2010) noted that self-efficacy has, in previous studies, been tied to reducing alcohol consumption, reduction of smoking, increased usage of condoms and safe sex practices, and an increase in positive physical activity. Self-efficacy has been shown to mediate behavioural change (Ashford et al., 2010; Olander et al., 2013).

As well, the act of intervening on a patient or participant's behalf to increase self-efficacy was well-established in the literature. Olander et al. (2013) investigated the research on increasing physical activity in obese patients which a specific taxonomy, Coventry Aberdeen LOndon REfined (CALO-RE), was used for the behavioural change techniques. Notably, Olander et al. (2013) found a small but very statistically significant effect on the interventions as they related to increase self-efficacy. Additionally, this effect size varied greatly dependent upon the type of intervention performed; for example, prompt self-monitoring of behaviour outcomes demonstrated an effect size of 0.468, as measured by Cohen's d, when compared with the average of 0.23. The inclusion of prompt self-monitoring in developed behavioural change theories suggests that the quantified self techniques, highly associated with self-monitoring, would relate to increased self-efficacy if developed in a meaningful way. Given that self-efficacy was tied to numerous positive physical and mental health outcomes, this suggested that regular use of technology-informed self-monitoring techniques can create powerful change on a personal level.

The nature of perceived self-efficacy beliefs to performance was explored by Bandura (2014). In an examination of children's mathematical ability, Bandura (2014) has demonstrated that self-efficacy, regardless of mathematical ability, demonstrated a significant and large effect on the accuracy of response. However, the distinction in accuracy had a much higher difference for those students with low and medium ability levels in mathematics dependent on self-efficacy beliefs: this distinction was explained by those students with low ability and high self-efficacy chose to rework more problems that they failed, were quicker to discard faulty strategies, solved more problems, and had a more positive attitude towards mathematics in general (Bandura, 2014). Bandura's (2014) contextualizing of self-efficacy also extended beyond the classroom: in an examination of physical strength and stamina, the vicarious experiences of a group was directly manipulated by providing feedback unrelated to their performance. In one group, the participants were informed they bested another group in an examination of strength, attempting to increase self-efficacy, while in another group, they were told they were outperformed, effectively manipulating self-efficacy beliefs downward (Bandura, 2014). This feedback was unrelated to their performance, but in subsequent tests, this manipulation of self-efficacy altered the physical effort that would be shown towards the following task: those participants with increased self-efficacy extended greater physical effort, whereas reduced self-efficacy implicated an impaired performance in further tests (Bandura, 2014). In these studies, their perceived self-efficacy was measured within the specific domains investigated: self-efficacy in mathematics, or self-efficacy in physical strength tests, but were highly related to the objective outcomes and demonstrated the relationship between self-efficacy and subsequent performance.

As well, the use of self-efficacy as a mediating agent for performance outcomes extends beyond objective measurements such as mathematical ability or physical strength and into emotional contexts; Weng et al. (2014) investigated the relationship of self-efficacy, work ability, and depression in the context of 109 post-liver transplant patients. Self-efficacy was significantly correlated with both work ability and depression with correlations of 0.49 and -0.34 respectively with p-values < 0.01 (Weng et al., 2014). The salient descriptors for both work ability and depression were their role as extremely significant predictors of subsequent employment status with very high effect sizes: work ability exhibited a t-score of 4.76 and depression of -3.26, each with a statistical significance of <0.001 (Weng et al., 2014). While Weng et al. (2014) noted that the generalizability of this study may be compromised by recruiting patients from only one treatment size for the sake of convenience sampling; ultimately, its significance in the context of this study is the identification of the role that self-efficacy can play in mediating emotional contexts, such as depression and depressive episodes. This, in conjunction with Bandura's (2014) research implicating prompt self-monitoring as an extremely effective technique for increasing self-efficacy within specific domains, suggested that quantified self-techniques can play a powerful role in increasing self-efficacy. Given self-efficacy's relationship as a predictor variable for innumerable positive outcomes, this indicated quantified self techniques can create positive impact in participant's lives.

Self Efficacy and Education

Many researchers disagreed on the nature of the relationship between educator experience and effectiveness. Klassen and Chiu (2010) discovered that experience has a parabolic relationship with effectiveness: effectiveness increased for the first fifteen years of experience, maintained until 28 years of experience, and declined thereafter. The researchers identified a nonlinear relationship between self-efficacy and years of experience in a large scale study of Canadian researchers using the Teachers' Self-Efficacy Scale designed by Tscahnnen-Moran and Woolfolk (Klassen & Chiu, 2010). Chingos and Peterson (2010) identified a similar conclusion using standardized test data and information from a central data warehouse: teachers saw a significant increase in value-added for students for the experience clusters of 1-2 years, 3-5 years, 6-12 years, and 13-20 years, but beyond 20 years, an increase in efficacy was not represented in the data (Chingos & Peterson, 2010). Hoy (2000) additionally investigated and identifies a decrease in self-efficacy during the first years of teaching, represented by the Bandura Teacher Self-Efficacy scale, the Gibson and Dembo short form, as well as multiple program-specific measurements designed by the researcher. Hoy (2000) tested the relationship between efficacy and experience, controlled for difficulty, support, and student socioeconomic status, and discovered a significant decrease in self-efficacy after the first year of teaching in all instruments utilized. It remained to be seen if this relationship continues into multiple years of practical experience in education, but Vogler, Van der Mars, Cusimano and Durst (1992) continued this line of research and investigated the relationship between the effectiveness of novice teachers against the effectiveness of experienced teacher and found no significant relationship between experience and efficacy. This study may have been confounded by a small sample size, with only ten teachers in either the experienced or inexperienced group to analyze the rate of effectiveness; as well, the classification of teachers into two groups based on years of experience removed the potential for regression analysis, which the interval nature of the data would allow. Additionally, Vogler et al.'s (1992) research using a classification analytical method between novice and experienced teachers could potentially determine the parabolic relationship identified in Klassen and Chiu (2010) between effectiveness and experience as no major difference between these two groups and did not allow for nonlinear relationship to emerge.

However, despite the lack of clarity on the true nature of experience, turnover rates are highly correlated with low rates of school effectiveness (Reid, 2010; Ronfeldt, Lankford, Loels, Wyckoff, 2013). Ronfeldt et al. (2013) explored this relationship in a large-scale quantitative study and found significant correlations when controlling for socioeconomic status, teacher efficacy, classroom size and support available. Though positive effects of turnover have been identified, notably teachers and employees who are less effective are more likely to leave, the overall effect has been identified as reduced collaboration and instructional effectiveness (Ronfeldt et al., 2013). High turnover rates indicated an educational atmosphere in turmoil, and by decreasing the turnover rates, the goals, atmosphere, and culture of these programs can be solidified, thus providing the basis for improvement in the future. Decreasing turnover rates of educators is fundamental for maintaining and increasing rates of success throughout several years.

Conclusion

Self-Efficacy has a substantial amount of rigorous support throughout decades of research demonstrating that it is well-established construct capable of high predictive validity. Self-efficacy's relationship to effectiveness has been demonstrated in numerous studies and in multiple cultural contexts (Ashford et al., 2010; Bandura, 2014; Olander et al., 2013). Most notably, self-efficacy has been highly tied to success in both instructional and leadership domains (Hoy, 2008; Klassen & Chiu, 2010). While there is no research currently identifying a correlation between self-tracking and self-efficacy, it is reasonable to hypothesize there is a connection between the belief of success in specific situations and the objective assessment of success in those situations. It is an implicit belief associated with this study's hypothesis that the self-tracking methods proposed by the quantified self movement can articulate this objective success and thusly increase self-efficacy within a domain. This study will test this hypothesis.

Summary

The pursuit of self-quantification provides a unique self-management tool. Many authors have written about the advantages of the pursuit of methods that promote well-being, salutogenic methods, rather than methods which provide relief from unhealthy situations and disease, defined in this context as burnout or other emotional heal illness outcomes. (Grant & Kinman, 2012). The use of quantified measures to examine the self is an attempt to gain insight into those individual salutogenic properties by providing objective information associated with those outcomes. While substantial literature discussing the advantages of resilience, emotional intelligence and self-efficacy existed, there was significantly less discussing the practical methods designed to build these aspects of well-being.

The conception of quantified self tracking methods associated with contemporary technologies is still very recent. The methodologies associated with the development of these techniques were often built my amateur researchers and untrained analysts and thusly did not have strong academic or theoretical foundations for many of the techniques and ideas associated with their best practices. However, these techniques have been noted to have provide an increase in quality of life for a multitude of participants and thusly bear further investigation to understand their relationship with contemporary metrics.

While positive emotional health is a complex and interconnected web of variables that cannot be easily manipulated in a workplace environment, this current research did question a relevant assumption: the relationship between regular, objective reports on emotional health and the subsequent impact those reports have on emotional health. This was also a practical concern, as many administrators note they do not have the time to promote emotional health in themselves or their staff (Weare & Gray, 2003). Both EI and self-efficacy have been established as highly connected to several positive outcomes: if these quantified self-tracking methods are associated with an increase in either psychological construct, the research indicated that an increase in work outcomes will result, as well as an increase in life and academic outcomes of student and staff alike. It suggested potentially very powerful results without significant commitment beyond the development of the technology and software.

Chapter 3: Research Design

This section of the proposal will investigate the appropriateness of mixed methods design in this study. My proposed mixed methods design will use the explanatory mixed methods approach as described by Creswell and Clark (2007). The dominant aspect of this investigation will be a quantitative survey designed to understand the relationship between EI, self-efficacy and quantified self approaches, while a qualitative interview will be used to explain and understand the data that emerges from the study. A limited number of participants will be invited to complete the quantified self intervention and assess both the participant's EI and regulatory self-efficacy in a pre and post-test method.

This study uses mixed methods, rather than a single methodology, in order to better explore the emergent trends that result from the data; due to the lack of research on the topic of quantified self and personal informatics, an in-depth investigation into both trends and contextual understanding is the most appropriate method for this topic. Ultimately, this study retains a pragmatic perspective and emphasizes the quantitative conclusions but also utilizes the qualitative data for better understanding. This study follows the assumption articulated by Creswell (2014) that the proper use of mixed methods combines the strengths of both quantitative and qualitative inquiry, and creates a greater understanding than either form of data would alone.

This study design clearly meets the above definitions of mixed methods research, as it incorporates both the quantitative assessments tools, in the use of the Profile of Emotional Competency (PEC) to assess EI levels and the Emotional Regulation Self Efficay (ERSE) scales to assess self-efficacy in the domain of emotional self-regulation, as well as a follow-up interview with select participants to integrate the qualitative data into the research study. The qualitative data will not be integrated into the quantitative dataset until the initial quantitative data is assessed and analyzed, as the numerical data provides the framework for the questions and participants for the qualitative phase of the study. As well, a self-efficacy guide regarding intrapersonal intelligence will be used.

History and Function of Method

Mixed methods emerged as a dialectic conclusion resulting from the disagreement between the postpositivist and constructivist paradigms (Creswell & Clark, 2011) and has become the third major research paradigm (Creswell & Clark, 2011; Johnson, Onwuegbuzie & Tuner, 2007; Tashakkori & Teddlie, 1998). However, there was some disagreement about what defined mixed methods research (Creswell, 2014). The fundamental distinction between definitions of mixed methods research was whether or not a researcher will define it as a philosophy or a series of methods (Creswell & Clark, 2007). Creswell (2014) listed mixed methods research specifically as a method, and he had thusly given it a method orientation: "[Mixed Methods research] is an approach to research... in which the investigator gathers both quantitative and qualitative data and integrates the two..." (Creswell, 2014, p. 2). Tashakkori and Teddlie (1998) defined it as a combination of quantitative and qualitative methods. Johnson et al. (2007), in a large-scale study of researcher's perspectives of mixed methods research, had offered the following as a general definition of mixed methods research: “Mixed Methods research is the type of research in which a researcher... combines elements of qualitative and quantitative research approach for the broad purposes of breath and depth of understanding and corroboration" (p. 123).

While the theory was not concretely defined until the late 1980s, many authors, such as Campbell and Fiske (1958), used terms such as triangulation to refer to the adaptation of quantitative and qualitative methods during the formative years of this theory (Creswell & Plano

Clark, 2011). This methodological approach emerged in several disciplines and locations almost simultaneously, as authors from sociology, evaluation, management, nursing and education wrote papers in the late 1980s analyzing and adopting the combination of quantitative and qualitative methods (Creswell & Plano Clark, 2011). While a number of academics believed that these methods could not be adopted due to the inherent postpositivist and constructivist links in the quantitative and qualitative methodologies respectively, the pragmatist paradigm began to become a more highly adopted worldview and is the most commonly linked to modern mixed methods research (Creswell & Plano Clark, 2011; Tashakkori & Teddlie, 1998).

Currently, mixed methods research is adapting to a number of criticisms levied at the method. While the fundamental questions regarding the mixing of paradigms has been mostly addressed, Creswell (2014) had examined many of the questions currently posed to the formative method. These questions include the concept of postpositivist privilege as mixed methods often have a strong quantitative emphasis, what value is associated with mixed methods, and the number of mixed methods design possibilities is seen as too numerous, creating confusion in researchers. These criticisms indicate a maturity in mixed methods research: they are no longer focused on the possibility of this method, but now focused on the best practices in this now widely-accepted method.

Theoretical Lens

Mixed methods research rarely uses the conceptual lens of either postpositivism or constructivism (Creswell & Plano-Clark, 2007). This was the source of many of the criticisms levied against this method in its formative years (Creswell & Plano Clark, 2007), which has resulted in a dialectic process, from which pragmatism has emerged as the most-often cited viewpoint for mixed method studies. Postpositivism had defined quantitative research and is the pursuit of objective truth while recognizing the impact of personal bias, while constructivism emphasizes the construction of meaning created by individuals.

Pragmatism is not a combination of the strengths from these two methods, but a response to them. Given the divide between quantitative and qualitative that, at times, became a story of opposition in which derogatory and heated words were passed from either side of the divide (Reimer, 1996), pragmatism is a rejection of the epistemological-first framework that had previously defined both quantitative and qualitative research; instead; pragmatism starts with the research question first and begins to look for tools to solve this question afterwards, regardless of their foundational epistemological relationship. Pragmatism is a philosophy that first examines what the impact of research will be, rather than its relationship to objective truth (Creswell & Plano Clark, 2007). This study will use pragmatism as a guiding epistemology.

Criteria of Method Quality

In this study, a potential concern for data quality is focused on the participant's use of the quantified self-tracking journal. However, given that this is specifically a study undertaken to examine the use of quantified self tools on non-analytical participants, if the participants do not use the tool often or properly, this is still important data. This study is an investigation into the usefulness of the method, and poor or improper use indicates a criticism of the method. All participants will be required to fully complete both the PEC and ERSE to be included in the study. Regarding the issue of quality associated with the qualitative interview and coding structure, quality will be maintained by the application of established coding strategies and the explanation that the qualitative results are designed to explain individual results and should not be generalized.

Design Purpose

This research study uses the complementarity mixed-methods design, as defined in Greene et al. (1989), as opposed to the triangulation method. Primarily, this is done as the complementarity design provides a rich understanding of the participants, while the triangulation method is more suited to increase the validity of constructs (Greene et al, 1998); as well, the use of established instruments to measure both EI and self-efficacy allows for greater generalizability.

It is worthwhile to note that the fundamental question of this research study – does either EI or self-efficacy increase when quantified self-tracking is applied – does not require qualitative methods and can be assessed purely by quantitative means. However, when possible, all quantitative measures should employ qualitative methods to enrich and provide depth (Martin, 1987). The qualitative measure allows for the assessment of anything that has not been pre-defined by the survey, and given that quantified self and personal informatics are an emerging technology and design, it is reasonable to assume that participants will have unforeseeable experiences that cannot be predicted. While a successful experiment with only a pre and post-test quantitative method may provide the rationale for the use of quantified self in self-improvement, it does not provide any meaningful information beyond that point. The participant's experience will provide the data to develop better practices in quantified self methods; this is essential in this study, as all research involving these methods have been using participants who both exhibit survivorship bias and are often associated with jobs that require high quantitative literacy (Choe et al., 2014; Nafus & Sherman, 2014). This allows for this research to better assess if the best practices for traditional quantified self methods reflect the best practices for non-traditional participants. This represents Creswell and Clark's (2007) assertion that mixed methods research can be used to both explain initial results and to enhance the study with a second method.

Mixed methods research attends to the weaknesses and strengths of both quantitative and qualitative research. Quantitative research has been criticized for losing the voice of its participants and not interpreting context, and qualitative research has been criticized by the implications of personal bias and lack of generalizability (Creswell & Clark, 2007). Mixed Methods is a practical method, in which the researcher uses the best tools available to solve the problem, regardless of personal paradigm or viewpoint. However, the challenges associated with mixed methods are the questions of time and resources, as increasing the amount of data collected increases the work and collecting multiple types of data compounds the difficulty (Creswell & Clark, 2007). However, the complexity of understanding the contextual applications of innumerable theories and hypotheses has created mixed methods in order to understand words, numbers and people in both a specific and general context.

Integration of Data

Data integration is a central component of mixed methods design, and Greene, Caracelli and Graham (1989) had demonstrated that most mixed methods research integrated data during the interpretation stage, while far fewer studies integrated data during the analysis stage. Green et al.'s (1989) results may have spoken to the difficulty inherent in adapting integration to the analysis phase, while the exploratory and explanatory methods designed defined by Creswell and Plano-Clark (2007) represented the integration during interpretation stage. Given that this study also adapts its methodology from Creswell and Plano-Clark's (2007) explanatory sequential method, it also adapts integration during the interpretation stage.

Fetters, Curry and Creswell (2013) have defined four types of data integration for mixed methods design: specifically, connecting, building, merging and embedding. This study's design will integrate the data through the connecting method of integration, defined as integration occurring when one type of data links to the other from the sampling frame (Fetters et al., 2013). This will be the primary method of data integration. However, the interview question design will also be informed by the results of the survey, which involves the connecting method of data integration, defined as purposely selecting follow-up samples based on their results in the first aspect of the study (Fetters et al., 2013). This connecting method of data integration is emphasized in this study due to the study's explanatory nature – the relationship of quantified self tracking and traditional psychometric variables has not yet been explored, and thusly the study will look for emerging themes to inform the qualitative aspect. Merging the data analysis will occur in the examination of the frequency of emergent themes as they relate to the success rate of the participants in the study. Embedding data analysis has not been considered, as this would likely be represented as a form of journaling; journaling has been highly researched and demonstrated to be an effective form of self-care and would likely confound the study's findings.

The integration of the mixed methods data procedures can often result in an issue of coherence between the qualitative and quantitative data sets; in mixed methods, this is often referred to as the fit of the data. Fetters et al. (2013) have defined three categories of mixed methods data integration fit, including confirmation, expansion, and discordance. Confirmation occurs when the qualitative and quantitative agree, expansion occurs when two sources of data diverge, and discordance occurs when the qualitative and quantitative are incongruous (Fetters et al., 2013). The fit of mixed methods data will be investigated in this study through connecting the conclusions of individual results associated with increasing or stagnating EI or self-efficacy with the qualitative responses of the participants.

Quantified Self Design

The self-tracking tool will be developed by the researcher into 15-minute time block that the participant can allocate, using Excel's data validation lists and automatically-updated macros, to categorize each 15 minutes of the day. As well, when completing the data entry exercise, the participants will be asked to record their mood. When this data is entered, a dashboard-style worksheet will be automatically updated and allow the user to examine their moods, and its relationship to the activities they spend their time on. This project will use Microsoft Excel, rather than a more advanced analytics tool, such as Python or R. While the more advanced tools have higher customization and greater flexibility, Excel provides a highly-accessible tool for the greatest number of people. Kevin Kelly, one of the co-founders of Quantified Self Labs, has noted that while there are innumerable apps out there designed to quantify the minute in our lives, many participants simply note their data in a spreadsheet (Mierau, 2015). Excel is highly advantageous, particularly for those not employed in analytics, because it is easy-to-use, powerful, and accessible.

One concern associated with the quantified self movement is the idea of experimental accuracy (Swan, 2012). This is a concern associated with any self-reported measure and its accuracy, but Beauchet et al. (2014) described the powerful effects of the principles of the quantified self in the context of self-monitoring geriatric care, and note that even older adults suffering from mild-to-moderate Alzheimer's disease are able to accurately monitor their own status, in a study exploring age, gender, nutrition, social resources, daily drugs taken, and physical activity. As well, the contemporary research on citizen science, listed in this study's literature review, also demonstrates the relative accuracy of data collected by amateur researchers.

Ethical Concerns

When quantified self methods approach methods of organizational change, there is a significant ethical concern regarding the implementation of these self-driven data gathering methods. In particular, the motivation and execution of the method determines how a researcher navigates this ethical quandary. Lupton (2014) categorized five classes of intention in quantified self-study: private self-tracking, communal self-tracking, push self-tracking, imposed self-tracking and exploited self tracking. The motivation and implementation for both private and communal self-tracking arises from the individual and does not pose ethical concerns. As well, the researcher will not be gathering this data; this will remain in the hands of the participant.

The data will not be gathered because it does not address the research questions, and there are substantial obstacles to surpass in moving from individual quantified self-study to collective intelligence is the concern of privacy. Pickard and Swan (2014) noted that many suggest few participants would be willing to share such sensitive information. However, most participants were willing to freely share their data given an incentive associated with improved public health but less likely to offer the information when a monetary incentive for themselves was included. This led the authors to describe potential sources of data as data altruists (Pickard & Swan, 2014). This conclusion suggested that the most expedient way to surpass the obstacle of privacy and guarded information is to provide a goal and conclusion which reflects shared values between the researcher and the participant. The challenge was not convincing the participant to collect the data but to share the data.

Confidentiality and Anonymity

The information assessed in this study is sensitive information, as the variables are intended to measure different aspects of a participant's life, stress, and happiness, as well as self-efficacy and EI, so confidentiality and anonymity must be assured. However, all potential participants will be informed of the conditions, requirements and procedures before they become involved in the project. A confidentiality agreement will be provided to all participants. All material gathered for the purpose of this study will only be used to develop this paper only. Participants will be gathered through postings at the local colleges and coffee shops in a convenience sample. The pre and post test surveys will be administered to the participants on an online platform, such as Fluid Surveys, which uses Canadian server data storage. The participants will be identified through the survey service with the email in order to join the pre and post-test scores datasets. The researcher will meet with each participant and explain the quantified self procedures to be tested, as well as the methods of interpretation and data collection. Each participant will collect and interpret data for a period of 14 days. This data will not be submitted to the researcher, but is solely for the participants own use. Following this, the participants will complete the post-test surveys. After a short analysis, the researcher will select a subsample of participants to interview about their experiences with the quantified self methods. No participants will be directly named from the interviews and no identifiable information will be used in the final version of the project.

Evaluation of the Study

Validity and reliability. The external validity of this study as it relates to all quantified self methods may come into question, as this study only uses one particular quantified self tool in a large, experimentally-driven field. While this assessment is associated with the tracking of time and mood, many self-tracking users are focused on very different variables, which may indicate different results. However, the surveys used in this study have demonstrated validity and reliability: the PEC questionnaire, developed by Brassuer, Gregoire, Bourdo & Mikolajczak (2013), was noted to have an internal reliability rating of 0.88, indicating that the measurements of intrapersonal and interpersonal emotional competence are highly repeatable in multiple studies. However, the ERSE has been developed for the specific purposes of this study and does not have external validity measures for reference. While it is based on the work of Bandura, Caprara, Barbaranelli, Gerbino and Pastorelli (2003), it has not been tested outside of the current study.

Type I and Type II errors. This study will utilize a standard t-test to examine the growth rates of intrapersonal competence. The Null hypothesis for the EI assessment will be set at:

H01: $\mu d = 0$

HA1: $\mu d > 0$

With alpha levels of 0.05. The hypotheses for the self-efficacy assessment will be set at:

H02: $\mu d = 0$

HA2: $\mu d > 0$

Conducting multiple t-tests in a single study does inflate the alpha rate. Given this, the Bonferroni correction will be applied to the alpha rates of these comparisons. The Bonferroni procedure provides a maximum alpha rate for the study by analyzing each hypothesis at the α / m significance level, where m is the number of hypotheses in the study (Frane, 2015). Two hypotheses are being tested with an alpha rate of 0.05, which provides a Bonferroni correction of testing each individual hypothesis at an alpha rate of 0.025, maintain the type I error rate of 0.05.

Data Analysis

The relevant data concerning the increase in EI or regulatory self-efficacy, as measured by the PEC or ERSE respectively, will be compared using a one-tailed paired t-test. This will be done using R and RStudio's statistical analysis package. Any participants with missing values will be removed from the dataset. The data will be categorized without transformation using the mean difference in pre and post test scores, with an alpha setting of 0.05 after the Bonferroni correction, which provides an alpha rating of 0.025 to each hypothesis test.

Processing. The data will be examined by the researcher and data points will be considered for outliers. If they are designated an outlier, they will be removed from the dataset. In this case, outliers will be defined as participants with extremely high or low scores, defined as ±2 standard deviations from the observed median and will be removed from the dataset. Additionally, participants with missing data in the form of pre or post-test PEC or ERSE submissions will be removed from the dataset.

Presentation. This data will be graphically displayed using the ggplot2 package for R using boxplots to examine the pre and post-test scores for the respective surveys. This will illustrate the distinction in both mean and variance between the pre and post-test scores on the surveys. As well, a numerical table will be displayed with the specific scores for the mean and variance of the difference between pre and post-test observations.

Research Methods

Questionnaire. According to Munn and Drever (1990), one of the greatest advantages of the questionnaire is the ability to use standardized testing measures to ensure the interviewer's bias does not implicate and distort meaning. This is very pertinent to the use of an external, well-developed measurement instrument such as the PEC or RESE, as the internal validity and reliability measures have been tested and approved by several researchers. This reduces the time constraints of the researcher and provides a more valuable tool and more generalizable findings. Additionally, the authors of the PEC provide this questionnaire free of charge to researchers. As it relates to mixed methods, Munn and Drever (1990) also noted that questionnaire often describe a phenomenon, but this method of inquiry can fail to explain and offer only superficial data. The use of interviews after the pre and post-test questionnaires can address this weakness of the questionnaire tool.

The questionnaire used to assess emotional competence will be the Profile of Emotional Competence (PEC), as defined by Mikolacjak, Brasseur & Fantini-Hauwel (2014). The PEC is a highly validated construct in a large-scale study (Brasseur, Gregoire, Bourdu & Mikolacjazk, 2013). This questionnaire uses a 5 point Likert scale to examine two constructs of emotional competence, being interpersonal and intrapersonal emotional competence. Specifically, the questionnaire will pose questions designed for the participant to self-report both their understanding of their own emotions, intrapersonal emotional competence, and their understanding of other's emotions, interpersonal emotional competence. Both are very pertinent topics for research, but this study is focused on the intrapersonal growth that may occur when someone undergoes quantitative self-tracking. This survey is a purely quantitative survey, and does not use any open-ended questions or incorporate the space for qualitative answers in the tool.

The more often used source of emotional intelligence is the MSCEIT, or Mayer-Salovey-Caruso Emotional Intelligence Test. However, given the current disagreement regarding the efficacy of the MSCEIT as it relates to measuring emotional intelligence accurately (Farrell & Austin, 2007; Fiori & Antonaki, 2012; Fiori, Antonietti, Mikolajczak, Luminet, 2014) have suggested a new test will more accurately represent recent research into emotional intelligence and competence. Additionally, Fiori et al. (2014) investigated this survey and discovered the MSCEIT did not provide distinguish well between participants who scored medium or high on the questionnaire, and when low-score EI participants were removed, the test did not predict performance significantly. This indicates that the MSCEIT does not have strong precision and is only suitable for testing populations who are below average in EI (Fiori et al., 2014), which is inappropriate for this study. As well, the PEC has a greater emphasis on the interpersonal and intrapersonal emotional competencies, which are the desired independent variables to be measured. This survey will be administered only in an online format to reduce the potential data shifts that can accompany using multiple modes of surveys (Dillman, 2007).

A new self-efficacy scale regarding the regulation of intrapersonal self-efficacy was developed by the researcher incorporating Bandura's (2001) principles for creating a self-efficacy scale. This scale was pretested through several academic peers and graduate students and was simplified into a self-efficacy scale designed to measure the perception associated with emotional origination and emotional regulation. The scale was designed with 21 distinct emotions, and participants are asked to rate either their understanding or self-control associated with the respective emotion on a 1-100 scale, as prescribed by Bandura (2001). The template for this instrument was also provided by Bandura's (2001) *Self-Efficacy Scale to Regulate Eating*

Habits and *Self-Efficacy Scale to Regulate Exercise,* examples in which he examines similar regulatory phenomena.

The structure of the emotions presented in this instrument are based on a simplified structure of the prime emotions theory detailed by Ekman (1992). These emotions listed in this tool are anger, disgust, sadness, fear, happiness, surprise and guilt. For each of these emotions, two configurations are used to help assess the internal validity of this tool. A table detailing these configurations is below:

Anger	Irritation, Displeasure
Disgust	Contempt, Revulsion
Fear	Anxious, Confusion
Sadness	Grief, Loneliness
Happiness	Joy, Contentment
Surprise	Awe, Interest
Guilt	Shame, Embarrassment

The prime emotions listed above will be examined for internal consistency for the individual participants. The grading for this instrument will have three distinct variables for each prime emotion.

Two scores will be produced for each prime emotion for their respective surveys related to *Understanding* and *Control*. A weighted average of these scores will be listed as the *Regulation* score. The statement questions on the third page will be analyzed individually to support the development of the qualitative portion of this study.

The instrument was designed for this study as a replacement for the Regulatory Self-Efficacy (RESE), as a suitable source for the RESE scale could not be found. This scale was designed by Bandura et al. (2003) and has been shown to have high validity in multiple cultural contexts. Given that the instrument for this study has been designed following Bandura's (2001) principles for self-efficacy instrument design and investigating many of the same issues as the

RESE, this self-designed instrument has both similar design and content. However, it does not have the demonstrated internal validity as a more developed survey instrument.

Sampling bias is of clear concern to this study, as it particularly excludes a subset of the population. Those working in analytical fields are well-established in the quantified self literature, and this study is particularly focused on those outside of the profession. However, that can imply a removal of a specific demographic set, such as young, highly-educated men who are more likely to be in the STEM fields. Additionally, many participants will be gathered online; Sue and Ritter (2007) warned against the potential of sampling bias that can be obtained from an online sample, as it tends to favour younger and more affluent participants than other methods (Patel, Doku & Tennakoon, 2003). The demographics of both samples obtained will examined for age, gender, and highest level of education obtained to inspect for sampling bias; demographic questions will be added to the PEC in order to examine for these factors, as well as to provide potential variables for discovery in the analysis phase.

The motivation of the participants is a possible cause of loss of data or loss of data quality. Dillman (2007) noted that the motivation to complete surveys is often left out of the questionnaire to reduce potential bias but is often left to the interviewer to encourage and explain the survey. Given that this pre and post test survey will be administered online, it must remain simple in order to encourage completion and reduce confusion. The simple, Likert-only nature of the PEC should assist the participants with a simple completion of the form, as well as keeping the demographic questions to only gender, age and occupation. As well, incentives will be offered to participants who complete the study in the form of raffle for Amazon gift cards. In combination, the simplicity and reward should motivate and encourage participants to finish the survey.

Recruitment of Participants

Participant recruitment is essential to the development of this study. Patel et al. (2003) qualified three phrases of participant recruitment: identification, targeting, and enlistment. The ideal goals are to both recruit a representative sample, as well as to recruit sufficient participants to meet the sample size and requirements of the study (Patel et al., 2003). Problems in recruitment can significantly slow the study, as well as reduce the generalizability of the study.

Participants will be recruited from the researcher's hometown. Flyers, indicating the goal and method of the intervention, will be distributed and placed in many gathering places in the town, such as coffee shops and employment offices. Additionally, the researcher will post recruitment advertisements on social media platforms. Participants will also be gathered via word-of-mouth. All participants who complete the self-tracking and both surveys will be entered into a draw for several $50 Amazon gift cards.

Each participant's informed consent will be gathered during the first information session on the project. The letter of consent is attached in the appendix to this study. Participants will be able to withdraw at any point if they choose to do so. Flyers will be placed in many local gathering spots, such as the college and coffee houses. Small incentives in the form of Amazon gift cards will be offered. The potential participants will be assessed for qualification.

Dependent on results, several of the participants will be asked for a short interview with the researcher to explain the findings. These participants will be gathered from both those who achieved growth in their intrapersonal competence, as well as those who stagnated or decreased in intrapersonal competence. This interview will help explain if the tool itself is problematic, or if the quantified tracking is not as applicable for those who do not work in quantified fields.

Qualitative Measures

Questionnaire participants. Several participants from two groups will be asked to participate in several short open-ended questions. These two groups will be participants who noted a high increase in either EI or regulatory self-efficacy and those who did not notice an increase. This is designed to identify where this method why this method worked well in some context and did not work well in others.

Questions. The questions will be informed by the quantitative phase of the survey. The underlying themes will be associated with the process of tracking their time expenditures, the relevance of the information presented, and, if possible, the nature of personal learning that occurred during the study. These will be short interviews that will only span several questions. Potential questions are included in the appendix.

Coding strategy. The initial coding strategy used will be Structural Coding. This method of coding implies the development of a conceptual phrase representing a topic of inquiry to a segment of data for a specific research question (Saldana, 2009). This coding strategy has been noted as acceptable for open-ended survey questions and is highly analytical in nature, which will allow for quantitative follow-up analysis of the emergent codes.

Framework of Constructs

Bandura's (1991) social cognitive theory of self-regulation informs the relationship between self-efficacy, effectiveness, and self-observation. This theory directly implicates the increase of self-knowledge as the direction for self-regulatory control, which, according to Bandura (1991), has strong correlations with sensitivity to depression, helpful or hindering thought patterns, and levels of perseverance in the face of obstacles.

Summary

This study will utilize the explanatory mixed methods design, which is a traditional mixed methods approach with a quantitative focus to analyze and interpret the relationship of regulatory self-efficacy, emotional intelligence and the process of quantified self tracking with a qualitative aspect will be added into this study to better understand and explain the results. The major concerns with this study relate to sampling, as the convenience sampling method will be used for pragmatic purposes, and this may cause bias in the sample. The significance level of this study will be set at 0.05 after a Bonferroni correction, given that multiple hypotheses are being tested in this exploratory study. The qualitative questions will be informed by the first phase of this study and are not yet articulated.

Chapter 4: Results

In the previous chapters, this project has described the rationale and method for studying the emerging quantified self methodology and relating this methodology to both self-efficacy and emotional intrapersonal intelligence. This project was undertaken to develop exploratory research into the re-emergence of self-tracking due to increased ease of use and technology that is associated with the quantified self movement. Chapter 2 described several avenues that this emerging method of self-study contains for personal growth, provided an overview of the current academic research focused on self-tracking as well as the academic background of the independent variables assessed. Chapter 3 described the methodology in which this exploratory study examined this emerging trend, what instruments will be used, as well as what analysis took place and definitive measures of a confirmed or unconfirmed hypothesis.

This chapter will report the results of both the qualitative and quantitative data gathering. This study was designed to address the lack of formal quantitative research focused on the effects of self-tracking as they relate to personal improvement. While a significant amount of qualitative research, in the form of focus groups, surveys and interviews, has taken place, very few studies have adapted traditional and tested psychological instruments to assess self-tracking. The hypotheses to be tested are related to interpersonal intelligence, intrapersonal intelligence, regulatory self-efficacy related to understanding personal emotions, and regulatory self-efficacy related to acting despite emotions. In all cases, the alternative hypothesis has been set as the mean difference in scores in the pre- and post-tests will be greater than zero with an alpha set at 0.95.

Sampling Method

A sample of convenience was chosen for this study; this allowed participants to self-select in this study by following up on either physical flyers in local gathering spots or an online social media advertisement. If a participant contacted the researcher, they were invited to participate in the study. Participants were only targeted from Terrace, British Columbia. While the geographic restriction did contribute to a smaller sample size, the surveys and time-tracking tools were completed by twelve of the fourteen participants in the original sample. The high rate of completion may be due to the incentives used in this study: participants were informed that at the conclusion of the data-gathering, all participants would be entered into a draw for one of three $50 Amazon gift cards. Given that this study was exploratory in nature, there were few reliability measures that can be examined. The demographics of the sample were of particular interest.

Demographics

This sample, while small, has been found to be representative of the larger population in terms of gender, age, and level of education. An even gender distribution was met for those who finished the experiment, with six male and six female participants. Additionally, the mean age of the participants was 38.8 with a standard deviation of 15.9 years. Given the work analyzing quantified self participants as those traditionally in STEM fields (Choe et al., 2011), the level of education is very relevant to this study. In this context, a sample approximating the level of education in Canada has been maintained: six participants had completed tertiary education, three identified as completing some college, two had completed high school, and one participant had not completed high school. This identified this sample of convenience as reasonably representative of the Canadian context, as the Organization for Economic Cooperation and Development (2014) indicated 53% of Canadian adults have completed some form of tertiary education. However, given the small sample size of this study and exploratory nature, this research should be used primarily as a tool for providing further purpose for in-depth research.

Survey Results

This study has also approximated the scores for the Profile of Emotional Competence (PEC), used in this study to investigate intra- and interpersonal intelligence. This study's examination into these measures indicate the intrapersonal (M=3.16, SD=0.57) and interpersonal (M=3.14, SD=0.52) approximate the normal representative results Brasseur et al.'s (2013) analysis (M=3.3, SD=0.62 for intrapersonal; M=3.3, SD=0.58 for interpersonal); both are within 25% of one standard deviation. However, given that both scores are below the averages indicated by Brassuer et al. (2013), this sample may be indicative of a slightly lower-than-normal interpersonal and intrapersonal emotional intelligence.

Both the PEC and the Emotional Regulatory Self-Efficacy Scale (ERSE) were administered online in a pre and post-test format. In the pre-test survey, participants were asked several demographic questions, such as their gender and age. In the post-test surveys, participants were asked several questions regarding their use of the tool, and if they found the tool useful or used the tool consistently. Of the 12 responses, two participants noted that they did not find the tool useful, eight participants found the tool useful, one participant found the tool extremely useful, and one participant declined to answer.

Emotional Intelligence

The intrapersonal domain of emotional intelligence is highly-related to the concept of self-awareness; quantified self-tracking was coined by Wolf (2010) as making participants conscious of their unconscious habits. Given this relationship, it was theorized that self-awareness would be increased through self-tracking by making unconscious behaviours tracked and clearly identified (Kido & Swan, 2012). However, in the context of this study, self-tracking did not provide a statistically-significant increase in either interpersonal or intrapersonal emotional intelligence.

Emotional intelligence was assessed by the PEC, developed by Mikloajczak et al. (2014). This test determines both inter- and intrapersonal intelligence through 50 questions on a Likert 5-point scale. The test analyzes the data through the multiple domains, which can be found in Table 1. Internal consistency has been demonstrated through Cronbach's alpha by multiple authors and been found to be acceptable (Brasseur et al., 2014; Totan, 2014). The PEC is not the most often used tool to assess emotional intelligence; in most studies, the MSCEIT is used as an instrument. However, this tool has been the subject of criticism in academia (Farrell & Austin, 2007; Fiori & Antonaki, 2012; Fiori, Antonietti, Mikolajczak, Luminet, 2014), and does not specifically assess the primary variable considered for this study, intrapersonal intelligence. This data was normally distributed, and no outliers were removed from this dataset, and all participants who completed the experiment provided answers to these questions for both the pre and post-test surveys. The averages and standard deviations of these responses are provided in Table 1.

The intrapersonal emotional intelligence scores, despite the small sample size, approximate normal distributions and no statistically significant difference was observed. The post-test PEC does appear to have a unimodal distribution with a large standard deviation. The mean differences between the intrapersonal scores does not appear to be statistically significant ($p=0.27$). For further detail, please refer to Figure 1.

Table 1

Pre and Post Test Scores and Standard Deviations for the PEC (n=12)

	Post		Pre	
	Mean	SD	Mean	SD
Intrapersonal Intelligence	3.27	0.73	3.22	0.78
Expression of Own Emotion	3.04	0.89	3.05	0.78
Identification of Own Response	3.38	0.41	3.42	0.52
Regulation of Own Emotion	2.96	0.93	2.95	0.97
Understanding of Own Emotion	3.55	0.68	3.42	0.80
Utilization of Own Emotion	3.42	0.73	3.27	0.83
Interpersonal Intelligence	3.31	0.71	3.22	0.68
Identification of Other's Emotion	3.33	0.92	3.42	0.85
Listening to Other's Emotion	3.44	0.75	3.22	0.65
Regulation of Other's Emotion	3.36	0.73	3.20	0.61
Understanding of Other's Emotion	3.53	0.61	3.42	0.75
Utilization of Other's Emotion	2.87	0.54	2.85	0.52

The interpersonal intelligence scores also approximate the same normal distributions and are not statistically significant differences. The standard deviations for the pre and post-test scores, 0.5 and 0.49 respectively, are lower than the intrapersonal intelligence, but still represent a high standard deviation. Refer to Figure 2 for a further description of the dataset. The mean difference between the scores is not statistically significant ($p = 0.14$).

In both interpersonal and intrapersonal emotional intelligence, this study does not reject the null hypothesis and there does not appear to be a significant increase in either domain after a two-week period of self-tracking. Given that the data appears unimodal in nature and the internal

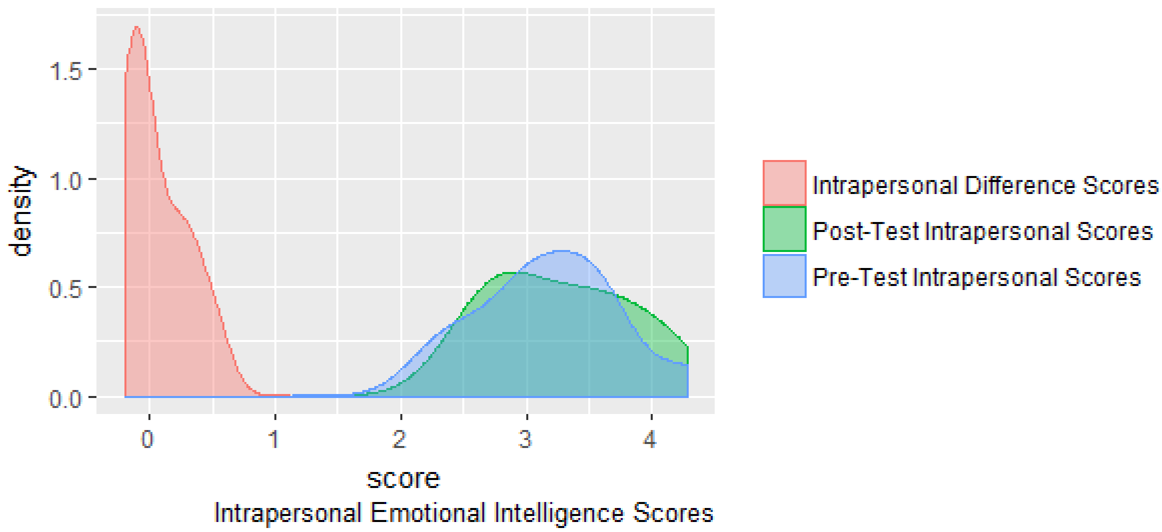

Figure 1. Intrapersonal Emotional Intelligence Scores Density

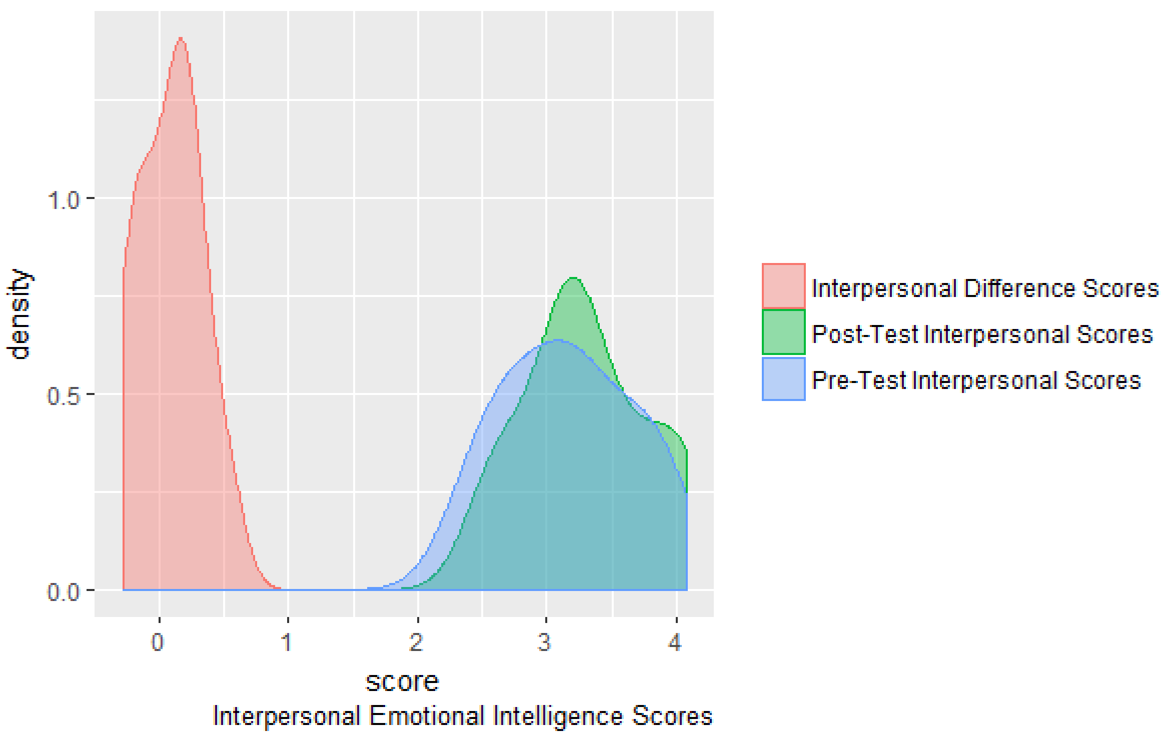

Figure 2. Interpersonal Emotional Intelligence Scores Density

consistency of the PEC has been demonstrated in external studies, this conclusion appears both reliable and valid, yet not significant.

Self-Efficacy

Self-Efficacy was a primary independent variable assessed in this study, and was the source of the only statistically significant ($p < 0.01$) relationship found in this design. Bandura's (2004) Social Cognitive Theory was linked to the quantified self movement through the similar goals both attempt to achieve, such as weight loss, reduction of smoking, or other habitual processes, and the subsequent association with behavioural change. Additionally, it was matched to this method through self-efficacy's relationship to goal-setting, reflection, and mastery experiences. The fundamental relationship between change and improved self-efficacy has been well-established, including desired behavioural change (Bandura, 1993; Zimmerman & Martinez-Pons, 1990) and improved learning outcomes (Bandura, 1989). Given that a significant relationship was found in this study between self-tracking and self-efficacy, it is likely that a relationship between self-tracking and the other positive outcomes associated with self-efficacy will also emerge from further study. In particular, it is possible that Bandura's (2004) domains of success and mastery, necessary aspects for increasing self-efficacy, have been further increased by providing simple and quantitative evidence of change.

The ERSE was developed for use in this study, using the guidelines for self-efficacy scales indicated by Bandura (2001) and Bandura et al. (2003). Given that this instrument was developed for this study, normative measurements cannot be compared against the sample's measurements. However, this indicates that an analysis of this tool's internal consistency is required. The ERSE was developed based on Ekman's (1992) theory regarding prime emotions, specifically anger, disgust, sadness, fear, happiness, surprise and guilt. For each of these

Table 2

Emotional domain conditions for Self-Efficacy instrument

Prime Emotions Matrix

Prime Emotion	**Secondary Emotion**
Anger	Irritation, Displeasure
Disgust	Contempt, Revulsion
Fear	Anxious, Confusion
Sadness	Grief, Loneliness
Happiness	Joy, Contentment
Surprise	Awe, Interest
Guilt	Shame, Embarrassment

Table 3

Overview of Prime Emotion Scores for the ERSE (n=12)

	Action Domain		**Understanding Domain**	
	Mean	**SD**	**Mean**	**SD**
Overall	162.9	66.6	207.7	56.1
Anger	152	62.2	211.1	54.9
Disgust	173.1	75.9	230.3	38.6
Fear	119.2	56.9	176.4	64.8
Guilt	141.7	71.9	194.8	62.2
Happiness	176.7	18.7	224.1	50.7
Sadness	133.8	55.8	182.4	65.9
Surprise	243.8	30.1	234.8	25.7

Table 4

ERSE Pre and Post-Test Scores Summarized (n = 12)

Value	**Mean**	**SD**
Understanding Difference	4.91	28.5
Pre-Test Understanding	211.1	54.9
Post-Test Understanding	220.4	46.2
Action Difference	**38.91***	42
Pre-Test Action	152	62.2
Post-Test Action	191	59.4

* $p < 0.01$)

emotions, two configurations are used to help assess the internal validity of this tool. Table 2 details these configurations.

The Cronbach's alpha for this instrument in this sample has been calculated at 0.78; given the small sample size, this measure of internal consistency is acceptable, though further study into the instrument itself will be required. Table 3 details the sum and standard deviations for each of the prime emotions as indicated, separated by Action or Understanding group. In this context, action refers to the ability to act despite the presence of this emotion, while understanding refers to the ability to understand the cause of this emotion. The scores and standard deviations for this test are described in Table 4.

While a small difference has been observed in regards to the understanding domain, a large difference has been determined in the action domain. In both domains, likely driven by the small sample size, the standard deviations are very large. The understanding domain appears to

Figure 3. Emotional regulation self-efficacy scores in the domain of understanding density plot.

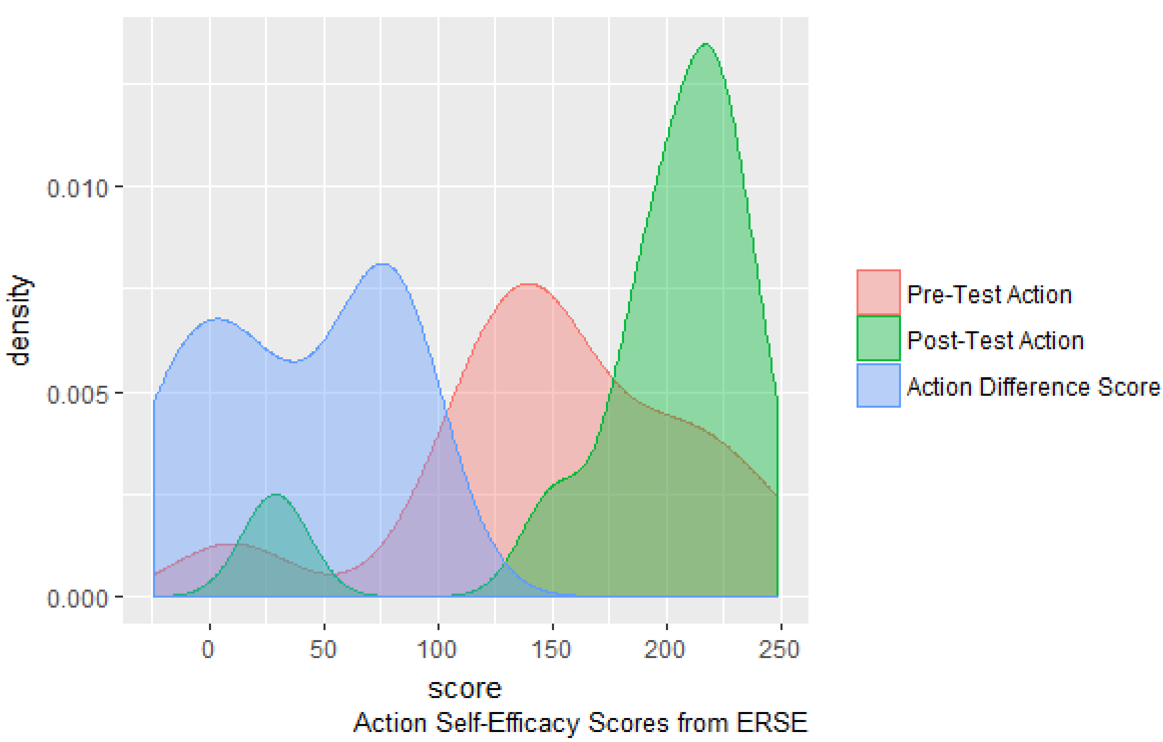

Figure 4. Emotional regulation self-efficacy in the domain of action density plot.

be unimodal with similar distributions for both the pre and post-test answers, and the difference score demonstrates a much lower standard deviation with a mean of 4.91 with a negative skew, see Figure 3.

In a paired-samples one-tailed t-test, no significant difference in the pre and post-test scores for the Understanding domain was observed ($p = 0.29$). The action domain demonstrates a bimodal distribution for difference scores, a positively skewed distributed for the pre-test, and a negatively skewed distributed for the post test, see Figure 4.

The participants responses to either the usefulness of the tool or to their consistency using the tool do not appear to represent the bimodal distribution of the self-efficacy action scores, as both participants who did not find the tool useful reported an increase in emotional regulation with regards to action. Despite the small sample size and bimodal distribution, in a paired-sample one-tailed t-test, a highly significant ($p < 0.01$) increase was observed. However, given the irregular shape of the data, it is likely that further investigation into the ERSE instrument is required. One or more confounds may be present in this data.

Qualitative Analysis

The qualitative analysis provided several valuable insights into the participant's experience in self-tracking. It was relevant to look at participants who experienced varying levels of success regarding their experiences with the self-tracking tool; to address this, participants were selected from the survey related to their self-described experience in this study: two participants were selected from the self-identified useful, while one participant from both the very useful and not useful categories were also selected for an interview. Of those participants selected, all agreed to further participate in this study. The primary analysis was focused on the participant's experience using the self-tracking tool; the questions posed to the participants to focus this analysis were designed to investigate two different aspects of this study: the effectiveness of the tool and if it increased self-control or understanding of the self. The qualitative responses were then coded using the Structural Coding method (Saldaña, 2009). This coding strategy was utilized as it is appropriate for open-ended survey design questions and allows for aggregation of themes; this will provide ease of analysis and presentation. Table 5 presents an overview of the themes and codes that emerged from this study.

With regards to the usefulness of the tool itself, the participant responses have been positive. Many participants have directly used the phase “very useful” (Participant 3), “satisfying” (Participant 1; Participant 4), “helpful” (Participant 4) or “interesting” (Participant 1), though the phrases “not very useful” and “little improvement” (Participant 2) did emerge. These results are expected, as the participants were selected to represent these results and further investigate the experiences represented.

The most consistent responses from participants focused around the idea of increased understanding, often through the lens of new personal realizations regarding either their mood or daily habits. New realization in this context, participants referred to greater understanding of their short-term mood responses to stimuli, such as a participant’s description revealing a better understanding of “my very short-term bursts of impatience and anger when trying to figure out things I don't understand" (Participant 2), as well as further understanding regarding their longer-term responses, such as Participant 4’s “I’m happier… when I’m productive” or Participant 1’s analysis that “interactions with people I cared about had the greatest impact on mood, whether negative or positive”. Awareness, mindfulness and reflection were consistent themes throughout the responses as well, as participants noted that “I was surprised that knowing I was going to have to write down what I was doing meant that I should be doing something better for myself”

Table 5

Themes, Codes, and Number of Utterances (in raw score)

Theme	**Utterances**
Difficulty	28
Digital Preference	5
Format Change	5
Consistency	4
15-minute increment challenges	3
Distractions	3
Forgetting	2
Life Events	2
Physical Size	2
Time-Consuming	1
Frustration	1
Usefulness	10
Very Useful	4
Satisfying	2
Helpful	1
Interesting	1
Little Improvement	2
Behavioural Change	14
Productivity	5
Fewer Distractions	3
Increased Control	2
Increased Mood	2
Task Control	1
Accountability	1
Increased Understanding	27
New Realizations	14
Awareness	6
Reflection	4
Pattern Recognition	3

(Participant 4) or “[it] gave me a chance to reflect on my emotional state which I eventually came to rely on as a way to tidy my thoughts before I went to bed” (Participant 3). Even for the participants who did not find the tool useful, focusing on emotions has been beneficial: "I don't think the tool has [increased my understanding], but I have thought more about my emotions" (Participant 2). Ultimately, all participants have noted a new understanding as a result of tracking their time and mood, though this conclusion is in disagreement with the results of the intrapersonal dimension of the PEC.

The participants have categorized self-tracking as very difficult and the tool as ineffective. In all interviews, each participant identified a desired format change: three out of four recommended a switch to a digital format, such as "a simple text file on my phone" (Participant 2), while the Participant 3 modified his or her tool to be simpler analog format on a smaller notepad. In all interviews, when a participant was asked what he or she would do differently, he or she recommended a change in format - to be either on a phone or reducing data entry by either tracking only mood or time, not both, or to create a task-based, rather than hourly-based, tracker. In future examinations of self-tracking, creating a simplified digital format for inputting data to reduce barriers would be advisable, though further research is required.

Additionally, all participants noted that consistency was a significant problem, and participants often noted they would “forgot to log multiple hours, and then things just piled up” (Participant 4), or “I already have bad habits when it comes to time management... so I just forget” (Participant 1). Quite often significant life events, such as health or work-related events, would negatively impact their ability to track their time thoughtfully, as the events would take precedence over self-tracking. As well, self-tracking was noted by many participants to be an extremely time-consuming process: "the stress of remembering to bring the tracker with me everywhere and write down every activity... didn't make it worth it" (Participant 2), and "[it] was just too time-consuming" (Participant 3). However, one participant noted that consistency was required for this personal intervention to have an effect on mood: "If I stop using my journal, even for a few days, I fall into an emotional rut and feel awful" (Participant 3). The high degree of difficulty, particularly the identified issues with consistency and time, have been written about by other quantified self researchers (Swan, 2012). This is most notable in Li et al. (2011) description of the Discovery phase in self-tracking, in which a substantial amount of time must be dedicated to self-tracking. This stage is often unsustainable for most participants due to the high degree of difficulty.

While it emerged as the least-mentioned theme, behavioural change is an essential component of this study. Participants regularly commented on their increased understanding or new realizations, but rarely mentioned that this contributed to greater control over their own emotions and actions. Control was an emergent theme, as one participant described succinctly: “it's given me a lot more control over [my emotions]” (Participant 1). The removal of distracting actions, or bad habits, emerged as one participant “found myself staying on task more easily and spending more time on the things I thought were important, rather than watching TV” (Participant 4) and another discovered “how much time I waste” (Participant 3). As well as the removal of distracting actions, the addition of positive and productive actions was present, as “When I was tracking my time, I had the push to not waste time, to use every 15 minutes… it forces me to be more productive” (Participant 3). This productivity was highly associated with the concept of personal accountability, as “the act of writing it down makes you more accountable to yourself, even if nobody else sees it” (Participant 3). While the theme of behavioural change is not as present as increased understanding, the participants who experienced some positive affect from this study have noted some effect.

Notably, the information apparent in the qualitative interviews does not represent the information found in the quantitative surveys. Participants noted the noticed increased understanding, but rarely noted that it affected their behaviours. However, the quantitative data suggests participants did not increase their understanding but did modify their behavioural habits and control. This qualitative conclusion is aligned with the current contemporary literature surrounding quantified self (Lie, Medynskiy, Froehlich, & Larsen, 2012) in which increased understanding is a consistently present theme. There were also multiple criticisms of the method, tool, and format. However, while participants did often critique the difficultly associated, for those that did provide detailed logs, all defined this experience as at least somewhat valuable.

Summary

In this chapter, a highly significant relationship between self-tracking and self-efficacy in the domain of emotional self-regulation was identified; however, there are major concerns regarding this relationship. Given the bimodal nature of the data and the untested nature of the ERSE, it is likely that there is a confounding agent not examined in the context of this study and requires further research. Additionally, the qualitative aspect of this research did not corroborate the quantitative aspect of this research. Outside of the statistically significant conclusion, emotional intelligence was not found to be related to the use of a self-tracker in this study, participants have noted that the strongly prefer digital tools compared to analog tools, and quantitative self-tracking data entry is very arduous for participants and a serious barrier to entry.

Chapter 5: Discussion

This study has provided a mixed-methods analysis supporting a connection between quantified self and self-improvement, though with serious limitations. This quantified self movement has been inspired by personal experimentation but has often been criticized as lacking scientific rigour and insufficient quantification methods (Choe, Lee, Pratt, & Kientz, 2014; Swan, 2009). However, despite these criticisms, many participants have noted that the quantified self movement has created increased understanding and helped foster personal growth. While the data revolution has been adopted by both business and research paradigms, individualized datasets have also been widely adopted by large groups of participants. Consumer-grade technology, such as wearable pedometers and heart-rate monitors, have further increased this adoption and expansion of the quantified self movement (Rivera-Pelayo, Zacharias, Muller, & Braun, 2014; Swan, 2012).

This study was designed to be an exploratory study and has attempted to establish academic support for the numerous positive life and affective changes reported by those who use quantified self-tracking methods. In this attempt, emotional intelligence, with an emphasis on the intrapersonal emotional intelligence domain, was not linked to self-tracking. However, emotional regulation self-efficacy in the domain of acting despite emotions has been established as significantly improved by self-tracking frameworks.

While this significant relationship has been established, further research is required. Primarily, the instrument itself, the ERSE, requires further review before this conclusion may be considered reliable. Additionally, further demographic variables should be investigated to look for confounding factors and explain the bimodal nature of the regulatory self-efficacy scores within the action domain that were statistically significant. Despite requiring further investigation, this preliminary research into the relationship between self-efficacy and self-tracking demonstrates a valuable insight into the quantified self movement: the act of self-tracking, without personal analytics, can inspire self-improvement. Increased self-efficacy has been linked to desired behavioural change (Ashford et al., 2010; Olander et al., 2013), and the qualitative interviews in this study have indicated that this method, in the right circumstances, has provided them with the ability to both further understand their time expenditures and emotions, as well as to offer greater self-regulatory control over their actions.

Discussion

A relationship has been established between self-efficacy and the quantified self-tracking methods described in this study. However, given the recent emergence of quantified self as a personal informatics paradigm and the exploratory nature of this study, this study is designed to inform further research, rather than serve as an independent and rigorous conclusion. Despite the serious limitations of this study, it does provide an established framework for investigating quantified self-tracking; the impact of data on the personal self has been shown to be significant in the domain of self-efficacy, and participants have described the tracking as positive, although arduous. This creates further rationale for studying the effect of quantified self techniques on individuals in a rigorous academic setting.

There are substantial concerns associated with the identified self-efficacy increase observed in this study. The rationale behind these choices will be further explained in the limitations section, but given the self-selected participants, self-identified survey tool, small sample size, and untested instruments, this study should be considered a rationale for further research into a possible connection between emotional regulatory self-efficacy and self-tracking, rather than definitive research identifying such a relationship.

No relationship was identified between emotional intelligence and quantified self-tracking in this study. Given that this study has focused on the concept of trait emotional intelligence (Benson et al, 2013; Nelis, Quoidbach, Mikolajczak, & Hansenne, 2009), rather than ability emotional intelligence, there is a potential criticism in that this study has only focused on self-reported measures, rather than a further investigation into the assessed ability to manage and regulate individual emotions and actions. However, given the exploratory nature of the work and the work demonstrating trait emotional intelligence as a positive predictor of workplace performance (Labbey et al., 2012), this is appropriate in this context. Due to the lack of evidence found in this study, considered alongside the issues associated with both the trait and ability constructs, there is no support in this study to continue investigating a potential relationship between emotional intelligence as it relates to self-tracking. However, given the presence of multiple participants indicating they achieved some form of increased understanding regarding their emotions in the qualitative portion of this study, there are further considerations regarding emotional intrapersonal intelligence.

A surprising aspect of this study was the apparent disagreement between the quantitative findings associated with no increased understanding, while the subjective qualitative interviews did support such a conclusion. This may lend further evidence to support the presence of a confounding agent not analyzed in this study, in conjunction with the bimodal nature of the regulatory self-efficacy data. However, the majority of the quantified self literature does support both conclusions regarding both increased understanding and increased self-regulation (Kido & Swan, 2012; Muller et al., 2012), though the mechanism which supports this growth is not clear. The absence of corroborating information between the quantitative and qualitative portions of this study may also indicate issues with the PEC. Further investigation related to the internal consistency and quality of instrument is required.

This study has also further reinforced the concept that quantified self-tracking serves as a reflective tool, similar to a form of journaling. Numerous authors have investigated and demonstrated the reflective benefits of journaling (Kerka, 2002; Lowe, Prout & Murcia, 2013; Schuessler, Wilder, & Byrd, 2012), though Epp (2008) noted that journaling requires structure to build reflective content, which the specific construct of quantified self-tracking tools may provide and many participants have noted that self-tracking promoted reflection and introspection. In journaling, the task of writing thoughts down was itself a reflective act (Kerka, 2002; Schuessler, Wilder, & Byrd, 2012); this conclusion may create a potential avenue for further research in the distinction between quantified self-tracking as it relates to either analog or digital tools. As this study has demonstrated, participants largely preferred digital tools in comparison with analog tools due to the ease of use. However, if the quantified self-tracking benefits are associated with the reflection that is present by the process of physically writing down time expenditures and mood tracking, a tool that is easier to use will provide fewer benefits to the participants. Reflection is a difficult and time-consuming task and reducing the difficulty may not provide further benefits.

The difficulty of self-tracking also furthers considerations into its use in citizen science. Citizen science is the shifting responsibilities of data collection methods from an individual researcher to lightly-trained amateur participants. Citizen science methods have been used in several contexts, including bird watching and counting (Bonney et al, 2009), health research (Pickard & Swan, 2014), and ecological research (Silvertown, 2009). There have been studies investigating the effectiveness of these data collection methods, and even in cases of extreme disparity in training between formal researcher and untrained amateur, was demonstrated to maintain a reasonable level of accuracy (Danielsen et al., 2014). However, given the participant's feedback regarding the issues associated with consistency and the difficulty associated with using the tool itself, citizen science data collection methods should be further formalized in this context, and the reflective self-tracking data provided in an analog format should not be analyzed without consideration of its likely inaccuracy and inconsistency. Citizen science methods should not be adopted related to participant's self-tracking, and the data they provide should be treated as a tool for reflection and self-regulation, not as reliable and valid data for analysis. However, if further improvements to self-tracking methodology are developed through smartphone or wearable technology, the potential for transcription errors or consistency issues is further reduced (Kuo et al., 2014) and this data may be considered more reliable.

Limitations of the Study

This study has several limitations which substantially reduce the generalizability. This study was limited in its small sample size, limited time frame, limited geography, untested instruments, self-selected participants, lack of a control group, and analogue self-tracking method. These factors reduce the ability to generalize conclusions. This combination of factors leads to this study being an indication of a potential relationship between self-efficacy and self-tracking, rather than definitive evidence for this hypothesis.

This study was primarily designed to serve as an exploratory study, as no other formal research had attempted to quantifiably identify a potential relationship between quantified self-tracking and either emotional intelligence or self-efficacy in an experimental design. The small sample size, time frame and limited geography are specifically resulting characteristics of this study as an exploratory study, as well as the sample of convenience method chosen for this study. It is not intended to provide generalizable conclusions for all individuals, but to foster further research into the growing phenomenon that is personal analytics and self-tracking.

Given the identified potential relationship between journaling and self-tracking, as both techniques are focused on self-reflection, the analog tool, rather than a digital tool, was a conscious choice of the researcher; this was designed to both reduce the technical fluency required for data entry, as well as to assess the effectiveness of simply self-tracking, rather than the effectiveness of any one tool in the quantified self ecosystem. The digital method was noted as preferable by most participants, but further research into the efficacy of analog and digital techniques is required.

While both trait and ability emotional intelligence has been described as a significant predictor of workplace performance (Joseph, Newman & O'Boyle, 2015) this investigation has analyzed the relationship of trait emotional intelligence as defined by the PEC. While trait emotional intelligence has been associated with increased effectiveness (Mayer, Salovey & Caruso, 2004; Rooy & Viswesavaran, 2003; Rosete & Ciarrochi, 2005), many contemporary studies have criticized this construct for lacking discriminant validity; in particular, detractors noted that the most commonly used instrument to measure trait emotional intelligence failed to distinguish between medium and high emotional intelligence participants (Fiori et al., 2014), as well as ability emotional intelligence to have multiple correlations with the personality factors openness, neuroticism, extraversion, conscientiousness and agreeableness (Fiori & Antonaki, 2012). However, given that the connection between self-reported emotional intelligence and performance and efficacy has been established (Dumfart & Neubauer, 2016), assessing only the self-reported measurement is appropriate for this investigation.

Summary

Self-Efficacy and self-tracking have been linked in the context of this study and warrant further investigation into their relationship. If this connection can be maintained in a larger study, this will indicate and further explain the potential benefits of self-tracking. As well, the mechanism in which quantified self-tracking supports behavioural change should be further investigated, particularly related to an analog or digital self-tracking tool, participant's ease of use, and the benefits derived from these distinct self-tracking techniques.

Emotional intelligence has not been demonstrated to have a connection with self-tracking; however, intrapersonal emotional intelligence is often defined as the understanding of one's own emotions, and this was an emergent and repeated theme throughout the qualitative analysis in this study. There is a disagreement between these two methods that requires further investigation, analyzing the relationship between intrapersonal emotional intelligence and understanding of one's emotions and if they are the same concept, as well as further expanding the emotional intelligence review to include more instruments and ability emotional intelligence measurements rather than trait emotional intelligence.

Citizen science is a powerful emerging phenomenon that would appear to be well-suited to the adoption of quantified self metrics; however, when related to analog tools that require consistent data entry, the difficulties associated with consistency and accuracy are very substantial and would likely create data quality errors if used in aggregate analysis. However, in the context of automated data collection methods and methods where the data input challenges are reduced, this data will likely be of higher quality and less likely to suffer from accuracy and reliability concerns.

Ultimately, this study is highly-limited by several factors. While the relationship identified is highly significant, it is likely there are more variables to consider in a larger-scope study. The limitations and design of this study indicate that this should be considered an exploratory framework and an impetus for further research into the emerging relationship between self-efficacy and self-tracking. While numerous participants have written about the benefits associated with self-tracking, the specific mechanism is unclear. A further investigation into self-efficacy may address many of those questions.

Chapter 6: Conclusion

This study has provided further reinforcement that quantified self tracking can provide the basis for behavioural change. Even in this small and limited scope, participants demonstrated significant increases in their personal control, as well as described such outcomes in the qualitative responses. The relationship between behavioural change and quantified self-tracking has demonstrated thoroughly in the research, but this further demonstrates quantified self improvement outside of the scope of the traditional users of quantified self metrics, computer scientists and data analysts (Choe et al., 2014). This relationship is unique in the academic literature as it focuses on increased a traditional psychometric variable.

Self-efficacy is a highly researched concept and linked to multiple positive outcomes, though rarely is it linked to self-tracking. The experimental nature of this study provides a unique conclusion for this study and a new avenue for research for further study. Given the abundance of rigorously reviewed material demonstrating the benefits of increased self-efficacy, this study has substantially increased the academic foundation of quantified self-tracking. It has also further investigated the mechanism in which quantified tracking provides behavioural change in participants.

Given the nature of the data, specifically the bimodal self-efficacy data and the disagreement between the conclusions of the PEC and the self-described qualitative data provided by participants, both questionnaires used in this study would benefit from further research into their construct validity and accuracy. The ERSE requires further study due to its untested nature, and while the PEC has been reviewed in multiple studies, the disagreement indicates this instrument may not necessarily measure what it is described.

Implications of Findings

Given that this research is exploratory in nature, this research has not definitively addressed any of its hypotheses outside of the context. Despite this, the research has implied several potential conclusions for self-improvement, furthering the academic research associated with the quantified self movement, solidifying the research connecting improved self-efficacy and goal setting, as well as rejecting a connection between improved emotional intelligence and self-tracking, although given the limitations of this study, this rejection should also not be over-generalized.

Most practically, this research identifies self-tracking as a viable means of self-improvement. Given the associated benefits of self-efficacy, self-tracking increasing self-efficacy demonstrated a potential avenue for personal growth for those who choose to pursue this path. However, given the difficulty participants have noted in this study, this method is best suited for those who might pursue this path traditionally, such as those in quantitative fields (Choe et al., 2014). While this method does provide a demonstrated benefit to the participant, it is not any easier or more efficient than traditional methods, such as journaling.

With regards to research, the most notable implication of this study was the addition of exploratory quantifiable research to the quantified self movement. Given the increase in the use of technology for self-tracking, where users will track themselves with tools from calorie counters to heart rate monitors, this research demonstrates a validity to self-tracking for the express purpose of self-improvement. The premise examined in this study was the relationship between awareness and behavioural change, represented by increased self-efficacy. While multiple studies have investigated the relationship between health metrics and increased awareness (Kempen et al., 2012; Kong et al., 2012; VanWormer et al., 2008), few have investigated the relationship between awareness and behavioural change as they relate to improved emotional and personal outcomes. In particular, this research reinforces the premise of Kido and Swan (2012), who argued increased awareness of unconscious behaviour serves as the basis of change. The increase in self-efficacy observed in this study demonstrated that data, or the act of collecting the data, served as a catalyst for change. This is the underlying premise of the quantified self, and this premise has been demonstrated here.

This conclusion is highly tied to the research associated with self-efficacy and goal setting; multiple authors have investigated and found significant positive relationships between self-efficacy and goal setting. In multiple studies (Bandura & Schunk, 1981; Schunk & Swartz, 1993; Zimmerman et al., 1992), the researchers demonstrated that goal setting was associated with high self-efficacy, but of particular note is Bandura and Schunk's (1981) research, in which the authors discovered a relationship between increased self-efficacy associated with mathematics and proximal goal setting when compared with distal goal setting. The relationships found between proximal goal setting, or short-term goal setting, when compared with distal goal-setting, or long-terms goals, is of the most importance when related to this study. While both goal setting methods were found to have significant increases in self-efficacy, proximal goal setting was shown to have a much larger raw effect in terms of increased self-efficacy. This conclusion has often been considered associated with Bandura's (2004) mastery experiences, in which a participant is given a challenge and overcomes it, increasing self-efficacy in this domain. In the context of quantified self-tracking, in which goals are not clearly defined, but granular data regarding how the day is spent is gathered and measured, significant increases in self-efficacy were noted. Though further research is required, short-term goal setting and granular data gathering may be highly connected tasks. Additionally, this study may raise a further question into traditional self-efficacy research this conclusion questions whether goal setting in particular was the cause for increased self-efficacy, or if the opportunity to regularly reflect and assess progress and unconscious actions that increased self-efficacy.

As well, while this study did not find a relationship between increased emotional intelligence and self-tracking, this conclusion itself is highly notable, as intrapersonal emotional intelligence, or understanding of the self, is highly connected in many quantified self articles (Kido & Swan, 2012; Wolf, 2010). There are many potential conclusions to emerge from this study in this domain, which include a rejection of the work associated quantified self metrics with increased self-understanding, as well as questioning the discriminant validity of the emotional intelligence construct. However, given the small sample size, the specific context in which the self-tracking took place, and the disagreement found in the qualitative phase of this study, this should be understood as an impetus for further research.

Recommendations for Further Research

A further large-scale investigation into the ERSE should be undertaken. This scale was built with the guidelines proposed in Bandura (2006) and provided the context by the Regulatory Self-Efficacy scale (Bandura et al., 2003). Unfortunately a copy of this scale was not available for this research. However, the guidelines and premise of regulatory self-efficacy had been tested by Pastorelli et al. (2001) and Caprara et al. (2008) and demonstrated high reliability and validity. In the context of this study, high reliability was demonstrated through a alpha value of 0.78, but given the small sample size, this result may be inaccurate. As well, the validity of this test is in question, as the results found in the quantitative aspect of this study do not agree with the results found in the qualitative; specifically, the survey results found no increased understanding of emotional regulation, but increased control over action during negative emotions, but the interviews found most participants noted increased understanding, but few noted increased control. Additionally, research focused on the outcomes associated with emotional regulatory self-efficacy, such as increased productivity, mood, and desired behavioural change (Olander et al., 2013) should be pursued. Given that self-efficacy has been associated with these outcomes, this is an alternative avenue to assess the relationship between self-efficacy and self-tracking.

The methods of self-tracking also require further review, specifically as it relates to either analog or digital tools relationship between ease of use and effectiveness for increased self-efficacy. This relationship is likely associated with the relationship to reflection and the parallels the journaling framework. The act of self-reflection required in journaling or self-tracking may be the cause of the increase in self-efficacy. However, if the tool's format is modified from analog to digital, the time spent inputting data would be removed, which may reduce the self-reflection in the process.

The relationship between self-tracking and self-reflection also presents a potential relationship between self-tracking and mindfulness. These concepts can be linked related to the rigor, thought process, and manual input required of the participant. If a participant is tracking their calories, a meal can potentially become a moment for self-reflection before data entry. Sharon and Zandbergen (2017) have briefly qualitatively analyzed self-tracking as a practice of mindfulness and found for many participants, it is not the analysis of the data that is necessarily the most powerful aspect of self-tracking, but the act of recording forces participants to be more mindful of their daily activities, moods, diet, and other factors that require data entry. Didžiokaitė, Saukko, and Greiffenhagen (2017), in a qualitative analysis of the everyday self-tracker only utilizing a calorie counter to lose weight, had found that tracking calories forced them to be more mindful of what they were eating throughout the day. Though there is currently little research on this relationship, Sharon and Zandbergen (2017) and Didžiokaitė et al.'s (2017) preliminary results attributed the increase in mindfulness to be related to the task of data entry. Further study related to reducing the barriers associated with data entry, the most requested modification by participants in this study, may have an unintended consequence associated with this potential outcome. Only a few studies have analyzed self-reflection and efficacy (Yost, 2006); many self-efficacy studies examined self-efficacy as the primary result of mastery experiences, while the reflection has not been emphasized.

Mindfulness has often been linked to the concept of meditation, in which a focused effort is made to bring attention to the present moment (Kabat-Zinn, 1990). Many researchers have investigated the relationship between mindfulness meditation and increased positive outcomes, such as increased self-control (Friese, Messnger & Schaffner, 2012), improved mental health outcomes (Brown, Ryan & Creswell, 2007) and emotional regulation (Raes, Griffith, Van der Gucht & Williams, 2014). However, the vast majority of these studies use a form of mediation-based exercises, such as the Mindfulness-Based Stress Reduction practice (Baer, 2003). A further quantitative analysis on the relationship between the well-established phenomenon of mindfulness and the process of self-tracking may be a viable avenue to better understand the impact of personal data analytics.

Self-Reflection

Throughout this study, I have discovered that in the realm of quantified self-tracking, it may be the gathering phase that is more impactful than aggregated data analysis. The granular task of understanding and becoming aware of individual activities is more impactful than overall data trends. This task presented to participants did not increase personal understanding regarding overall goals or behaviours, the intended goal of this study, but it provided control over individual and disaggregated actions and feelings. This improvement was the result of a myriad of individual actions and choices; these choices were made less difficult in an environment in which the participant is forced to be aware of those choices. Without a specific research question, quantified self-tracking serves its most useful purpose in allowing participants a glimpse into the granular data as it occurs.

This is related to Li et al.'s (2011) Discovery phase of quantified self tracking but is not synonymous with this concept. Specifically, the outcome variable is not assigned, and dependent variables are not correlated or compared against the conclusion. Instead, participants are made aware of their individual choices within the context of their aggregated choices. This may be highly related to the success of food journaling activities which have inspired the highest rates of weight loss (Kong et al., 2012; VanWormer, French, Pereira, & Welsh, 2008); specifically, participants are made aware of the daily choices they make by writing their activities and decision in a logbook. This, in a larger scope, allows them to consider the actions in a more mindful manner; ultimately, this is the tool which inspires behavioural change in this context.

Conclusion

This dataset has provided the rationale for further investigation into the relationship between emotional self-regulation in the action domain when compared with quantified self-tracking. Given the exploratory nature of this study, its small sample size, the bimodal nature of the statistically significant conclusion, and developing instruments, this investigation should not be considered strong evidence that quantified self-tracking increases emotional self-regulation in the action domain, despite the high statistical significance. Most notably in this study is the untested nature of the ERSE, which does not have normative measures in it; this instrument requires further study before this conclusion can be considered accurate. This study does strongly imply that quantified self-tracking has little or no relationship with either the intrapersonal or interpersonal domains of emotional intelligence.

This study has indicated that action can be regulated by writing tasks and moods down, despite the presence of powerful emotions. This suggests that a tertiary characteristic is being increased by the act of self-tracking. Further investigation into what this characteristic may be is warranted. Reflection is a potential candidate for further research, given self-tracking's parallels with the journaling process; mindfulness, related to the concepts of deliberate action and self-awareness, is a possible avenue for further research, as indicated by its presence as an emergent theme in the qualitative portion of this study. There is little formal academic work that currently exists examining a potential relationship between mindfulness and self-tracking. The majority of the quantified self mindfulness-based literature is based on self-experiment and is often informal in nature.

The self-tracking should be, in an ideal state, a simplified and lean tool that provides an easy-to-enter digital format for participants to use; however, given the implications regarding reflection and mindfulness apparent in this study, this simplified and lean process may not be the most effective. The greatest challenge in self-tracking is consistency and time expenditure, but the challenges may also be inherent in effectively developing behavioural change. In order to build an effective tool, we must better understand the relationship between these disparate concepts.

Ultimately, this research has indicated that self-tracking is a viable alternative to journaling for those who are more inclined towards quantitative data. Data can serve as the catalyst for change in participants, and desired behavioural change can be realized through the methodologies present in the quantified self movement. However, despite the significance of the conclusions reached in this study, further research into this phenomenon is required. The difficulties associated with self-tracking, the relationship of reflection, mindfulness, analog or digital tools, and the long-term effects of self-tracking are still unknown.

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