Emotional intelligence as a predictor of work performance: An investigation using the situation-specific model

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ABSTRACT

This study addressed weaknesses in the emotional intelligence (EI) construct of predicting the performance of organisation members. Typically, research conducted on EI's association with outcomes such as work performance has used a simple, linear approach to determine the links between EI and selected variables, which has proven to be unsuccessful. Consequently, scholars have called for consideration to be given to the context in which work is performed. The context of the study was the informationally opaque, and thus emotion-laden, small and medium enterprise (SME) credit risk assessment setting in a 'big four' bank in South Africa. The study set out to understand ability-EI's influence on work performance outcomes when context is considered.

To test the relationship between the variables, the study adopted a deductive research approach. The sample consisted of 70 loan officers who were directly involved in the underwriting of the loans. Key strengths of the study were the introduction of a contextual moderator variable, the use of objective measures for work performance and the use of a hierarchical multiple regression model to test the main and indirect effects, which included moderation.

The results indicated that EI problem-solving abilities do not predict work performance of loan officers in the credit risk assessment space, even when context is considered. This is despite the fact that the MSCEIT V2.0 test instrument was found to be reliable, in that it measured problem-solving abilities consistently.

This study extends the extant literature on the predictive validity of the ability-based EI construct by answering the call to context. From a practical point of view, this study contributes to the application and refinement of the situation-specific framework. Furthermore, in applying the 'gold standard' to the conducting of EI research, the study highlighted the gaps when strictly following the recommended approach. Finally, the study revealed that the conceptualisation of the contextual moderator and work performance measurements is critical to the outcome. Hence, it is recommended that the application of the 'gold standard' for EI research be simplified, and that the conceptualisation and operationalisation of the moderator and dependent variables be reconsidered.

Key words: emotional Intelligence, work performance, call to context, small and medium enterprise, credit risk assessment, loan officer, hard information, soft information, risk grade, post-issuance loan performance, delinquency, charge off

DECLARATION

I, Bongani Mageba, declare that the thesis, which I hereby submit for the degree of Doctor of Philosophy at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Bongani Mageba
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Date: 2023-30-06

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When I embarked on my doctoral journey, I knew that it would be more than a mere academic exercise. I was fulfilling a lifelong dream – one that had eluded me earlier on in life because of other priorities. I was also on a crusade to reach the pinnacle of my academic career, as I had sought to do in various other areas of my life. Hence, at this juncture, I would like to acknowledge the following individuals who have provided support, advice and ongoing prayers, and from whom I have gained so much strength.

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1 CHAPTER 1 – INTRODUCTION

This chapter introduces the rationale for and subject matter of the thesis and outlines the following sections: the background, the problem statement, the purpose statement, the research question and objectives, the scope, the limitations, the importance and benefits of the study, and the structure of the thesis document.

1.1 BACKGROUND

The promise of the emotional intelligence (EI) construct was that it could contribute to our understanding of individual differences as well as predict important life outcomes in the workplace, school and home settings (Côté, 2014). Indeed, possibly like no psychological construct had done before, EI could – so it was argued – enhance our understanding of human intelligence (Côté, 2014). As a result, EI received substantial attention from both practitioners and scholars. Since the introduction of the ability-based emotional intelligence theory in the early 1990s, there has been a fundamental shift in practitioner and academic literature regarding predictors of work performance (Mayer & Salovey, 1997; Salovey & Mayer, 1990). Until the advent of the theory, many in business and academic circles had generally accepted that general mental ability (GMA) or cognitive ability was the main differentiator and predictor of human performance.

Decades later, the promise remains unfulfilled (Grobelny et al., 2021; Joseph et al., 2015; O'Boyle et al., 2011). Extant literature suggests that EI accounts for a small variance (only 0.4%) beyond what is accounted for by other predictors of work performance (O'Boyle et al., 2011). Reflecting on the state of the EI field, Antonakis (2015) makes an impassioned plea to researchers to "drop the hype, keep the hope, but pay attention to all the evidence. Not only is it the moral thing to do; it is also the economical thing to do" (p. 16). In responding to the controversy and criticism, this study adopts the situation-specific model to test the theory of EI by referencing a unique context (Côté, 2014).

Prior to the introduction of the theory, rationality and logic were considered superior to emotions (Mayer et al., 2008). Emotions were feared and needed to be suppressed. The ground-breaking contribution by Salovey and Mayer (1990) heralded a new era. Before the emergence of the emotional intelligence field, eminent scholars such as Dewey (1909), Thorndike (1920, cited in Thorndike & Stein, 1937) and Gardner (1983), under the banner of social intelligence and multiple intelligences, had argued for a broader definition of the causes of human success. Given that the introduction of the EI concept was in an environment in which the field was not only underdeveloped but also uncoordinated, it was to be expected that the reception would be negative at worst and mixed at best (Mayer & Salovey, 1993; Mayer et al., 1999). However, the linking of emotion to cognition by Salovey and Mayer (1990) provided a platform for the emergence of the construct. By doing so, they ensured that the EI theory was kept in the well-established, traditional space of cognition but was also sufficiently differentiated to attract attention. This was a sound move for the introduction of a new construct.

Early in its life, the concept received an unexpected boost. Goleman (1995, 1998b) popularised it by authoring two best sellers, *Emotional Intelligence* and *Working with Emotional Intelligence*, and his all-time best-selling article in the Harvard Business Review, 'What makes a leader?' (Goleman, 1998a). Retrospectively, the contribution by Goleman can be viewed as both a blessing and a curse. It was a blessing in that the concept became immensely popular. However, his contribution also prompted a deviation from the discipline of scientific endeavour. Unsubstantiated claims regarding its utility were made (Gibbs, 1995; Goleman, 1995; Watkins, 2000). One of the enduring legacies from this period is that emotional intelligence remains a divided field characterised by definitional ambiguity and a confounding method-construct.

The scholarly debates on the different conceptualisations of EI have advanced substantially over the last few decades. We now know that of the three streams of EI – that is, ability-based EI, mixed EI and self-report ability EI – it is only ability-based EI that can be regarded as an intelligence (Côté, 2014; Fiori et al., 2014; Joseph & Newman, 2010; Joseph et al., 2015; MacCann et al., 2014; Mayer & Salovey, 1997; Mayer et al., 2008). Many scholars regard ability-based EI as the best because of how the construct, the theoretical model and the measurement tool are conceptualised and operationalised. The construct is aligned to cognition, the theoretical model captures the problem-solving areas, and the measurement tool is a maximal performance test that reliably measures abilities. However, it suffers from an incremental validity and predictive validity deficit. The unexpected weakness in the association between EI and work performance outcomes caused what has been variously described as the "researcher's dilemma" (Cherniss, 2010, p. 112) and an "ugly state of affairs" (Joseph & Newman, 2010, p. 72). This puzzle has resulted in a situation in which researchers must choose between theory and data.

In the ongoing conversations among researchers, there have been calls to attend to the context in which EI abilities are deployed. These calls are for researchers to explore other research models instead of the commonly used bivariate approach, which thus far has produced sub-optimal results (Cherniss, 2010; Côté, 2014; Daus & Ashkanasy, 2005; Jordan et al., 2010; Ybarra et al., 2014). The most substantial of these directives came from Côté (2014), who provided best practice guidance on how to conduct ability-based EI research in organisations.

The small and medium enterprise (SME) credit risk assessment environment is the context for this study. Loan officers within this customer segment operate in an informationally opaque environment (Campbell et al., 2019; Chen et al., 2015). There is a lack of objective information on the borrower to use for loan underwriting and this places the loan officer in a difficult position where they have to make decisions based on risk and uncertainty. Despite the development of credit systems technology aimed at correcting the asymmetry between the borrower and the loan officer, the credit risk assessment environment remains uncertain (Filomeni et al., 2016; Filomeni et al., 2021). The uncertainty relates to the credibility of the client and the soundness of the financial transaction, which could have major adverse implications for bank balance sheets and the sustainability of the SME lending market. Consequently, the outcome of decisions cannot be known in advance; hence, the need to consider the role of emotions in decision-making to ameliorate the adverse outcomes.

This study investigates what few previous studies have explored. To advance the discussion on emotional intelligence in organisations, this study:

a) adopts the most conceptually valid construct of EI at this point – that is, the ability-based model, as conceptualised by Salovey and Mayer (1990).
b) employs the situation-specific research model which introduces a contextual moderator variable to test new relationships between the EI construct and work performance outcomes. This has the potential to produce a much richer understanding of the concept of EI.
c) reflects the multilevel nature of the EI construct and the multidimensional nature of work performance, thus creating favourable conditions for the deployment of EI by referencing the relevant work context.
d) creates the potential to learn something new about the relationship between EI and work outcomes, by integrating the SME credit risk assessment environment and the work performance of loan officers.

In summary, despite the limitations, most existing studies continue to use the bivariate approach when studying EI in organisations (Côté, 2014; Ybarra et al., 2014). This approach is one of the simplest forms of statistical analysis and involves only two variables, an input variable and an outcome variable (Baron & Kenny, 1986). This may limit our understanding of the predictive ability of the EI construct and the importance of capturing individual differences, as with other well-established psychological constructs. The consideration given to the context into which EI abilities are deployed differentiates this study from others and advances knowledge. The addition of context approximates more closely the environment in which work is performed, thus allowing for the measurement of outcomes using the independent variable at various levels of the moderator (Ashkanasy & Dasborough, 2015; Côté, 2014; Daus & Ashkanasy, 2005; Jordan et al., 2010; O'Boyle et al., 2011; Ybarra et al., 2014).

1.2 PROBLEM STATEMENT

There is a general consensus among organisational management scholars that individual differences in mental ability are among the key differentiators of human performance (Côté, 2014; Joseph & Newman, 2010; Mayer et al., 2008). However, it has been found that, at best, general mental ability can predict 10–40% of success or variance in performance (Mayer & Salovey, 1997; Schmidt & Hunter, 1998; Schmidt et al., 2016; Zeidner et al., 2004). Thus, an exclusive view of individual differences based on cognitive intelligence leaves much of the variance unexplained. Hence, this study builds on EI as an additional explanatory variable for the performance of organisation members.

The introduction of the Salovey and Mayer (1990) conceptualised EI construct promised to enhance our understanding of human abilities. One of the central insights from their conceptualisation was that "many intellectual problems contain emotional information that must be processed; this processing may proceed differently than the processing of non-emotional information" (Mayer & Salovey, 1993, p. 433). They further reasoned that individuals who achieved high scores in EI tests showed outcomes that differed in important ways from those who achieved low scores (Mayer & Salovey, 1997).

Notwithstanding the promise of helping to predict work performance outcomes, research results have been mixed (Grobelny et al., 2021; Joseph & Newman, 2010; Joseph et al., 2015; Mayer et al., 2008; O'Boyle et al., 2011). In primarily adopting the bivariate research approach, EI research has failed to deliver a model that has enhanced our understanding of the predictive power of EI abilities in organisations. Researchers have called for consideration to be given to alternative models (Côté, 2014; Ybarra et al., 2014). There has been a strong push to move beyond the simple predictor–outcome relationships to other relationships that may emerge through an examination of mediator and moderator relationships. This is because EI is a latent variable and work performance is multidimensional in nature (Motowildo et al., 2014). Furthermore, individual difference research (EI research) is premised on the exploration of various relationships (Edwards & Lambert, 2007).

However, only a few studies have taken heed of this call (Côté & Miners, 2006; Farh et al., 2012; Yip & Côté, 2013). Consequently, more than three decades since the introduction of the concept, fundamental questions are still being asked about the heuristic value of the ability-based EI construct.

This study explores the relationship between EI and work performance by using the situation-specific model in the context of SME credit risk assessment. In doing so, the study assists researchers and practitioners to understand how EI responds to different moderators. This, in turn, clarifies the heuristic value of EI in organisational management settings.

1.3 PURPOSE STATEMENT

The theory of emotional intelligence has been conceptualised to explain individual differences in life outcomes, over and above the explanation provided by cognitive intelligence (Mayer et al., 2016; Salovey & Mayer, 1990, Salovey & Mayer, 1997). However, using the linear approach to test the EI theory has exposed the conceptualisation to criticism because of weak results (Côté, 2014; Ybarra et al., 2014).

The purpose of this study, therefore, was to test the theory of EI which postulates that a set of abilities relating to emotions and emotional information enhances our ability to predict and understand individual differences in work performance using the situation-specific model. This model argues that EI explains the unique variance when context facilitates its deployment (Côté, 2014). The study achieves this by testing the relationship between the EI and work performance of loan officers moderated by their work context, which is the credit risk assessment environment for SMEs.

1.4 RESEARCH QUESTION AND OBJECTIVES

The primary aim of this study was to examine the relationship between emotional intelligence and work performance, and additionally to determine whether this relationship is moderated by context. It builds on emerging literature that suggests that referencing how work is done may produce different outcomes in the measurement of performance (Cherniss, 2010; Côté, 2014; Ybarra et al., 2014). Thus, this study's research question was: What is the role of emotional intelligence in terms of work performance in the SME credit risk assessment environment?

To this end, the key research objectives were as follows:

a) To examine the relationship between emotional intelligence and work performance using the specific-situation model.
b) To understand the influence of context on the relationship between emotional intelligence and work performance.

1.5 RESEARCH SCOPE

The scope and limitations are presented in this section.

1.5.1 Scope

Whilst the EI construct has attracted huge interest, its predictive and incremental validity has been weak (Goleman, 1995; Joseph et al., 2015; Schneider et al., 2016). This study examined the role of EI on work performance outcomes when the context in which work is done is taken into account.

The study focused on loan officers in one of the 'big four' banks in South Africa. The loan officers are responsible for the loan application process for the SME segment. A core part of their responsibility is to interact with SME customers to obtain both hard and soft information which is utilised in the decision to grant credit or not. Given that the context for SME lending is informationally opaque, the loan officers have to rely on relationships and use their interpretive judgements to assess the probability of default, thereby introducing emotions (Campbell et al., 2019). The study was conducted during the period 2018–2019.

1.5.2 Limitations

The study's core focus was the role of the ability-based EI construct in predicting work performance outcomes. Côté (2014) advises that personality and cognitive ability, as established predictors of work performance, must be controlled for. The study therefore controlled for these two well-known predictors of work performance to avoid spurious outcomes from the tests. Furthermore, the study controlled for the demographic variables of age, gender and race, which is regarded as best practice in ability-based EI research (Côté, 2014; Miners et al., 2018).

Finally, the study controlled for two more variables which are specific to the SME credit risk assessment work context: job tenure and repeat lending (Campbell et al., 2019; Filomeni et al., 2016). Extant literature establishes these context-specific variables as possibly having an impact on the performance of loan officers (Campbell et al., 2019). The loan officers are confined to one segment within one bank and therefore the study's findings cannot be imputed to the general banking environment in South Africa.

1.6 IMPORTANCE AND BENEFITS OF THE STUDY

The theoretical, methodological and practical contributions of the study are described in this section.

1.6.1 Theoretical Contribution

The introduction of the theory of EI provides a framework for the study to investigate the role of emotion abilities in influencing important life outcomes. As discussed earlier, much of the research on the predictive and incremental value of the construct has adopted the linear or bivariate approach, which has demonstrated limited success. Côté and Miners (2006) refer to this approach as incomplete and overly simplistic. As such, several scholars have called for a variation of the study of EI and any important criterion by considering the context in which work is done as it could improve the predictive and incremental validity of the construct (Cherniss, 2010; Daus & Ashkanasy, 2005; Jordan et al., 2010; Schneider et al., 2016; Ybarra et al., 2014). There is a gap in the EI literature in terms of what emotional intelligence problem-solving abilities can predict over and above cognitive ability.

This study is primarily an answer to the calls by various scholars to explore the role of context. It adopted the situation-specific model to address the question of the utility or heuristic value of the ability-based EI construct (Côté, 2014). The objective was to explore if the EI construct has a differentiated effect on a criterion, in this case work performance, because of its deployment in the SME credit risk assessment context. This will enhance our understanding of and ability to predict individual differences in work settings.

The second theoretical contribution flows from the application of the EI theory in the context of SME credit risk assessment. Few studies have applied this theory in this context (for example, Bacha & Azouzi, 2019; Roland & Olalekan, 2020). Even where it has been applied, the studies have largely used traits, intuition and emotion characteristics, with Roland and Olalekan (2020) using mixed EI. This study, therefore, addresses the critique by Ybarra et al. (2014) that EI research is dominated by the goal of assigning people scores and is devoid of context. Thus, by testing the ability-based EI theory in the SME credit risk assessment context, the study provides new insights for researchers on the role of EI in decision-making under uncertainty. Ultimately the study will contribute to the integration of the EI literature and the literature on work performance in the SME bank lending space.

1.6.2 Methodological Contribution

From a methodological perspective, the primary contribution is the introduction of a contextual variable (Cherniss, 2010). This means that the conceptual framework is not merely a simple mediation or linear framework. As a result, the use of the contextual variable, risk grade (credit risk assessment), as a moderator calls for a different approach. Risk grade is a variable of interest because it constitutes data on the borrower, which reflects the probability of default using data points from the borrower's previous financial behaviour (Campbell et al., 2019). This risk grade score, which is hard information about the context and soft information obtained through the interaction or relationship with the customer, may be at odds, thereby introducing emotions. Hard information refers to "objective, quantitative data that can be communicated at a distance without any material loss of content (such as borrower financial statements, balance-sheet ratios, repayment records, etc.)" (Filomeni et al., 2016, p. 2). Soft information, on the other hand, is defined as "subjective knowledge accumulated over time by loan officers in the course of repeated face-to-face interactions with borrowers (such as subjective assessments of the quality of the firm's strategy, management, customer relationships, reputation, etc.)" (Filomeni et al., 2016, p. 2).

Second, the choice of work performance measures, delinquency and charge off, as dependent variables introduces both short-term and long-term measures, respectively, of the financial risk. According to the bank's credit policy, a loan is defined as charged off when payment has been outstanding for 180 days (six months) and the matter has been transferred to the legal department for collection. Delinquency, on the other hand, is when a borrower has fallen behind on their payment for a single day after the agreed payment date. Both are adverse measures of performance that are reflective of the post-loan issuance performance (Campbell et al., 2019). They are based on loan data and reflect loan quality post the loan officer's interpretive judgements and integration of hard and soft information to assess the risk presented by the borrower.

Lastly, most previous studies in this area have followed the linear model or the simple mediation model. There have been some attempts to vary this approach, such as the compensatory model (Côté & Miners, 2006) and cascading model (Joseph & Newman, 2010). The conceptual framework for this study is different from that of most previous studies on EI and can be referred to as a moderation model. With moderation models, the moderator has the effect of changing the strength or direction of the dependent and independent variables (Baron & Kenny, 1986; Edwards & Lambert, 2007; Muller et al., 2005; Namazi & Namazi, 2016; Ro, 2012). Hence, the appropriate statistical technique for the testing of the hypothesis is hierarchical multiple regression because of its ability to test multiple relationships (Edwards & Lambert, 2007; Joseph & Newman, 2015; O'Boyle, 2011).

1.6.3 Practical Contribution

The popularity of the EI construct in business circles has far surpassed its utility in theory or scientific endeavours. This is largely because of its popularisation by Goleman in his award-winning works (Goleman, 1995, 1998a).

This study makes a practical contribution by refining the framework used by researchers and practitioners to understand and predict human abilities across many contexts. The study calls for further development of the 'call to context' extant literature to advance the application of the EI theory and the Mayer–Salovey–Caruso Emotional Intelligence Test (MSCEIT) measurement tool in real-life environments.

The SME credit risk assessment context specifically introduces risk and uncertainty due to the informationally opaque environment. The environment creates high expectations and there are clear and objective measurements of outcomes. A further practical contribution is that the model can help employers, managers and leaders to locate skills in advance. This is crucial for an industry that sets out to maximise human effort and where the management of risk is important.

1.7 STRUCTURE OF THE THESIS

Chapter 1 introduces the study by presenting the background, the problem statement, the purpose statement, the research question and objectives, the scope, the limitations, and the importance and benefits of the study.

Chapter 2 presents a critical review of the literature**.** The chapter is divided into five sections. The first four sections, covering the construct, model, measurements and outcomes, represent the key areas of debate within the EI theory literature. The fifth section is a review of the 'call to context' literature which explicates the various theoretical contextual models and motivates for the use of the specific-situation model. The last section of the literature review, which is a sub-section of the 'call to context' literature, provides insights into the SME credit risk assessment context, specifically the role played by loan officers and the link to EI theory. This chapter concludes with the presentation of the hypotheses.

Chapter 3 presents the overarching research methodology aimed at answering the research question. Outlined in the chapter are the research paradigm, the research design, approach and strategy of inquiry, the population and sampling, the unit of analysis, the data collection methods, the operationalisation of variables, assumption checks, exploration of the data, inferential statistics and the data analysis.

Chapter 4 presents the results obtained from the hypothesis testing and the data analysis. The chapter begins with the descriptive statistics, then moves to the assumption testing and the hypothesis testing and concludes with a summary of the results.

Chapter 5 discusses the results presented in Chapter 4 in detail within the context of the relevant literature relating to EI and the SME credit risk assessment environment. The discussion of the results includes the methodology and approach used for the analysis. The chapter ends with a discussion of the implications of the findings for the discipline and field of research.

Chapter 6 presents the conclusions and the contributions of the study at three levels, namely the theoretical, practical and methodological levels. It then discusses the study's limitations and provides recommendations for future research and overall conclusion. Finally, the thesis ends with a reference list, abbreviations referred to in the text, the outline of the MSCEIT test and the appendices relating to the data collection and the administration of the psychometric tests.

1.8 CONCLUSION TO THE INTRODUCTION

In summary, this introductory chapter in the thesis provided the background to the study and the development of the EI construct. It further highlighted the gap that still exists in relation to the incremental and predictive validity of the construct when it comes to life outcomes. The study responds to 'the call to context' by adopting the situation-specific model and by referencing the SME credit risk assessment environment. The literature review that follows is geared towards understanding the key constructs and relevant debates in the extant literature.

2 CHAPTER 2 – LITERATURE REVIEW

2.1 INTRODUCTION

The literature review is divided into two sections. The first section reviews the ability-based emotional intelligence (EI) theory which is the main theoretical framework for the study. It also outlines how EI has developed to become one of the leading theories used in business research to explain individual differences in important outcomes, such as work performance. Furthermore, this section highlights the gap in consensus on the predictive and incremental validity of the theory.

The second section aims to arrive at a better understanding of the SME credit risk assessment context as it relates to the EI theory and to position it as an appropriate space in which to explore the knowledge gap. The key focus is on the informationally opaque SME credit market and how EI problem-solving abilities may affect the decision-making process of loan officers.

Figure 1 below sets out the key sections in the overall literature review.

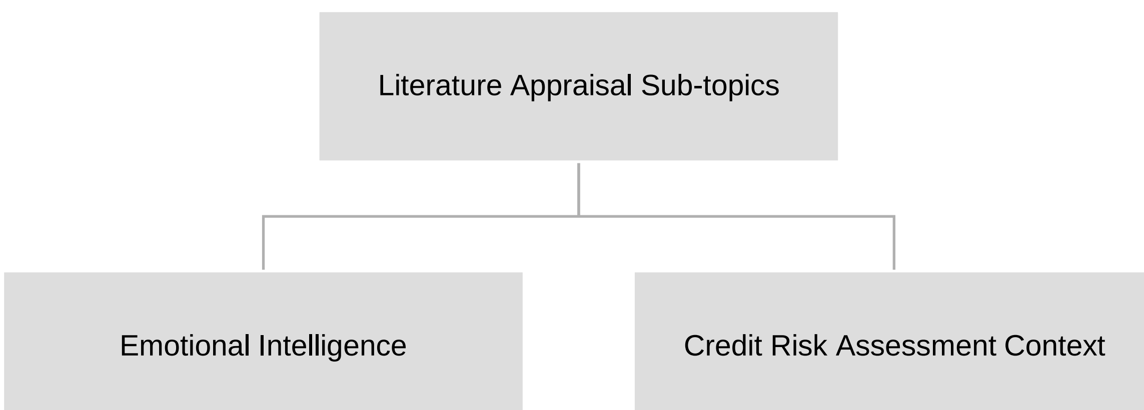

Figure 1. Overall literature review (Source: Author).

The literature review lays the foundation for the presentation of the conceptual framework, the hypotheses and the research question. Two paradoxes appear in the study. On the one hand, the ability-based EI framework emerges as conceptually and methodologically sound, but it suffers from predictive and incremental validity problems (Côté, 2014; Mayer et al., 2008; Miners et al., 2018). On the other hand, SME loan officers are expected to assess the risks associated with granting credit to borrowers when they do not have sufficient hard information (Campbell et al., 2019; Filomeni et al., 2016; Lipshitz & Shulimovitz, 2007). This study tests the relationship between the ability-based EI model and work performance using the SME credit risk assessment context.

2.2 THEORY OF EMOTIONAL INTELLIGENCE

According to Côté (2014), “research on emotional intelligence investigates whether a set of abilities about emotions and emotional information enhances our prediction and understanding of the outcomes of organisation members such as their job performance and their effectiveness as leaders” (p. 460). The purpose of this literature review is to trace the development trajectory of the ability-based EI construct and its suitability for answering questions relating to predictive and incremental validity.

Research on EI theory has advanced to a point where there is consensus on the preferred construct, method-model and measurement tool (Dasborough, 2019; Joseph et al., 2015; Schneider et al., 2016). The theory introduced by Salovey and Mayer is a little more than three decades old (Salovey & Mayer, 1990). It has attracted a following in academia, the popular press and business circles because of the claims that it makes. Its popularity, however, often surpasses the conceptual clarity required for a theory to be useful in the business environment (Cherniss, 2010; Dasborough 2019; Joseph & Newman, 2010). Hence, it is important at the outset to clarify the origins of the construct and the different schools of thought that informed the formation of the theory and produced the fractured scholarship. In so doing, the case for the ability-based emotional intelligence construct, the choice construct for this study, as opposed to the mixed-abilities or self-report approach, is made clear.

2.2.1 Social Intelligence, the Precursor to Emotional Intelligence

Many researchers, based on their interpretation of extant literature, attribute the origins of social intelligence to Thorndike. However, Landy (2005), in a thorough, scientific review of the theory of EI, strongly criticises the construct. He facetiously argues: “To say that ‘social intelligence’ was central to E.L. Thorndike’s view of intellectual ability would be akin to saying that Italian food is central to the Pope’s view on social justice” (p. 414). He suggests that Dewey (1909) should be recognised as the first scholar to discuss this construct. Joseph and Newman (2010) and

Schneider et al. (2016), whilst disagreeing with Landy on his interpretation of Thorndike's views on social intelligence, agree that Dewey is the originator of EI. This is not a trivial disagreement as it reflects the contestation that has surrounded EI for years.

One of the early scholars, Thorndike (1920), defines social intelligence as "the ability to understand men and women, boys and girls – to act wisely in human relations" (p. 276). He also sees social intelligence as present in the "nursery, on the playground, in barracks and factories and salesrooms, but it eludes the formal standardised laboratory" (Goleman, 2001, p. 16). Another key inspiration for the development of the EI theory was Howard Gardner. In the 1980s, Gardner announced the theory of multiple intelligences, which creates a link between emotions and intellectual functioning (Gardner, 1983). He provided a platform and the inspiration for researchers who believe that there is not just one construct or measure that explains the variance in individual performance – no matter how powerful the construct. Even Gardner attracted strong criticism for his conceptualisation of multiple intelligences beyond cognitive intelligence (Locke, 2005). It is clear, therefore, that the path towards the acceptance of this construct as a form of intelligence has been rocky (Mayer et al., 1999).

Locke (2005), a strong critic of the theory, states: "It is simply arbitrary to attach the word 'intelligence' to assorted habits or skills as Howard Gardner and EI advocates do, on the alleged grounds that there are multiple types of intelligences" (p. 426). Locke believes that "the agenda is not scientific but political" and one of "egalitarianism" (p. 426). Much of the criticism by both Locke (2005) and Landy (2005) is directed at the popular, non-scientific variants of EI, which will become evident below. To Locke (2005), the fate of EI would be the same as social intelligence "representing a content class of declarative knowledge that is not substantively different from general intelligence" (p. 427). We therefore observe a division between two main streams. In the one stream there are those who fundamentally dispute not only sources of EI but also the introduction of an altogether new intelligence. In the other stream there is an emerging group of scholars who believe that EI has always existed but has not been brought into the mainstream of scientific endeavour. For these scholars to deny the existence of EI as a part of core intelligences would be to convey an incorrect impression of the causes of individual differences that lead to individuals' success.

Indeed, as the field of EI has advanced, empirical evidence has increasingly supported the view that the ability-based EI theory "should be considered an additional group factor of intelligence with the same status as constructs such as fluid (process-dependent) and crystallised (memory-dependent) intelligence" (MacCann et al., 2014, p. 369). Of course, the conceptualisation of EI has now reached a stage that is far removed from when the construct was first introduced and regarded as having the undesirable effect of "muddying the waters" and even the potential to "rock the boat" (Mayer & Salovey, 1993, p. 61). Now there is general acceptance of the conceptualisation and framework that are being operationalised (Côté, 2014; Kong, 2014; Miners et al., 2018; Sanchez-Garcia et al., 2015).

In the early days of the construct, the areas of contention were whether EI is a distinct intelligence under the umbrella of social intelligence and, more specifically, whether it can be regarded as an intelligence at all (Landy, 2005; Locke, 2005). This debate has now progressed in the light of empirical evidence that has emerged, particularly regarding the ability model of EI. At its current stage of development, the main area of contention is whether EI can predict outcomes over and above general mental ability (GMA) – specifically, whether EI can enhance our ability to predict and understand the outcomes of the members of an organisation. The debate, therefore, revolves around its utility.

Figure 2 below illustrates how the EI literature review will proceed in this chapter.

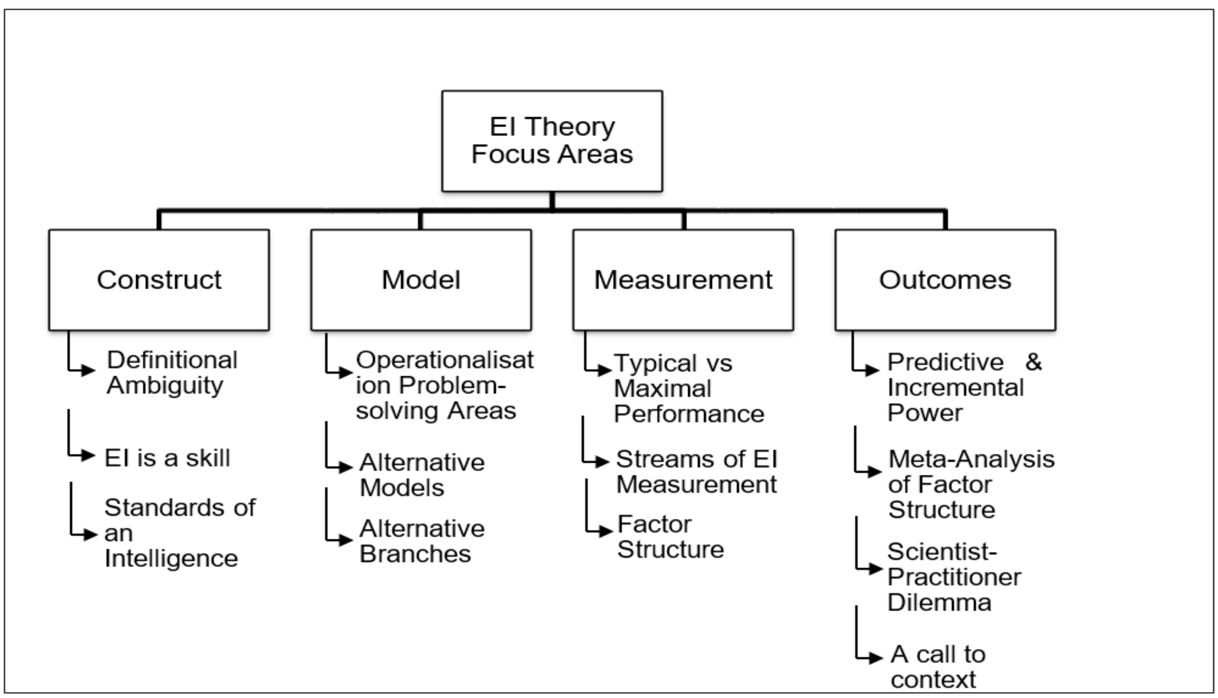

Figure 2. Literature review topics on emotional intelligence (Source: Author).

The main headings used in the literature review, as reflected in Figure 2 above, have been extracted from extant literature and highlight the key elements of the construct and its development. This reflects the ongoing debate amongst researchers. The purpose of Figure 2, therefore, is not to suggest that all the points below the main headings will be discussed. Rather, the literature review will highlight the state of the EI field in general and specifically the ability-based model by focusing on the key elements pertaining to the headings: Construct, Model, Measurement and Outcomes.

2.3 CONSTRUCT OF EMOTIONAL INTELLIGENCE

Salovey and Mayer (1990) provided the first definition of the term emotional intelligence, whereas Payne (1986) was the first to introduce the term into the English lexicon (Ashakansy & Dasborough, 2015). In a ground-breaking paper, Salovey and Mayer (1990) defined EI as the “ability to monitor one’s own and others’ feelings and emotions, to discriminate among them and to use this information to guide one's thinking and actions” (p. 189). In a later update, the authors advanced their original definition by including the view that emotions make thinking more intelligent. In their paper, Mayer and Salovey (1997) suggest that "emotional intelligence involves the ability to perceive accurately, appraise and express emotion, the ability to access and/or generate feelings when they facilitate thoughts, the ability to understand emotion and emotional knowledge; and the ability to regulate emotions to promote emotional and intellectual growth” (p. 10).

In another seminal article, Mayer et al. (2008) paraphrased the definition as follows: "Emotional intelligence concerns the ability to carry out accurate reasoning about emotions and the ability to use emotions and emotions knowledge to enhance thought" (p. 511). There are several other definitions and conceptualisations of EI that have been proposed by researchers. However, this section argues that they do not provide the necessary evidence for EI to be regarded as an intelligence and that the EI construct, as promoted by the founding scholars, is the most scientifically apt and therefore the ‘gold standard’ (Côté, 2014).

When Salovey and Mayer (1990) made their seminal contribution, it not only opened up a new area of research, but it also resulted in a disparate field of literature converging into a coherent structure (Mayer et al., 2016). Different parts of psychology and practice were united through the belief that “an exclusive cognitive view of intelligence misses the important *adaptive functions* [my emphasis] served by other psychological features responsible for success" (Barret & Gross, 2001, p. 286). This thinking stood in stark contrast to the early criticism of the EI construct by some researchers (Landy, 2005; Locke, 2005) who propagated the view that nothing beyond cognitive intelligence could explain the variance in life outcomes. Indeed, these scholars believed that EI contained no special properties and that it was not a mental aptitude.

However, early on in the development of the construct, the original authors were keen to signpost a few crucial points. They emphasised that EI is a skill or an ability that is relevant to success in life (Ansari & Malik, 2017). The basis for their thinking seemed to be that "many intellectual problems contain emotional information that must be processed; this processing may proceed differently than the processing of non-emotional information" (Mayer & Salovey, 1993, p. 433). They further emphasised that the construct's importance was its ability to differentiate reasons for success at an individual level. In other words, EI is an individual difference construct that is traceable back to individual ability (Grobelny et al., 2021; Motowildo et al., 2014).

Building on the understanding that EI is an individual difference ability, researchers made several claims. Goleman (1995) claimed that EI accounts for over 85% of outstanding performance among top leaders. Therefore, EI can matter more than the intelligence quotient (IQ) in predicting life outcomes. Gibbs (1995) argued that "in the corporate world … IQ gets you hired but EQ gets you promoted" (p. 59). Watkins (2000) added another dimension: "Use of EI for recruitment decisions leads to a 90th-percentile success rate" and "what distinguishes top performers in every field, in every industry sector, is not high IQ or technical expertise, it is EI" (p. 91). Altogether these were considered outrageous as they lacked empirical support. Barrett et al. (2001) facetiously referred to them as the "Madison Avenue approach to science and professional practice" (p. 10). To him and many others, this was an unwarranted 'fadification' of the field. In as much as their claims have led to the exponential growth of the field, this has come at the expense of a coherent theory. The current study argues that there is no support for such claims and instead research should focus on finding more instances in which there is closer alignment between theory and practice.

Much of the criticism levelled at EI seems to have emanated from its fractured scholarship. The three most recognised originators of alternative conceptualisations of EI are Goleman, Boyatzis and Bar-On whose contributions, whilst significant in their own right, fractured the field. Goleman (1995) defines EI as a "learned capability based on emotional intelligence that results in outstanding performance at work" (p. 85). Boyatzis (2011) later built on this definition to include competencies that denote self-awareness, self-management, social awareness and social skills at appropriate times and in appropriate ways with sufficient frequency to be effective in the given situation (Boyatzis et al., 2000). Bar-On, in contrast, was the first to coin the term emotional quotient (EQ) and he also developed the first test of emotional intelligence (EQ-i). He defines EI as “an array of non-cognitive capabilities, competencies and skills that influence one’s ability to succeed in coping with environmental demands and pressures” (Bar-On, 1997, p. 25). Whilst these conceptualisations shared some common elements with the original definition provided by the founding scholars of EI, such as emotion appraisal and management, there were vast differences between them. These differences have led to accusations of definitional ambiguity.

Various scholars have emphasised that definitional ambiguity has contributed to the construct leading a double life, where it has been lauded in business practice but challenged in academic circles (Daus & Ashkanasy, 2003; Daus & Ashkanasy, 2005; Jordan et al., 2003; Jordan et al., 2010). We now know, through factor analysis and other studies, that the differences are not just fleeting disagreements; they have significant implications for the model, measurement and results. Those who argue against the introduction of EI as another form of intelligence have used the weakness of definitional ambiguity as a core reason why it does not, and should not, exist (Landy, 2005; Locke, 2005). These critiques fail to note that they have conflated all the EI conceptualisations into one; yet they should not be considered the same. A variation is those scholars who have challenged the construct but have not negated its essential existence (Davies et al., 1998; Matthews et al., 2004). For those who have been more accepting of the construct, this has been a necessary and expected step towards achieving reasonable levels of clarity (Cherniss, 2010; Côté, 2014; Jordan et al., 2010; Joseph et al., 2015; Mayer et al., 2008; Miners et al., 2018).

From the outset, the founding scholars of EI expressed their concerns about these types of conceptualisations, which extend the construct to include competencies like zeal and persistence or other personality-related competencies. They insisted that any additions to or variations in the concept, as originally defined by them, must meet the standards for an intelligence, as will be discussed below.

The term ‘emotional intelligence’ contains two powerful ideas, emotion and intelligence, which are indicative of the scope and boundaries of the construct. They are independent of each other and hence draw from different fields of research. They represent specialisations in the domain of general intelligence (Côté & Miners, 2006). However, when combined, they are complementary.

Indeed, one of the distinguishing factors of ability-based EI is that it embraces the intelligence construct. Intelligence refers to a mental aptitude, which Mayer et al. (2008) define as a "person's capacity to perform a psychological task, such as solving a problem, so as to meet a specified criterion such as correctness, novelty, or speed" (p. 510).

This study adopts the recent revision of the definition of intelligence by Mayer et al. (2016), leaning on Carroll (1993), who regard intelligence as "the capacity to carry out abstract reasoning: to understand meanings, to grasp the similarities and differences between two concepts, to formulate powerful generalisations, and to understand when generalisations may not be appropriate because of context" (p. 290). Emotions are defined as "an integrated feeling state involving physiological changes, motor-preparedness, cognitions about action, and inner experiences that emerges from an appraisal of the self or situation" (Mayer et al., 2008, p. 508). The scientific validity of any EI construct should reside within this framework of definitions or nomological networks of emotion and cognition. It should acknowledge the interconnected terms and ideas that researchers have used in these fields to comprehend this area of study. This study contends that the additional conceptualisations of EI have contributed to definitional ambiguity because they are generally too broad and therefore fall short of this key requirement.

One of the key criteria for standards of intelligence was set out by Mayer et al. (1999). This was in response to seemingly outrageous claims being made about the utility of the EI construct. Since then, other scholars have expanded on this criterion to include factors that confirm intelligence (for example, Antonakis et al., 2009; Côté & Miners, 2006; Joseph & Newman, 2015; MacCann et al., 2014; Orchard et al., 2009; Schneider et al., 2016). The established criteria for an intelligence ability are that it must demonstrate convergent, correlational and discriminant validity. Using this framework, MacCann et al. (2014) concluded that ability-based EI – as indexed by the primary mental abilities (PMA) of emotion perception, emotion facilitation, emotion understanding and emotion management – should be classified as an additional group factor of intelligence with the same status as constructs such as fluid and crystallised intelligence. In other words, EI qualifies as an intelligence because all the problem-solving areas (branches) cohere to a single factor (convergent validity), the construct shows a positive manifold with other markers of intelligence (correlational validity) and it is not like any other existing group factor of intelligence and therefore measures something different (discriminant validity). Legree et al. (2014), using the same data as MacCann et al. (2014), reached the same conclusion about ability-based EI being a group factor of intelligence. These studies add meaningfully to the conceptual and definitional integrity of the construct.

Two additional criteria were added by Schneider et al. (2016) which are useful for this investigation. First, the new construct should be linked to specific neural modules that evolve to help humans survive and reproduce. The authors argue that this is a useful criterion to distinguish between any other skill and an intelligence or an ability. Second, the new construct must predict important outcomes, even after accounting for more established cognitive abilities. In other words, it must predict useful outcomes above and beyond already established cognitive abilities; it must add to our knowledge of human abilities. This study builds on the conclusion that ability-based EI is an intelligence, but it specifically probes whether EI adds meaningfully to the prediction of important outcomes within an SME credit risk assessment context. This is an area in which debates continue unabated.

In conclusion, the above discussion establishes the ability-based construct of EI as the only one that meets the standards for intelligence and therefore qualifies to be referred to as an ability. This study does not, therefore, concern itself with the general criteria for standards for intelligence, except for whether EI adds meaningfully to the prediction of important outcomes within a chosen area of focus. Indeed, in their study, MacCann et al. (2014) make it clear that the findings with regard to EI being a group factor of intelligence only apply to the ability model of EI. Whilst the advent of the EI concept has been much maligned, the construct is currently well established.

It is suggested, based on empirical evidence, that EI no longer faces existential challenges. Most scholars now draw explicitly and exclusively from this conceptualisation (Ansari & Malik, 2017). The focus has progressed to whether it can provide parsimonious and credible solutions to real-life problems (Grobelny et al., 2021; Joseph & Newman, 2010). The results in this regard are mixed. To some extent, this depends on how the construct is operationalised and measured. A well-developed construct allows discussion about the construct itself without the need to immediately get into the discussion about measurement (Joseph et al., 2015). This is true of ability-based EI, for instance, as opposed to mixed EI, which often results in a conflated discussion of construct and measurement. The next section considers the operationalisation of the construct as distinct from its measurement, which will follow in subsequent sections.

2.4 MODEL OF EMOTIONAL INTELLIGENCE

The introduction of the four-branch model by Mayer and Salovey (1997) signified a critical development in the life of the construct. The authors introduced a hierarchical model that consisted of four branches or dimensions representing each of the four abilities. These branches are distinct psychological processes, arranged from the simplest to the most complex, in an almost causal relationship with no dimension enjoying any privilege over another (Barrett & Gross, 2001; Elfenbein & MacCann, 2017; Rivers et al., 2012). Each of the branches represents an opportunity for problem-solving.

The operationalisation of a construct is one of the most important steps in establishing the construct's scope and boundaries. It offers a view of what the construct is based on or the content areas from which it derives samples (Joseph et al., 2015). Furthermore, the operationalisation provides direction on which aspects are important to measure. Ability-based EI, unlike mixed EI, is positioned close to cognitive ability (MacCann et al., 2014). The founding scholars conceptualised it as a mental aptitude and hence its definition is consistent with definitions of intelligence. One of the key areas of contention regarding ability-based EI is the number of abilities and how they equate to the four-branch model, which is outlined below (Elfenbein & MacCann, 2017; Fiori et al., 2014). Elfenbein and MacCann (2017), for example, propose a different taxonomy with six narrow, problem-solving abilities but no measurement tool has been developed for it. As much as these debates are crucial, this study does not go into detail about them. Instead, this section argues that the four-branch model is the most appropriate illustration of the EI problem-solving areas and therefore a good framework to use for the measurement of EI.

Extant literature (Brackett & Salovey, 2006; Côté, 2014; Mayer & Salovey, 1997) suggests that the four branches (see Figure 3 below) can be categorised, from the simplest to the most complex task, as follows:

a) Ability to **perceive** emotions – the ability to accurately perceive emotion in oneself, others and stimuli in the wider world;
b) Ability to use emotions to **facilitate** thought – the selective and deliberate generation of emotional states to facilitate performance in different types of cognitive tasks;
c) Ability to **understand** emotions – an understanding of how emotions combine, change over time and change from one situation to the next, and the ability to reason with them;
d) Ability to **manage** emotions – the regulation or management of one's own and others' emotions in relation to set goals and strategies.

Figure 3. Hierarchical model of emotional intelligence (Source: Adapted from Mayer & Salovey, 1997).

The abilities are interrelated, part of one unit, yet at the same time are separated by when and where they occur in the information-processing stages (Elfenbein & MacCann, 2017; Schneider et al., 2016). Their hierarchical nature shows their causal nature. According to MacCann et al. (2014, p. 359), the model further conceptualises that "the lower two branches (perception and facilitation) collectively form the **'Experiential EI'** area, representing the direct processing of information in one's immediate environment, unmediated by higher-level strategic planning. Similarly, the two higher branches (understanding and management) collectively form the **'Strategic EI'** area, representing the strategic judgments and higher-level deliberate processing of emotional information".

Fiori et al. (2014), who concur with the operationalisation, highlight that the originators of the model stressed that, whilst there are different dimensions to the model, EI is in effect one global factor underpinned by these various dimensions. Mayer et al. (2008) contend that the joining of EI abilities in this manner means that ability EI and the four-branch models are an integrative model. An integrative model joins different dimensions into a coherent structure. The branches operate individually and together to predict outcomes.

Researchers, in pursuing the further development of the construct, have come up with alternative conceptual models for EI, including the proposed introduction of a new branch. The new proposals have been largely based on ability-based EI and are concerned with linking ability EI to work performance outcomes. Côté and Miners (2006) proposed the compensatory model, whereas Joseph and Newman (2010) proposed the cascading model.

In the first study, the authors challenged the linear effects models of EI and the assumption of linear contributions to outcomes. Instead, they argued that there may be other effects, such as intervening or moderating variables. In their findings, the authors argued that EI is a useful predictor of job outcomes because of its compensatory and interactive relationship with cognitive intelligence. In other words, job outcomes not achieved through high cognitive intelligence could be achieved through high EI. In the second study, the authors emphasised the progressive structure of EI and its relationship with other personality and psychological variables. The authors isolated the Emotion Regulation branch and its relationship with job outcomes. They concluded that personality traits and cognitive ability are crucial precursors to EI processes. These models present interesting empirical results in that they offer some illumination of EI and outcomes and therefore have added incrementally to our understanding of EI, but they have not successfully superseded the theoretical strength offered by the original model (Côté & Miners, 2006; Joseph & Newman, 2010; Joseph & Newman, 2015; Mayer et al., 2016; Ybarra et al., 2014).

Additionally, Côté and Hideg (2011) proposed a new dimension of EI that has not received the necessary support to warrant its inclusion in the four-branch model. The authors argued that the ability to influence others via emotion displays was an interpersonal ability, as opposed to the intrapersonal abilities suggested by the existing dimensions. It is not clear if this ability is independent from extant constructs and if it can be measured. Hence, its adoption and integration into the broader EI thinking have not been successful.

Despite the meticulous way in which the four-branch model has been conceptualised, as well as its popularity in business and academic circles, some fundamental questions have been raised regarding its fidelity. The question most relevant to the current study is whether the four problem-solving areas are an accurate representation of the abilities involved. Mayer (2015), in an interview, and Mayer et al. (2016), in a paper, make significant concessions regarding the four-branch model, and the problem-solving areas and abilities. These are outlined below.

Following the rebuttal of the early criticism, when Mayer (2015) and Mayer et al. (2016) argued that the abilities map directly to the problem-solving areas and, in turn, to the branches, they now concede that the four-branch model and the depicted branches are still valid, but the abilities underpinning them are yet to be fully confirmed (Mayer et al., 2016). Specifically, the authors argue that “the four-branch model of emotional intelligence demarcates emotional problem-solving overall. We no longer expect, however, that the specific mental abilities involved in emotional intelligence will necessarily coincide with the specific problem-solving areas described by the four-branch model” (Mayer et al., 2016, p. 292). This seemingly leads to a separation of the areas of problem-solving and human mental abilities. The model, the authors argue, remains intact but the connection between the mental abilities and problem-solving areas is tentative.

This shift is crucial because it has implications for the operationalisation of the four-branch model. The authors’ submission that the human abilities do not necessarily map directly to test content is a significant statement for the model. It was clear, however, from the early days of the construct development process, that the founding scholars had left a window of opportunity open to learn from other researchers regarding the integrity of the four-branch model. In their conceptualisation of the model, they theorised that the using or facilitation branch was structured differently from the rest. They reasoned that “branches 1, 3 and 4 involved reasoning about emotions, branch 2 uniquely involved using emotions to enhance reasoning” (Mayer et al., 2001, p. 234). They had indirectly embraced the possibility that branch 2 (Emotion Facilitation) may be redundant with respect to the other branches, specifically the Emotion Perception or the Emotion Understanding branches. Indeed, the factor analyses results confirmed their suspicions.

The four-branch model has served as the basis for several academic reviews (Elfenbein & MacCann, 2017). Some of the reviews have focused on the structure of the framework and others have focused on the possible existence of more problem-solving areas. In response, the founding scholars put forward, for the first time, a revised four-branch model of EI. The new model now includes more instances of problem-solving areas than in the past (Mayer et al., 2016). It comes with restated definitions of the types of reasoning involved, with some new and others expanded upon. In effect, it shows a better structuring and organisation of the reasoning areas. Figure 4 below shows the restated problem-solving areas:

Table 1. The four-branch model of emotional intelligence, with added areas of reasoning[a].

The Four Branches	Types of Reasoning
4. Managing emotions	• Effectively manage others' emotions to achieve a desired outcome[b] • Effectively manage one's own emotions to achieve a desired outcome[b] • Evaluate strategies to maintain, reduce, or intensify an emotional response[b] • Monitor emotional reactions to determine their reasonableness • Engage with emotions if they are helpful; disengage if not • Stay open to pleasant and unpleasant feelings, as needed, and to the information they convey
3. Understanding emotions	• Recognize cultural differences in the evaluation of emotions[c] • Understand how a person might feel in the future or under certain conditions (affective forecasting)[c] • Recognize likely transitions among emotions such as from anger to satisfaction • Understand complex and mixed emotions • Differentiate between moods and emotions[c] • Appraise the situations that are likely to elicit emotions[c] • Determine the antecedents, meanings, and consequences of emotions • Label emotions and recognize relations among them
2. Facilitating thought using emotion[d]	• Select problems based on how one's ongoing emotional state might facilitate cognition • Leverage mood swings to generate different cognitive perspectives • Prioritize thinking by directing attention according to present feeling • Generate emotions as a means to relate to experiences of another person[c] • Generate emotions as an aid to judgment and memory
1. Perceiving emotion	• Identify deceptive or dishonest emotional expressions[b] • Discriminate accurate vs. inaccurate emotional expressions[b] • Understand how emotions are displayed depending on context and culture[c] • Express emotions accurately when desired • Perceive emotional content in the environment, visual arts, and music[b] • Perceive emotions in other people through their vocal cues, facial expression, language, and behavior[b] • Identify emotions in one's own physical states, feelings, and thoughts

Note. [a]The bullet-points are based on Mayer and Salovey (1997) except as indicated in superscripts b and c. Within a row, the bulleted items are ordered approximately from simplest to most complex, bottom to top. The four-branch model depicts the problem-solving areas of emotional intelligence and is not intended to correspond to the factor structure of the area.
[b]An ability from the original model was divided into two or more separate abilities.
[c]A new ability was added.
[d]Note that the Branch 2 abilities can be further divided into the areas of *generating emotions to facilitate thought* (the bottom two bulleted items) and *tailoring thinking to emotion* (the top three bulleted items).

Figure 4. The restated four-branch model of emotional intelligence (Source: Mayer, Caruso & Salovey, 2016).

It is not yet clear, from a research perspective, what the full implications of the shift are likely to be. These will be uncovered through further research in the area. However, whatever the implications, this study follows the path taken by previous researchers in this area – that the four-branch model is the predominant and most credible model for the ability-based EI construct (Fan et al., 2010; Joseph et al., 2015; Legree et al., 2014; MacCann et al., 2014).

From the article by Mayer et al. (2016) on the founding scholars, we learn three important lessons about the four-branch model. Importantly, the foundational principles underpinning the model remain intact. First, the problem-solving areas depicted in the model remain unchanged. Second, the model represents the problem spaces that individuals create to solve emotion-related problems. Finally, the model is well theorised and provides for a parsimonious way to characterise the problem-solving areas. A matter that continues to be elusive is the appropriateness of the structure of the MSCEIT measurement tool to capture the problem-solving areas, as theorised (Gignac, 2005; O'Boyle et al., 2011; Sanchez-Garcia et al., 2015). This is addressed in the next section.

2.5 MEASUREMENT OF EMOTIONAL INTELLIGENCE

The value of an individual difference construct is its power to explain the variance in individual performance in a manner that matters for important life outcomes. Hence, Maul (2012) points out that "the valid measurement of a cognitive attribute such as emotional intelligence (EI) is in many ways a prerequisite for deep exploration of the nature and structure of this ability and the ways in which it connects with other cognitive and behavioral phenomena" (p. 1). The four-branch model principles update by the founding scholars could be crucial for measurement purposes. The principles from the revision that are applicable to this section on measurement are the following:

a) Emotional intelligence is best measured as an ability.
b) A test's contents and the problem-solving area involved must be clearly specified as a precondition for the measurement of human abilities.
c) Valid tests have well-defined subject matter which draws out relevant human mental abilities (Mayer et al., 2016).

In this section of the literature review, these principles are discussed, whilst it is argued that the MSCEIT V2.0 represents an appropriate measurement tool, despite some identified areas of weaknesses. Furthermore, the role of cognitive ability and personality in the prediction of work performance is discussed.

From the first test to measure EI – the Multifactor Emotional Intelligent Scale (MEIS) – to the current version of MSCEIT V2.0, the founding scholars have been clear that these tests are designed to measure ability (Brackett & Salovey, 2006; Mayer et al., 2003; Mayer et al., 2008; Mayer et al., 2012; Mayer et al., 2016; Roberts et al., 2016). This is because intelligences are best measured as abilities, which is borne out by extant literature on intelligence and cognition. Carroll (1993) defines ability as "the possible variations over individuals in the liminal [threshold] levels of task difficulty ... at which, on any given occasion in which all conditions appear to be favorable, individuals perform successfully on a defined class of tasks" (p. 8). Ability tests look for maximum performance from the test taker; hence, they are also referred to as performance tests

(O'Connor et al., 2019). The expectation is that the individual will exert maximum effort under a given set of circumstances. They are required to operate at the maximum level of knowledge and speed. When individuals do so, it results in "the performance that individuals exhibit when they have accepted instructions to maximize effort for a period and are aware that they are being evaluated" (Côté, 2014, p. 461).

In contrast to typical performance tests, individuals are expected to rate how they would behave under given conditions (Dasborough, 2019). In other words, these tests are based on individuals assessing descriptive statements about themselves. Researchers have consistently pointed out that typical performance tests, including peer review and self-report tests, whether ability-based or otherwise, are unsuitable for measuring intelligence because of a lack of reliability (Fiori et al., 2014; Lievens & Chan, 2010; Mayer et al., 2012; Rivers et al., 2012). They are unreliable because they are underpinned by flawed assumptions that human beings accurately estimate their own performance.

These different approaches reflect a critical difference in the study and application of EI. The field can be categorised into three streams of research. Figure 5 below shows each of these streams.

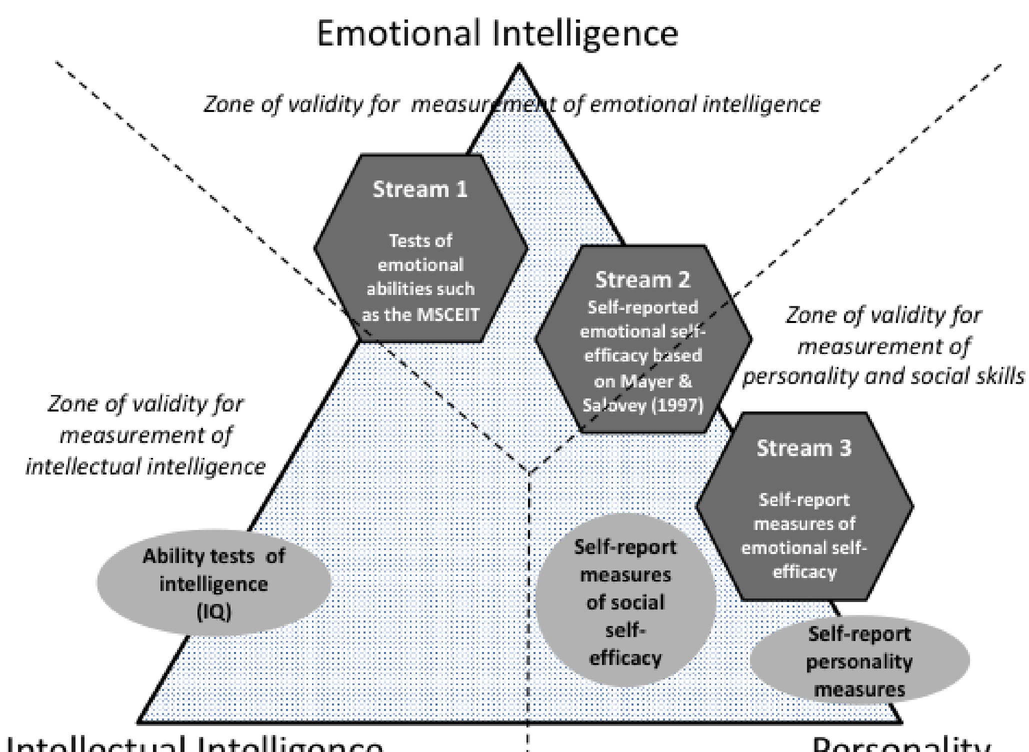

Figure 5. A taxonomy of measures of emotional intelligence (Source: Ashkanasy & Dasborough, 2015).

Daus and Ashkanasy (2005) provide the following explanation for the different conceptualisations and measurement tools:

> "**Stream 1** is based on the Mayer–Salovey–Caruso ability model of emotional intelligence and uses their measure(s) (the MSCEIT, or earlier, MEIS); **Stream 2** is also based on the Mayer–Salovey–Caruso ability model, but utilises either a peer- or self-report methodology; and **Stream 3** comprises a group of broader, 'mixed models' that include dimensions or components not included in the original definition of emotional intelligence." (p. 455)

This study adopts Stream 1 measurement tools as its basis, for the reasons mentioned above.

One of the most contested issues regarding the ability-EI measurement tool, the MSCEIT, has been whether the four-branch model is well reflected in the factor structure (Gignac, 2005; Maul, 2011; Rossen et al., 2008; O'Boyle et al., 2011; Sanchez-Garcia et al., 2015). The contestation has revolved around the number of well-fitting structures, as these are reflective of the fidelity of the instrument. This is an important aspect of the structure of the test which to date remains inconclusive. However, there is an emerging body of literature on the most appropriate structure (Schneider et al., 2016). To highlight the importance of the matter, Rossen et al. (2008) suggest that "research on tests is important for construct validity as it determines the extent to which observed scores on a test covary among themselves and how they covary with the underlying theoretical structure" (p. 1259). There are many ways that this problem can manifest to affect a test's validity. Regarding the MSCEIT, some of the literature highlights the problem that domains may overlap too much, to the extent that they could become redundant with respect to one another.

Gignac (2005) concluded that there was too high a correlation (.97) between the Emotion Perception and the Emotion Facilitation branch-level factors, which could not be seen to measure distinct problem-solving areas. After this initial review, a few papers using different and more sophisticated approaches followed, questioning the existence of branch 2 (Emotion Facilitation), with all coming to the same conclusion (for example, Fan et al., 2010; Farh et al., 2012; Palmer et al., 2005; Rossen et al., 2008). They also concluded that there are data to support a three-factor model and one general-factor model but not a four-factor model because of the high covariation between branches 1 and 2; nor a two-factor model (Joseph & Newman, 2010; Joseph et al., 2015; Legree et al., 2014; MacCann et al., 2014). Mayer et al. (2016) have accepted this feedback.

The results, however, should be seen in context. MacCann et al. (2014) point out that the findings from confirmatory factor analysis (CFA) studies and meta-analysis (Fan et al., 2010) that branch 1 may be redundant vis-à-vis branch 2 do not necessarily invalidate the distinction made between Emotion Perception and Emotion Facilitation within the four-branch theory.

There are various reasons why the Emotion Facilitation branch is not supported by the factor structure. It could be that individuals solve such problems using other abilities (Mayer et al., 2016). We share in the frustration expressed by Mayer (2015) that some of the discussions regarding factor structure quickly become technical and, in the process, deviate from the considerable substance that has been built around the construct. Indeed, there are many studies that have used the full MSCEIT test battery, while fewer studies have focused exclusively on the Emotion Facilitation branch to test relationships between predictors and outcomes and have produced acceptable results (Joseph et al., 2015; O'Boyle et al., 2011).

As much as the MSCEIT is regarded as the best available instrument for the measurement of EI, there are pitfalls to having this as the only tool (Elfenbein & MacCann, 2017). MacCann and Roberts (2008) and Fiori et al. (2014) refer to this as a sub-optimal state of affairs for research insofar as assessments of the utility of the test mostly rely on the properties of one tool. There has been further criticism levelled at the scoring method or rubric and the test validation. On the first issue, Maul (2012), one of the harshest critics, points out that the consensus-scoring method has caused controversy and, despite the founding scholars providing a comprehensive response to his criticisms, he remains unconvinced. Mayer et al. (2012) and MacCann et al. (2014), however, defend consensus scoring over alternative methods as both valid and consistent with theory. Furthermore, they highlight that it is even used in traditional cognitive intelligence test scoring.

On the second issue, Fiori et al. (2014), using the item response theory, question whether the test measures what it sets out to measure and to what level of accuracy. The authors make a contentious finding that the test is best employed for clinical samples that are expected to be low in EI. The founding scholars warned on numerous occasions that no reliance should be placed on single-task items. Instead, the scores should always be interpreted at branch level and overall score level (Caruso et al., 2002; Mayer et al., 2004). Additionally, both Maul (2012), a critic of the tool, and other researchers (MacCann et al., 2014) found no such result with the test. This finding has not been replicated in any further studies. Instead, researchers agree that the test has been crucial in informing our understanding of the EI construct. Moreover, the results generated can be associated with the individual's level of EI.

The process for the validation of the MSCEIT continues. The instrument is clearly designed to reflect the theorised EI construct and its operationalisation through the four-branch model. In this regard, it represents the best measurement tool for this mental ability. There are, however, some areas for further improvement. For instance, the test would do well to utilise veridical scoring (right and wrong answers), as this would settle the debate on consensus scoring. More importantly, it would be helpful to have clarity regarding the redundancy of the Emotion Facilitation branch. However, as Schneider et al. (2016) warn, the existence of an intelligence should not be predicated on the results of a factor analytic structure. This step, whilst crucial, is one of many that confirm the existence of an intelligence construct. Despite some challenges to branch 2 (Emotion Facilitation), this study included all four branches. I am confident that the full MSCEIT V 2.0 provided the best examination of individual EI problem-solving abilities.

2.6 MEASUREMENT OF COGNITIVE INTELLIGENCE AND PERSONALITY

Personality traits have shown evidence of correlation with some components of EI but they have not been significant. Indeed, O'Boyle et al. (2011) conclude that the Big Five have the weakest relationship with ability measures of EI and the strongest relationship with cognitive ability. The Big Five personality traits measure has five factors:

a) Agreeableness – represents the tendency to be warm and cooperative.
b) Conscientiousness – reflects the degree to which people are organised, hardworking and dependable.
c) Emotional stability – is the tendency to avoid negative emotional experiences and fluctuations in emotions.
d) Extraversion – concerns individuals' level of gregariousness, assertiveness and sociability.
e) Openness – relates to people's typical levels of creativity and curiosity.

The Big Five traits will be measured using the **Basic Traits Inventory (BTI)**, as described in the methodology section of this thesis, whereas cognitive intelligence will be measured using the **Matrigma test**, which is also described in the methodology section. Further, Côté (2014) suggests that demographic variables and relevant work-related or context variables should be measured. Previous studies have controlled for age, gender and race (Côté & Miners, 2006; Farh et al., 2012). A relevant work context variable is job tenure. The number of years experience could matter for the population.

2.7 USEFULNESS OF EMOTIONAL INTELLIGENCE

One of the promises of the EI construct and its main attraction is that it may be able to predict important life outcomes in the workplace, home or school setting (Grobelny et al., 2021; Mayer & Salovey, 1997; Mayer et al., 2008; Salovey & Mayer, 1990). For business management scholars and practitioners alike, the key attraction of this construct is the promise that it relates to the performance of organisation members in a way that complements the explanatory power of general intelligence and exceeds the power of personality and other competing constructs (Côté, 2014; Mayer et al., 2008; Schmidt et al., 2016). At this juncture, however, the empirical results from the many studies conducted in the workplace are not convincing. In many respects, this presents a puzzle. A study of medical school students is one of the few that have shown positive results (Libbrecht et al., 2014). In this review, I argue that despite the significant progress made in building our knowledge of ability EI, there is much we still do not know about the incremental and predictive power of this construct (Côté, 2014).

Traditionally, individual difference predictors relating to the work performance criterion have been dominated by cognitive intelligence tests (Lievens & Chan, 2010). Hence, O'Boyle et al. (2011) argue that in "determining whether a variable extends our understanding and prediction of job performance, it must account for variance beyond what is already accounted for by established predictors" (p. 802). Yet it must also show relative importance alongside the established predictors (Grobelny et al., 2021). In this regard, Mayer (2009) is clear on what they had hoped for: "Our own and others' ongoing research indicates that emotional intelligence may well predict specific, important life variables at about the level of other important personality variables (e.g., 2 percent to 25 percent of the variance explained)" (p. 84). According to O'Boyle et al. (2011), the combined R^2 for cognitive and personality constructs was R^2 = .423, a significant 42.3%, whereas for emotional intelligence it was 6.4% (0.03 contribution). Therefore, like previous studies of this nature, the current study aims to improve on the low scores, but it is expected that these scores will not be fundamentally different from these results.

A chronological review of the meta-analytic studies conducted on the predictive power and incremental value of ability-based EI and its relationship to work and job performance highlights the problems relating to the measurement of the construct. The power of meta-analytic studies is that they employ a statistical technique to simplify the scope and breadth of literature in an area by pooling together the results of many independent studies (Antonakis, 2015).

One of the early studies was conducted by Van Rooy and Viswesvaran (2004) but it did not make much of a distinction between the different strands of EI. Despite the many limitations of that study, such as the small number of studies under consideration, the authors argued that their findings revealed that the construct of EI held a lot of promise for future research. The concern about the findings lay in the relatively low (moderate) predictive power (p =.23) of EI for work performance (and, unlike with the personality construct, the lack of incremental validity) over and above general mental ability (GMA). It was nevertheless a useful study in that it brought to the fore several key issues, such as the relationship between individual EI sub-tests and work performance, while also forming the basis for future meta-analytic studies on this topic.

Shortly after the first study, Van Rooy et al. (2005) conducted an examination of the differences between ability EI (stream 1) and mixed EI (stream 3). The study was conducted within the context of growing interest in non-cognitive predictors in the workplace. The authors warned that the two models are not the same and that calling them the same thing would be a “jingle fallacy” (Van Rooy et al., 2005, p. 458). According to that study, their correlation was a low .14, which confirms that their conceptualisations were different. In more recent studies, it has been confirmed that their differences are not merely because of measurement procedures. In other words, the differences are not merely structural but are substantive, and are based on their underlying psychological properties (Fiori et al., 2014; Joseph et al., 2015; Joseph & Newman, 2010; MacCann et al., 2014). This lay the foundation for more focused meta-analytic studies to be conducted, which would be confined to each of the streams and not combined under the broad umbrella of EI. This is crucial because acknowledgement of their differences allows their strengths in terms of an important criterion to be thoroughly tested.

It was not until the study by Joseph and Newman (2010) that much more definitive attention was given to the potential scope for prediction by the ability-based EI construct. These authors observed the distinctive patterns between mixed EI and ability EI in terms of their relationship with job performance. Importantly, they noted that even though the ability-based EI model is superior in terms of theoretical conceptualisation, it suffers from not being generalisable, except in cases of ‘high emotional labour jobs’, whereas mixed EI, which has already been discounted for the purposes of this study, shows strong predictive validity. Although these authors noted the big differences between these types of EI in favour of mixed EI, they cautioned against mixed EI because of its unknown content and theoretical value. This was one of the first studies to focus on inconsistencies in the predictive power of ability EI. These authors referred to the state of the

EI field in general as a paradox (Joseph & Newman, 2010) in that its popularity far surpasses its proven utility.

Around the same time, O'Boyle et al. (2011), in a comprehensive and wide-ranging meta-analysis, investigated the predictive power and incremental value of all three streams. After overcoming the first hurdle, which showed stream 1 accounting for a negligible increment validity of only 0.4% over and above cognitive ability and personality, the authors employed dominance analysis and epsilon weight techniques which they argued were much more appropriate for models with correlated predictors such as the ability-based EI model. The findings were consistent with the differentials that had been established between these streams in previous studies:

> "**Stream 1** explained only 6.4% of the variance and showed a small R^2 (0.03) contribution. **Streams 2 and 3** results accounted for higher levels of variance. Stream 2 showed a contribution of 13.5% of the explained variance and an R^2 of (0.065) and Stream 3 similarly showed an explained variance of 13.2% and an R^2 contribution of 0.065." (O'Boyle et al., 2011, p. 803)

Overall, the conclusion reached by O'Boyle et al. (2011) was a significant step forward in the advancement of the EI theory. It achieved two outcomes. First, it tempered, by using empirical methods, the early enthusiasm fuelled by Goleman (1995) and others that EI is the most useful predictor of work performance within organisations and is far superior even to cognitive ability. Second, departing somewhat from the position of Joseph and Newman (2010), the O'Boyle et al. (2011) study confirmed the heuristic value of all EI streams as good predictors of work performance, although to different degrees. In other words, it seemed to confirm a hierarchy of incremental validity among the three streams. The ability-based EI construct (stream 1), with its strong properties and a strong measurement tool, was the least convincing. Mixed EI (stream 3), with its well-known weakness of being a grab of constructs, produced the second strongest results. Self-report ability EI (stream 2), even though it can be forged and has social desirability problems, produced the best results for the prediction of work performance.

This has been described as the "researcher's dilemma" by Cherniss (2010, p. 112) and an "ugly state of affairs" by Joseph and Newman (2010, p. 72) because scholars must choose between theory and data. The theory behind ability EI is well reasoned. However, the findings require a trade-off between theory and data because of the underwhelming empirical results. Clearly, the results from meta-analytic studies have defied the early expectations of researchers. The question is, why do mixed EI and self-report ability EI show a significantly stronger relationship with job performance, beyond cognitive ability and personality, than ability EI?

This question intrigued Joseph et al. (2015) enough for them to want to open the black box of mixed EI. The results from previous studies consistently showed that self-report and mixed EI delivered better results as lead predictors of job performance. However, their properties are not sufficiently well understood. These authors found that "mixed EI offers a high-utility mixture of individual traits to predict job performance" (p. 303). Specifically, the authors note that "the results demonstrate that a majority of the variance in mixed EI measures is captured by these constructs (i.e., 62%; multiple R = .79), suggesting these measures tend to sample content from various well-established construct domains in psychology" (p. 316). Furthermore Joseph et al. (2015) opined:

> "Based upon these findings, the current study offers the unique insight that the predictive merit of mixed EI can be almost fully explained after one considers ability EI, self-perceptions (i.e., general self-efficacy and self-rated job performance), personality [conscientiousness and extraversion – my addition], and cognitive ability." (p. 316)

Once these constructs are controlled for, the relationships between mixed EI and job performance dropped to near zero.

The significance of the results is that they illuminated this dilemma. We now know, based on empirical evidence, that mixed EI (streams 2 and 3) has shown better results because of heterogeneous domain sampling. Their power can be attributed to well-known psychological content domains which have established relationships with job performance. Once these attributes are controlled for, mixed EI has near-zero predictive power. Crucially, Joseph et al. (2015) concluded that this may mean that mixed EI does not add much parsimony to the scientific endeavour to establish an emotional intelligence ability.

The most recent, yet significant, meta-analysis was by Grobelny et al. (2021). Even though critical of the previous four meta-analytic studies, it once again confirmed the value of these type of studies in advancing our knowledge of EI. The value of the study was in its narrow focus on task-based job performance (not experimental studies) and predictive validity and not incremental validity. Furthermore, the authors used the most robust methodology for the conduct of meta-analytic studies. With a focus on performance-based ability (ability EI), self-report ability EI and self-report trait EI, the study confirmed the predictive validity of EI and job performance in organisational settings. Specifically, it found that the self-report measure of ability EI was most predictive, followed by the self-report trait EI and lastly the performance-based ability EI.

With the help of meta-analytic studies, we have better insight into the predictive power of EI and its relationship with job performance. However, the construct that integrates emotion and cognition the best, and promises to enrich our understanding of human abilities across many contexts and domains, still falls short of expectations. This can be seen as either the end of the road, or alternatively, as a call for a different approach to the study of ability EI. This study responds to this challenge by testing the theory using a different approach in a different setting.

The theory of the EI framework (theory, model and measurement) provides the best tool to predict human abilities in different settings. If general intelligence is about the "ability to understand complex ideas, to adapt to the environment, to learn from experience, to engage in various forms of reasoning, and to overcome obstacles by taking thought" (Neisser et al., 1996, p. 77), we can therefore reason that, consistent with intelligence literature, emotionally intelligent individuals will show that they have information about emotions that others ignore. They will also demonstrate that they are able to produce appropriate solutions to issues about emotions and produce them quickly (Côté, 2014).

2.7.1 Hypothesis H1 – Relationship between Emotional Intelligence Branches

Emotion Perception was conceptualised as the most basic, or the least cognitively complex, of the problem-solving areas/abilities. It is the first ability in a hierarchy of psychological skills underlying EI. The other skills build upon it. It is concerned with the ability to acquire important information about others' attitudes, goals and intentions (Côté, 2014; Mayer et al., 2008; Mayer et al., 2016; Mayer & Salovey, 1997). Additionally, this branch and the **Emotion Facilitation** branch "represent the direct processing of information in one's immediate environment" (MacCann et al., 2014, p. 359). Together they are referred to as experiential factors because of their closeness to sensations (Sanchez-Garcia et al., 2015).

Emotion Understanding and Emotion Regulation, according to MacCann et al. (2014), represent strategic judgements and deliberate processing of emotional information. **Emotion Understanding** is defined as the ability to interpret the meaning that emotions convey regarding relationships. This is because it involves the ability to evaluate and plan actions based on the information provided by sensations and emotions (Sanchez-Garcia et al., 2015).

Emotion Regulation is the most psychologically complex of all the EI problem-solving abilities. It is the ability that helps regulate the magnitude or duration of one's own and others' emotions (Côté, 2014; Gross, 2013; Rivers et al., 2012). It refers to the ability to integrate logic and emotions to make more effective decisions (Sanchez-Garcia et al., 2015). It means that one must have the capacity to manage emotions successfully, when appropriate. The combined integrative functioning of the branches is important for them to influence various outcomes.

I therefore hypothesise that:

H1: Emotion Perception correlates with Emotion Facilitation which correlates with Emotion Understanding which, in turn, correlates with Emotion Regulation.

H1$_0$: Emotion Perception does not correlate with Emotion Facilitation, which does not correlate with Emotion Understanding, which does not correlate with Emotion Regulation.

2.7.2 Hypothesis H2 – Relationship between Emotion Perception and Work Performance

This ability requires that the individual attend to the stimuli in their environment. In an update of the four-branch model reasoning areas, Mayer et al. (2016) – refer to Figure 4 **–** highlight that the updated reasoning areas for this ability are derived from the "ability to identify emotions in one's physical states, feelings, and thoughts, and proceeds to such developmentally advanced tasks, as we saw them then, as the ability to discriminate between truthful and dishonest expressions of feeling" (p. 294). The ability can be crucial in environments where the work performed is based on interaction between the loan officer and borrower and there is a heavy reliance on the value of soft information to form impressions (Lipshitz & Shulimovitz, 2007; Wilson, 2016).

I therefore hypothesise that:

H2: Emotion Perception predicts work performance.

$H2_0$: Emotion Perception does not predict work performance.

2.7.3 Hypothesis H3 – Relationship between Emotion Facilitation and Work Performance

One of the most disputed abilities from a confirmatory factor analysis point of view is the ability to facilitate emotions. However, it is intuitive in that in a hierarchical model it follows the appraisal of emotions. Furthermore, Schneider et al. (2016) advise that an ability is more than its factorial structure. The ability is about selecting, generating and leveraging the appropriate emotions to facilitate performance of a number of cognitive tasks (Côté, 2014). It also works in support of memory and judgement. The ability can be crucial in SME environments where the messaging and communication are not driven purely by hard facts and numbers. During the various approval stages, the ability can be crucial in driving the desired outcomes aligned to the loan officer's objectives (Filomeni et al., 2016; Lipshitz & Shulimovitz, 2007; Wilson, 2016).

I therefore hypothesise that:

H3: Emotion Facilitation predicts work performance.

$H3_0$: Emotion Facilitation does not predict work performance.

2.7.4 Hypothesis H4 – Relationship between Emotion Understanding and Work Performance

Scholars have said this ability is the most closely allied to cognitive processing and abstract reasoning (Mayer et al., 2001; Mayer et al., 2008). It represents the capacity to analyse the cause-and-effect relations between events and emotions. Individuals who have high levels of Emotion Understanding can apply better reasoning about the outcome of events, thus altering their behaviour over time. Yip and Côté (2013), for instance, found that a high Emotion Understanding ability helped individuals to discount the effects of anxiety which was unrelated to decisions involving risk.

In an environment where approving or rejecting a loan cannot be completely left to credit-scoring technology but is largely premised on relationships, the link between cause and effect is important.

The frequent and personal contacts between the borrower and loan officer do not have the capacity to reduce or eliminate the information asymmetry completely and hence there is always the residual risk that cannot be controlled in the evaluation of borrower risk.

I therefore hypothesise that:

H4: Emotion Understanding predicts work performance.

H4$_0$: Emotion Understanding does not predict work performance.

2.7.5 Hypothesis H5 – Relationship between Emotion Regulation and Work Performance

Importantly, Emotion Regulation occurs within the context of the individual's ability to set emotion regulation goals, select emotion regulation strategies and implement these emotion regulation strategies. It is about using emotions strategically, cultivating the emotions that are helpful and managing the harmful ones. Newman et al. (2010) refer to the Emotion Regulation ability as the active ingredient in EI abilities. This entails the processing of information, which is guided by higher-level strategic planning, including effective decision-making (Sanchez-Garcia et al., 2015). As the last step before work performance, this ability turns the complex use of emotions into discernible results. In the context of an SME credit risk assessment, the loan officer's motivation for a borrower's loan to be approved requires a systematic assessment of risk under uncertainty and the management of feelings because of the clear link to quantifiable outcomes which can have consequences for the lender (Campbell et al., 2019; Lipshitz & Shulimovitz, 2007).

I therefore hypothesise that:

H5: Emotion Regulation predicts work performance.

H5$_0$: Emotion Regulation does not predict work performance.

2.8 A CALL TO CONTEXT

EI theory has proven to be beneficial for the study of emotions and cognition. We know that the streams most predictive of work performance (streams 2 and 3) are mostly due to their being a combination of constructs and are not redundant in terms of cognitive ability (Joseph et al., 2015). However, the construct (stream 1), the only one that meets the standards for an intelligence, has not lived up to expectations of it. Instead, Grobelny et al. (2021) concluded that it is stream 2 (self-report ability-based EI) that is the strongest predictor of EI. Indeed, with the ability-based EI construct, it was assumed that measuring it would provide a powerful predictive tool, over and above what is already established in terms of various phenomena of interest – predominantly work performance. This level of significance has not been achieved for the construct, which continues to be the puzzle in the EI field. Whereas some researchers have continued to follow the common bivariate approach to finding answers to the puzzle, there is emerging literature that calls for a different approach. This section argues that to advance the field, it is necessary to adopt new models that consider the context of the study of EI.

Scholars have therefore called for consideration to be given to contextual factors impacting work performance, which is why this section makes reference to a call to context. The emerging literature is calling for EI research to be refined by exposing the construct, the model and the measurement to different settings and contexts (Antonakis, 2015; Antonakis et al., 2009; Ashkanasy & Dasborough, 2015; Cherniss, 2010; Côté, 2014; Côté & Miners, 2006; Daus & Ashkanasy, 2005; Jordan et al., 2010; O’Boyle et al., 2011; Ybarra et al., 2014). These calls are growing; thus, this section of the literature review provides a motivation for why they are relevant and appropriate for the next phase of the theory development process.

The call to context argues that EI may have a differential effect on a criterion such as work performance, depending on the situation in which the ability is utilised (Jordan et al., 2010). For example, Newman et al. (2010, p. 69) concluded that emotional labour, defined as “the process of regulating both feelings and expressions for organizational goals”, is a key contextual moderator variable for customer service-related jobs. In contrast, Côté and Miners (2006) found that EI exhibits a weaker association with job performance among employees with higher cognitive intelligence. The inquiry into context is in recognition of the multidimensional nature of work performance (Lievens & Chan, 2010). The thinking is that job context may strengthen or weaken the influence of abilities on work outcomes. The arguments have not concerned the proposed change to construct or method. In fact, the leading measure of ability-based EI, the

MSCEIT, is decontextualised (Lievens & Chan, 2010; Mayer, 2015). The authors of the instrument make it clear that this was a deliberate design strategy to ensure that they do not oversample other constructs like practical or personality intelligence. An example of recognising context would be to consider an aspect of work or a job setting to more closely approximate the role that EI plays in the production of results.

Investigations of the explicit consideration of context and its influence on an individual difference predictor and job performance criterion are sparse. An important contribution of Ybarra et al. (2014) is that they argue for an explicit consideration of context because it enables a more accurate prediction of a job performance criterion. Ybarra et al. (2014) call out the current problem with EI research, saying: “The EI field is dominated by the goal of assigning people some kind of score devoid of context to try [to] quantify the abilities underlying emotional intelligence” (p. 99). To these authors, this situation is untenable because decisions are context bound – as are behaviours. Additionally, they note: “We forgo much understanding if we ignore how people make sense of social situations and influence situation forces play in emotional intelligence” (p. 99). I concur with the approach and argue that job context is crucial for the deployment of EI abilities.

Two studies have specifically explored the role of context – Farh et al. (2012) and Yip and Côté (2013). In the first study, the authors looked at the moderating role of job context by examining the mechanisms of context-based boundary conditions for the emotional intelligence–performance relationship. Using a trait activation framework, the authors found that the relationship between EI and workplace outcomes increased in job environments where there were high managerial work demands. The Farh et al. (2012) study highlighted the importance of the Emotion Perception branch in these types of roles and, more importantly, gave additional perspective to what the authors referred to as a “person–situation interactionist perspective” and its importance in understanding phenomena related to EI (p. 897).

In the second study, the authors, using the lens of the Emotion Understanding branch, investigated whether feelings of incidental anxiety have an impact on risk-taking decisions. The authors found that individuals with high emotion understanding ability could avoid a high level of affect heuristic or incidental anxiety, which enhanced their ability to take risks. The Yip and Côté (2013) study is one of the closest to this (the current) study because of the uncertain and risk-taking work context to which the EI theory was applied. Taken together, these studies demonstrate the value of the EI construct to the work performance criterion when context is considered. They provide a better explanation of the relationship between EI and work criteria.

Côté (2014), in a seminal paper, advances three overarching models of EI research and their relationship with work criteria or work performance. Côté's (2014) major contribution was providing definitions of the three main research models and how they relate to the work performance criterion. Of relevance to the current study is the **situation-specific model**, but alongside it is the **validity-generalisation model** and the **moderator model**. Each of these models is an integrative model – that is, they combine several specific abilities to obtain an overall sense of EI. Figure 6, Figure 7 and Figure 8 below depict these three research models:

Figure 6. Validity-generalisation model (Source: Côté, 2014).

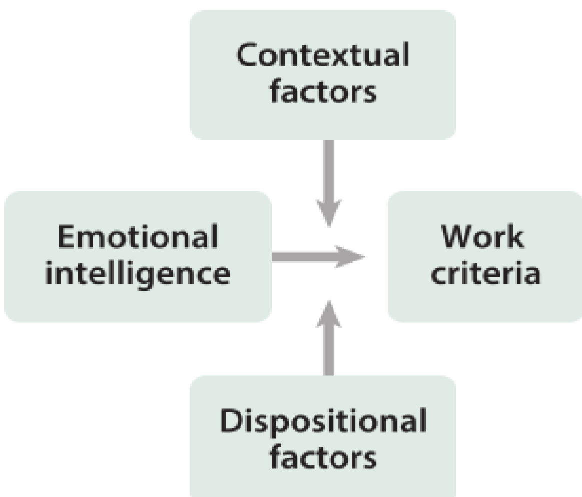

Figure 7. Situation-specific model (Source: Côté, 2014).

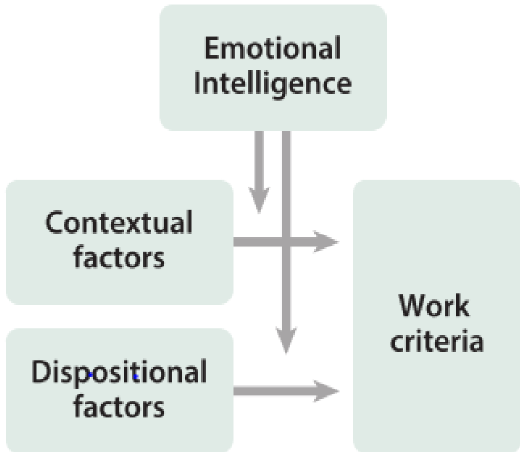

Figure 8. Moderator model (Source: Côté, 2014).

According to Côté (2014), the **validity-generalisation model** “proposes bivariate associations between EI and criteria that are consistent across organisational contexts and employee dispositions” (p. 471). Furthermore, “it predicts that EI will exhibit incremental validity over competing predictors, particularly other individual differences, because the benefits of EI are unique” (p. 472). This is a purist model that is agnostic to context or dispositions and has been shown to have limitations in terms of predicting the work performance criterion. However, this model has received the most attention in academic literature. Scholars are now calling for research to move beyond bivariate relationships or models.

The **moderator model** contends that “the levels of EI of organisation members shapes how they express their dispositions and how they react to organisational contexts” (Côté, 2014, p. 474). This model predicts that “EI serves as a moderator variable that enhances or attenuates the effect of various contextual or dispositional factors on work criteria” (p. 474). Hence, the moderator and situation-specific models are an attempt to move beyond the bivariate relationship between EI and the criterion (Lievens & Chan, 2010). Increasingly, scholars are suggesting that these two models should constitute a central approach to making new discoveries about EI and work performance. I concur with this thinking and chose one of the models in a bid to better understand how EI as an individual difference predictor works with the work performance criterion when context is considered.

The current study adopted the **situation-specific model of EI** to examine the relationship between ability-based EI and work performance, thereby helping to expand our knowledge of human abilities. The study is designed to answer the call to context and thereby contribute to the emerging body of knowledge in this area. Côté (2014) describes the situation-specific model as follows: “The association between a predictor and a criterion varies depending on the job or employment setting” (p. 472). It predicts that “EI explains unique variance in criteria when the organisation context or employee dispositions facilitate its deployment. Alternatively, EI exhibits smaller or no associations with criteria in the absence of opportunities to deploy it. In addition, there may be conditions in which deploying EI is harmful to individuals and/or organisations” (p. 472).

According to Ashton-James (2003), “a true measure of emotional intelligence must place respondents in a context where they can actually experience the emotions that they are asked to respond to” (p. 448). This model allows researchers to study individual differences in work performance by referencing elements of the setting that are specific to how the work is performed. Furthermore, it considers the multidimensional nature of work performance.

Gary Johns (2006, 2017) in his seminal articles outlines the importance of considering context in organisational research. He highlights that while there is, in some respects, context blindness in organisational research, with potentially adverse outcomes, it is the underappreciation of context that is more prevalent. He defines context as “situational opportunities and constraints that affect the occurrence and meaning of organisational behaviour as well as functional relationships between variables” (2006, p. 387). Context, as defined, is applicable to most research areas and is crucial both for theory building and practice.

This study’s design and approach have been significantly influenced by the work of Johns (2006, 2017). In elucidating the credit risk assessment context, this study focuses on the key dimensions of context. On the one hand, it goes into detail to describe the omnibus context – that is, it uses the journalistic approach to tell the story of who, what, when, where and why (section 2.8.1). On the other hand, looking through the task context lens, the study goes into detail to describe the discrete context with a view to clarifying possible relationships between variables (section 2.8.2). This includes the description, amongst other things, of the uncertainty, accountability, resources and autonomy at both an individual and an organisational level. It is important to note, as per Johns, that the discrete context is in fact nested within the omnibus context. The rest of this section captures the call by scholars while also describing these important elements of the context so as to deal with the issue of predictive validity of ability-based EI research.

The next section describes the context of the current study and references elements of the setting that are relevant to how the work is performed. The loan officer and the SME credit risk assessment context, as an appropriate setting for testing the EI theory, are relevant because the work is performed in a climate of uncertainty where the precise future creditworthiness of the borrower is unknown (Lipshitz & Shulimovitz, 2007). The environment is measured and strongly focused on outcomes. This study argues that a more explicit emphasis on how context influences EI is likely to improve the effectiveness of EI assessments which are designed to predict the criterion of interest.

2.8.1 Credit Risk Assessment in the SME Environment – Decision Context

In section 2.8, it was argued that job context is crucial for the deployment of EI abilities. According to Côté (2014), "the association between a predictor and a criterion varies depending on the job or employment setting" (p. 472). This section outlines the role of loan officers in the SME credit risk assessment environment as well as the lending and loan approval processes. Furthermore, it addresses the question: what is the role of context as it relates to theory? In other words, what do we know and what do we not know about the role of EI in work performance, as measured by post-issuance loan performance?

The study context is that of a large bank headquartered in South Africa with operations in more than 12 other African countries. The bank has more than R1.1 trillion in total assets and a market capitalisation in excess R140 billion. The size of the credit book for the segment under study is R20 billion with approximately 200 000 customers holding 40 000 credit facilities. The retail and business banking section of the bank is responsible for the origination of loans for SMEs. Given the government's goals of stronger economic growth and the transformation of the economy into a more inclusive one, there is a strong emphasis in South Africa and the banking sector on funding SME customers (Akinsola & Ikhide, 2019; Mazanai & Fatoki, 2012). Regarding the bank that is the focus of this study, SME customers seeking funding have the option of approaching any of the approximately 600 physical branches in the country or, alternatively, their loan officer if they already have an established relationship with such a person. The loan officer plays a crucial role, from the start of the application process until the loan decision outcome is communicated.

Loan officers generally seek to originate good loans, which requires them to minimise the risk of two types of errors – Type I and Type II errors (Campbell et al., 2019). A Type I error is where there is a likelihood that a loan could be refused to a deserving customer, whereas a Type II error is where there is a likelihood that a loan could be extended to an undeserving customer, which then becomes a bad loan on the books of the financial institution (Chen et al., 2015). This study focuses specifically on Type II errors.

One of the most significant steps in the loan-granting process is the screening of borrower information by the loan officer (Agarwal & Ben-David, 2018). Many scholars argue that banks are in the business of producing information (Liberti & Petersen, 2019). The screening process entails the consideration of hard information together with soft information. The definition of hard information, according to the literature, is that it is "objective, quantitative data that can be communicated at a distance without any material loss of content (such as borrower financial statements, balance-sheet ratios, repayment records, etc.)" (Filomeni et al., 2016, p. 2). Soft information, in turn, is defined as "subjective knowledge accumulated over time by loan officers in the course of repeated face-to-face interactions with borrowers (such as subjective assessments of the quality of the firm's strategy, management, customer relationships, reputation, etc.)" (Filomeni et al., 2016, p. 2). Campbell et al. (2019) further illuminate the nature of soft information by saying that it is "private, qualitative, and costly-to-obtain and verify information" (p. 4). Despite the challenges that soft information present, the literature confirms that it captures what hard information cannot and plays a crucial role in the lending process (Campbell et al., 2019; Chen et al., 2015; Filomeni et al., 2016; Liberti & Petersen, 2019).

Banking literature highlights that the act of lending and the assessment of credit risk are different for various credit or customer segments (Campbell et al., 2019). For example, there is a significant difference between the commercial and institutional lending segment, on the one hand, and the SME and personal segments, on the other. Lending to the SME sector relies much more on soft information because of the lack of readily available and relatively easy-to-process hard information (Chen et al., 2015; Filomeni et al., 2016). SME credit markets are informationally opaque, thus exacerbating the information asymmetry between the loan officer and the borrower. Consequently, loan officers in the SME credit market must use "firm-specific subjective intelligence and not hard characteristics to assess borrower risk" (Campbell et al., 2019, p. 4). Filomeni et al. (2021) point out that this remains a challenge, despite the development of credit systems and technologies aimed at the 'hardening' of soft information. These systems, which are largely designed to reduce information asymmetry rather than the cost of obtaining soft information, have not succeeded in lessening the burden.

As explicated above, loan officers in the SME segment (sector) play a crucial role in the assessment of risk and in the decision to grant credit to the borrower. Campbell et al. (2019, p. 3) explain: “Loan officers are expected to accurately interpret and reflect on soft information which requires greater cognitive processing and effort to be effectively evaluated than hard information”. In other words, the loan officers’ interpretive adjustments and inferences are instrumental to the value attached to soft information in the lending process and subsequently the loan quality (Brown et al. 2020; Lipshitz & Shulimovitz, 2007). To further illuminate the responsibility that loan officers carry when supplying information to the credit-granting process, Campbell et al. (2019, p. 3) make the point that “low quality loan issuance resulting from incorrect assessment of risk can have the undesired effect of distorting credit allocation, adversely impacting the funding of valuable projects and economic activity”. Consequently, there are concrete monetary costs to poor-quality loan decisions. This could be a problem given the professed importance, to banks and the government, of the SME sector in driving economic growth. This is one of the reasons why there is an increase in academic research focusing on the role of loan officers in credit risk assessments within the SME sector.

According to Lipshitz and Shulimovitz (2007, p. 215), much of the “research on loan officers’ context can be grouped into three areas: (a) the constituents of the decision process; (b) the process of the loan officers’ decision-making; and (c) the quality of the loan officers’ decisions” (my emphasis). This study focuses on the third area because it aligns to the study of emotions and its impact on outcomes. There are several other academic studies that have approached this topic by looking at other determinants of the quality of loan officers’ decisions, such as their level of numeracy, the differences between new and experienced loan officers, the different risks presented by new and existing clients, whether the loan information was requested before the start of a weekend, and loan officers’ proximity to the head office, among others (Brown et al., 2020; Lipshitz & Shulimovitz, 2007).

The emerging consensus is that, despite the growth of credit technologies for approving or rejecting a loan, relationship-based lending is hard and even more so with new clients where the information asymmetry gap is the largest (Filomeni et al., 2016; Filomeni et al., 2021; Liberti & Petersen, 2019). Furthermore, it is not a linear process or decision, especially in the informationally opaque SME environment. Rather, as Lipshitz and Shulimovitz (2007) point out, uncertainty abounds in the credit-granting process. The uncertainty “encountered by loan officers is, accordingly, inadequate understanding of the current situation rather than the ignorance regarding the nature, probability, or utility of future outcomes” (Lipshitz & Shulimovitz, 2007, p.

220). The process arouses feelings and emotions because of its unpredictable nature and the full effect can only be understood through post-loan issuance performance (Brown et al, 2020). The next section discusses the application and lending process in detail.

2.8.2 SME Loan Application and Lending Process

Loan officers have the authority to start the discussion with the borrower and to guide them through the various stages until a final credit decision is obtained. The bank operates a decentralised lending model with loan officers situated at the branch level. At the point of contact, the loan officer is central to the collection of information (both hard and soft) about the customer (Agarwal & Ben-David, 2018). The process of establishing the borrower’s needs and managing the information requirements considers the existing lending and credit-granting policies (Brown et al., 2020).

About two-thirds of the total volume of applications specific to the bank under study are automatically scored, representing about 20% of the value of credit granted to SMEs on a monthly basis. The balance of the applications (80% of the value of credit granted) are not automatically scored; they are processed manually. These applications have either been referred or declined. This study focuses on the latter loan applications that require manual processing. Owing to the manual approach used, the assessment of hard and soft information is performed by the loan officer who needs to make a judgement call as to the quality of the borrower.

The SME credit application process for the population in question is outlined in Figure 9 below. The loan officer plays a crucial role in the first three steps prior to the automated scoring process. They receive the application, request documents, interview the borrower and eventually capture the application on the system. This early/foundational process is important as it is where impressions are formed and gaps are identified (Agarwal & Ben-David, 2018). Some of these impressions are carried through into the credit approval process. The final stage of the application process entails an automated technology system activity where the borrower’s application is scored. This initial score, called the risk grade, is unique to the borrower and varies from 1 to 5, with 5 being the riskiest. The output is algorithmic and based on past financial behaviour; thus, it scores things like timeous and full payment of bills by the borrower. The outcome of the scoring is one of three options: an approval, a decline or a referred application.

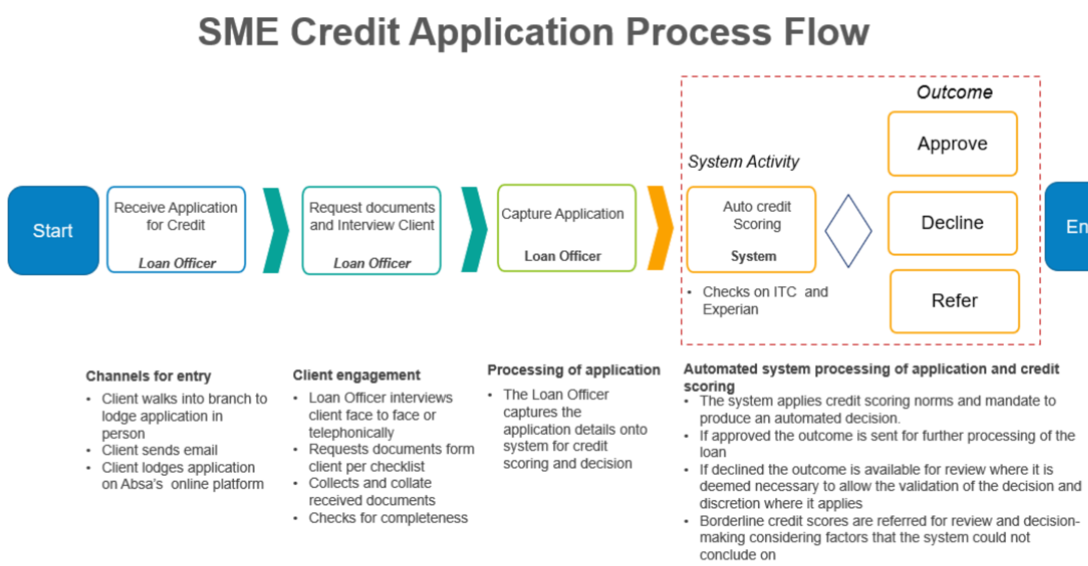

Figure 9. SME credit application process flow chart (Source: Author).

In the case of approved applications, the process ends at this point. With the referred and declined applications, the loan officer has the full discretion to decide if a further review is required. If they feel strongly about the need for a further review, the credit approval process is outlined in Figure 10 below.

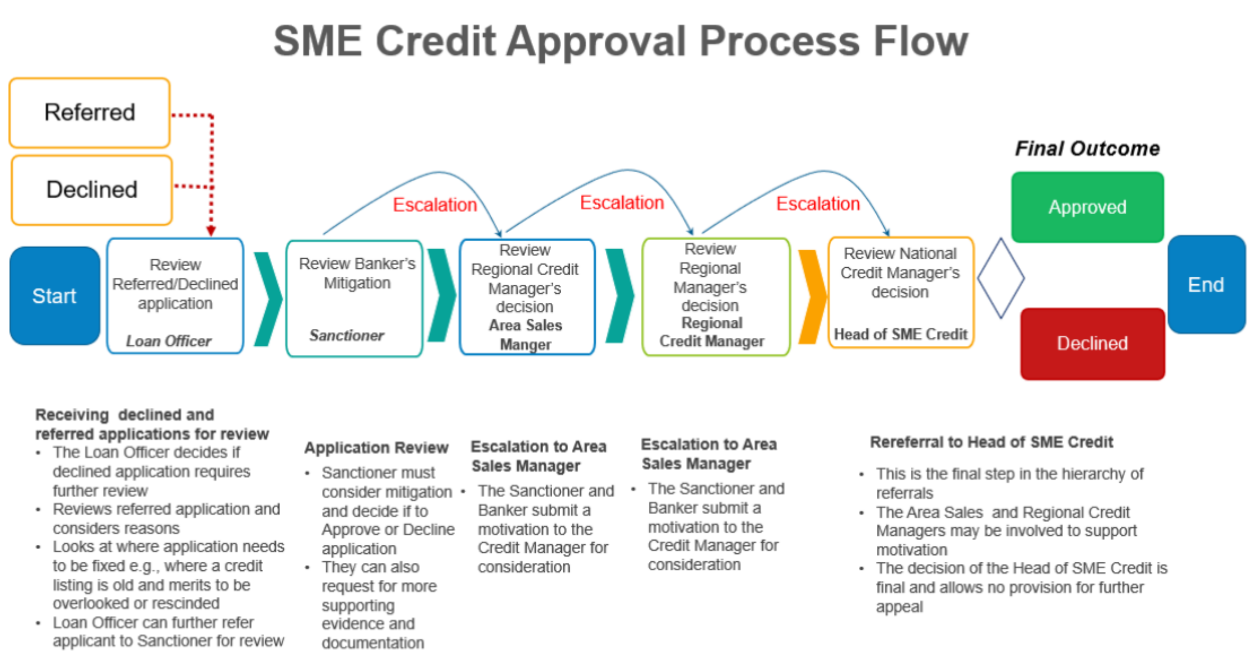

Figure 10. SME credit approval process flow chart (Source: Author).

Amongst the various elements in the credit approval process, the risk grade score is initially afforded much importance. It is indicative, both to the loan officer and others involved in the assessment of the credit risk, of the borrower's propensity to default. Brown et al. (2020), Filomeni et al. (2016) and Liberti and Petersen (2019), in three closely related papers on the process described below, offer more light on this subject. However, the challenge with SMEs is that the risk grade score – which is hard information and therefore easier to collect and transmit – is not sufficient to provide a clear picture of the borrower. Hence, the loan officer prepares a case for mitigation based on soft information collected, on the strengths of their relationship with the borrower. The case for mitigation gives rise to three possible types of escalation:

- First escalation – local: The loan officer challenges the outcome with the credit sanctioner by explaining the reasons behind the credit profile. The challenge is initiated by integrating subjective, qualitative data about the borrower. Using their proximity to the borrower, the loan officer sets out to obtain relevant information about their historical financial behaviour which could have affected the risk grade score rating. Reasons might range from a relatively minor matter of a few missed or partial instalments to bigger issues like poor health, job loss, temporary business issues or even broader economic challenges. Furthermore, the loan officer may introduce detailed, current information about the business and its owners, the quality of its management, ownership structure, product line diversity, market positioning strategy, sectoral opportunities and any formal contracts it may already have secured (Brown et al., 2020; Filomeni et al., 2016; Liberti & Petersen, 2019). This soft information is much more current and, in some instances, forward looking than the risk grade score, which is historical. The possible outcome from this challenge is an *integrated assessment* or *view* (my terminology) of the borrower.

- Second escalation – region: Many applications are decided on after the *integrated assessment*/*view* which now incorporates both an explanation for the buyer's financial behaviour and a qualitative view of the borrower (Filomeni et al., 2016). In a case where the application is rejected and the loan officer believes that the credit sanctioner has not fully considered the new information (hard and soft) about the borrower, they are entitled to send the application to the regional credit manager for review. The regional credit manager starts a completely new application or zero bases the application so as not to be influenced by the subjective views of the previous process, which involved the loan officer and the credit sanctioner. Notwithstanding all the other information collected about the borrower, this is a fresh assessment by someone using a fresh pair of eyes. In such a case, the loan officer can introduce additional information. At this point, the loan officer often has their senior regional leader, the area sales manager, face off with the regional credit manager. The outcome is a *modified integrated assessment/view* (my terminology) of the borrower.

- Final escalation – head office: If the application is still declined and the loan officer feels strongly about it, they (together with their executive of the region, the coverage area sales manager) can approach the head of SME credit to challenge the outcome of the *modified integrated assessment/view.* This is the last stage, which then produces a *final assessment/view* (my terminology) that overrides all previous considerations. An approval at this stage could be prompted by a further motivation or proposals to mitigate the borrower's credit risk by stipulating differentiated pricing (interest rate) according to the credit risk posed by the borrower or by adjusting the loan terms (maturity and collateral requirements) as well as considering the broader socioeconomic environment. Likewise, reasons for a decline could be special risks posed by the industry of the borrower, regulatory issues which could compromise the value of the firm and unmitigated risks in terms of financial behaviour (Filomeni et al., 2016).

Throughout the process, the loan officer adds certain soft or qualitative information, which is often available only to them. It is very difficult to separate the context in which the information is collected and the collector of the information, thus restricting its 'universal' use (Liberti & Petersen, 2019). Every time the loan officer collects information, they are making an assessment and exercising their judgement and discretion based on their relationship with the borrower. It is possible that training and experience may influence the quality of information collected, the time in the job (tenure), and whether it is a new or a repeat borrower (Filomeni et al., 2021). As the soft information is intended to influence the loan approval outcome, loan officers are at the centre of the credit risk assessment process, which is in keeping with the notion of relationship lending.

The credit risk assessment environment for SMEs is dynamic and uncertain. Despite the process being informationally opaque and therefore a breeding ground for emotions, there is no established link between EI and the loan officer's SME credit risk assessment context (Brown et al., 2020; Lipshitz & Shulimovitz, 2007). In the past, a few studies explored behavioural effects on lending, frictions imposed by distance and confounding effects of events (Campbell, et al., 2019; Filomeni et al., 2016). Figure 9 and Figure 10 above, depicting the credit application and approval processes respectively, illustrate that the credit risk assessment environment for SME lending is fundamentally narrative based. Unlike the system of loan underwriting for commercial and institutional businesses, where the process of building a credit score is based on hard information which ultimately decides the outcome, the process for SMEs is much more about the loan officer's reliance on hard-to-obtain, qualitative, soft information (Filomeni et al., 2016; Filomeni et al., 2021). It is evident that the influence that loan officers have on credit risk assessments can either complement or override the hard information from financial statements. Thus, loan officers have the ability to diminish or add to the post-loan issuance performance (Brown et al., 2020; Wilson, 2016). All this points to the fact that human behaviour and emotions loom large throughout the process.

In conclusion, extant literature regards the credit risk assessment process in the SME environment as more than simply a financial transaction between two economic players. Rather, it involves crucial interactions between loan officers and borrowers (Brown et al., 2020; Lipshitz & Shulimovitz, 2007). To assess the credibility of borrowers, loan officers must make sense of impressionistic, qualitative, and soft information. Soft information is costly to obtain, and its transmissibility is limited to the context and the collector. The use of technology to 'harden' soft information and close the gap between the two types has been found to have limitations (Filomeni et al., 2016). Thus, when loan officers collect soft information to incorporate into the risk assessment process, they have no idea of the possible effect and impact of their actions on the quality of future decisions (Campbell et al., 2019). This study reveals that more needs to be done to uncover how best to deploy human abilities to achieve better decision-making in this sector. Given the higher levels of cognitive processing required, it is expected that EI (psychological processes) would play a noticeable role in the processing of soft information and its integration into the credit approval process. It would therefore be reasonable to expect that contextual and work-related variables play a significant role in the observed differences between individual loan officers.

2.8.3 H6 – Relationship between Credit Risk Assessment Context with Individual Emotional Intelligence Branches and Work Performance Outcomes

Given that loan officers operate in an uncertain environment, emotions must inevitably play a critical role. Whilst responding to borrower needs, loan officers are expected to avoid Type II errors (granting bad loans) which could have adverse consequences for the bank's loan book

(Wilson, 2016). In the SME context, loan officers are employed to use their discretion to guide the loan application process by integrating relevant pieces of soft information.

Lipshitz and Shulimovitz (2007) stress that the loan officer's interpretive assessments and judgements influence the assessment of risk. The risk grade score is an algorithmic output based on hard information which reflects things like payment history and debt-to-income ratio. Though important, it is not sufficient to screen borrowers and assess the probability of their defaulting. The risk grade score is revealing and provides an opportunity for the loan officer to incorporate soft information into the credit underwriting process. Soft information is subjective and impressionistic and is influenced by the context and the collector of the information. Its journey through the credit application/approval process is not frictionless but it has the effect of complementing or changing the risk assessment.

It would seem, therefore, that the inclusion of soft information and its transformation through the credit approval process stirs emotions and affects the size or direction of (that is, it moderates) the relationship between EI and post-loan issuance performance (work performance). See Figure 11 below for a graphical illustration.

I therefore hypothesise that:

H6a: Credit risk assessment (risk grade) moderates the relationship between Emotion Perception and work performance (delinquency and charge off).

H6a$_0$: Credit risk assessment (risk grade) does not moderate the relationship between Emotion Perception and work performance (delinquency and charge off).

H6b: Credit risk assessment (risk grade) moderates the relationship between Emotion Facilitation and work performance (delinquency and charge off).

H6b$_0$: Credit risk assessment (risk grade) does not moderate the relationship between Emotion Facilitation and work performance (delinquency and charge off).

H6c: Credit risk assessment (risk grade) moderates the relationship between Emotion Understanding and work performance (delinquency and charge off).

H6c₀: Credit risk assessment (risk grade) does not moderate the relationship between Emotion Understanding and work performance (delinquency and charge off).

H6d: Credit risk assessment (risk grade) moderates the relationship between Emotion Regulation and work performance (delinquency and charge off).

H6d₀: Credit risk assessment (risk grade) does not moderate the relationship between Emotion Regulation and work performance (delinquency and charge off).

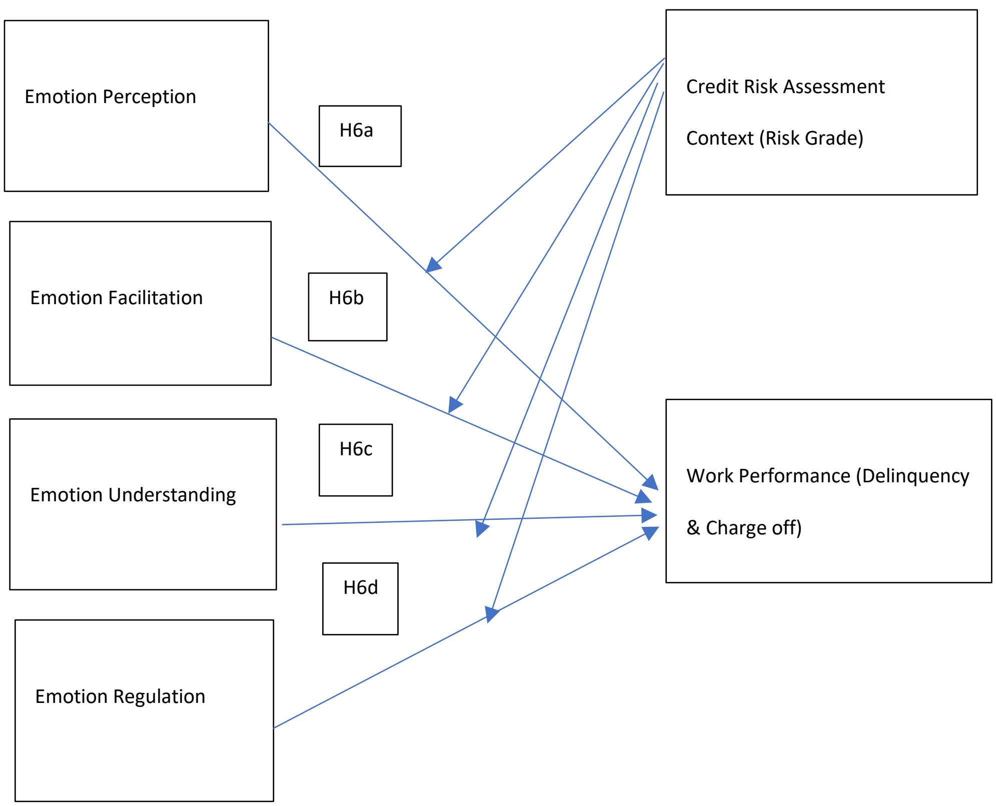

Figure 11. Moderation analysis (Source: Author).

2.8.4 H7 – Relationship between all the Emotional Intelligence Abilities and the Credit Risk Assessment and Work Performance Outcomes

Many studies have shown how EI abilities promise to perceive, facilitate, understand and regulate emotions so as to predict important personal and work outcomes (Mayer et al., 2008). However, O'Boyle et al. (2011) opine that for a predictor to extend our knowledge of a phenomenon, it must account for a variance beyond what is already accounted for by established predictors and show relative importance alongside them. The extant literature's findings in respect of EI abilities are mixed at best. This study argues that the introduction of contextual factors (moderator variable) that approximate more closely the context for the deployment of abilities is likely to improve our understanding of EI abilities as a predictor of important life outcomes. See Figure 12 below.

I therefore hypothesise that:

H7: Emotional intelligence abilities (together) moderated by credit risk assessment (risk grade) predict work performance outcomes (delinquency and charge off).
H7$_0$: Emotional intelligence abilities (together) moderated by credit risk assessment (risk grade) do not predict work performance outcomes (delinquency and charge off).

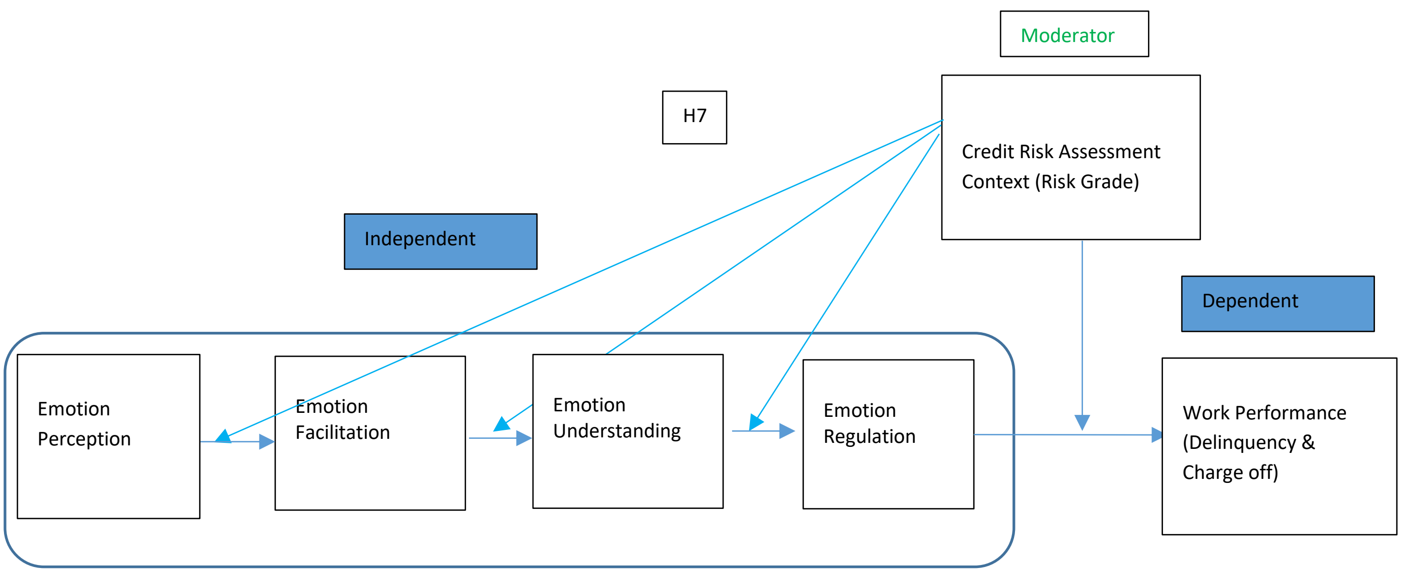

Figure 12. Moderation model (Source: Author).

2.9 CONCLUSION TO THE LITERATURE REVIEW

The literature on EI aims to build a theory of emotion and cognition. The founding scholars are to be commended for their contributions. The construct brings together two underlying concepts, cognition and emotion. Because of the construct's dual nature, several of the early debates by scholars focus on why the construct could not be classified as an intelligence. It is regarded as a contradiction in terms. Since its introduction, EI has advanced significantly to a point where scientific research has classified it as a second stratum of intelligence, at the same level as cognitive intelligence (MacCann et al., 2014; Schneider et al., 2016). According to Krueger et al.

(2009), “emotional intelligence is a distinguishing feature of human social exchange and should be viewed as complementary to cognitive intelligence and, when considered together, will provide a more complete understanding of human behaviour” (p. 22489). Indeed, the initial promise of the EI construct was that it would allow for the prediction of human abilities in various areas of life – in school, work, home and other contexts.

The introduction of EI into academic and business settings generated both an interest and a following. Scholars and practitioners alike, operating from different vantage points, have scrutinised it and contributed to its growth and development, leading to a divergence in the field (Elfenbein & MacCann, 2017). The contribution by Goleman (1995) is a case in point. A review of the extant literature shows that the divergent contributions of scholars can be grouped into three main streams:

a) **Stream 1** which is based on the Mayer–Salovey–Caruso ability model of emotional intelligence;
b) **Stream 2** which is based on the same model as in a) above, but utilises a self-report methodology; and
c) **Stream 3** which comprises ‘mixed models’. It is not aligned to the original definition of emotional intelligence and is a combination of all dimensions, including personality (Ashkanasy & Dasborough, 2015; Daus & Ashkanasy, 2005).

This divergence has resulted in a lack of consensus in terms of the key dimensions of the construct, model, measurement and outcomes. A key objective of this study is to respond to the concerns surrounding the outcomes – that is, the unexpected weakness in the relationship between the EI construct and work performance.

Many scholars have argued, and this study concurs, that the ability-based model of EI is the most theoretically valid (Ashkanasy & Dasborough, 2015; Côté, 2014; Daus & Ashkanasy, 2005; Joseph et al., 2015; Legree et al., 2014; Mayer et al., 2008; Mayer et al., 2016). It is the ‘gold standard’ because it meets the standards set for an intelligence. It is the most influential model when it comes to the operationalisation of the construct – the four-branch model. Even though the four-branch model has been challenged in terms of how the abilities match the test structure, it remains a theoretically sound model. The measurement tool, the MSCEIT V2.0, is the most advanced measure and means of operationalising the construct and model (Legree et al., 2014), even though more recent work has reopened the debate on the number of abilities (Joseph &

Newman, 2015; Mayer et al., 2016). The criticism surrounding how the abilities or problem-solving areas map to the test content continues.

The debate surrounding the results of the confirmatory factor analysis of Emotion Facilitation (branch 2) is particularly fierce and controversial. Some researchers have highlighted that this is partly due to the overreliance on one measurement instrument (Fiori et al., 2014; MacCann & Roberts, 2008). Despite the raging debate, the research results (though mixed) confirm that ability EI is a coherent construct with a hierarchical structure comprising four models: a single-factor model, a two-factor model, a three-factor model and a four-factor model (MacCann et al., 2014; O'Boyle et al., 2011). The current state of the EI field is such that, despite all these crucial endorsements of the ability-based model as the most appropriate for scientific inquiry, there is a confounding factor of predictive and incremental validity (Grobelny et al., 2021).

As much as the ability-based EI construct is theoretically strong, it remains practically weak. The key gap seems to be its weak and mixed results when the construct is used to predict an important criterion, especially the work performance criterion (Côté, 2014; Grobelny et al., 2021). The theory has fallen short of the original claims of enhancing predictive capacity. Many studies have approached this problem using the validity-generalisation research model, which emphasises bivariate (linear) outcomes between EI and criteria. Because it possibly misses the substantive associations between EI and criteria, this research model has been shown to produce weak results (Côté, 2014; O'Boyle et al., 2011). It is a model that is agnostic to context and dispositions and therefore reveals its limitations. To some extent it may offer a misleading impression of the importance of EI. This has created a paradox, in which scholars must make a choice between theory and data. At present, the best conceptualised EI construct produces unacceptable results.

To advance our understanding of the ability-based EI construct, Côté (2014) argues for the need to consider other research models. Côté (2014) advanced two alternative models for consideration: the specific-situation model and the moderator model. The current study uses the specific-situation model for reasons already mentioned. Côté's (2014) seminal contribution added to the emerging literature calling for consideration of context (for example, Cherniss, 2010; Farh et al., 2012; Jordan et al., 2010; Lievens & Chan, 2010; Ybarra et al., 2014). It argues that "the importance of EI for performance probably will vary with the job specific situation, the outcomes and the kind of people" (Cherniss, 2010, p. 122). In other words, there may be elements specific to a work environment that, when considered, may produce a strong or different relationship between the abilities and work outcomes. By answering this call, this study seeks to build on this literature. In addition, it seeks to close the gap between the early assumptions underpinning EI theory with respect to key work performance phenomena and to extend the promise of EI.

The choice of the SME credit risk assessment context, as an appropriate research setting in which to test the theory of EI, has already been argued. SME lending is relationship driven by human interactions and not merely based on an algorithmic credit score (Filomeni et al., 2021). The SME credit markets are informationally opaque and therefore uncertainty abounds. Loan officers are critical to the task of gathering soft, impressionistic information on the borrower, accurately interpreting it and incorporating it into the risk assessment process (whose outcome is unknown) (Brown et al., 2020). The loan officer's depth of experience, written and verbal motivations, and cognitive processing of the information as well as the context in which the information is collected all play a role.

It seems reasonable, therefore, to hypothesise that some loan officers may perform better than others based on their EI problem-solving abilities (Campbell et al., 2019; Wilson, 2016). Despite the advancement of credit underwriting technology, the work that SME loan officers do is directed by human effort and the outcomes are unpredictable (Filomeni et al., 2016; Filomeni et al., 2021). Therefore, we know that the work is not extruded through the building of a credit score but rather through interpretive judgements; it is also laden with emotions (Agarwal & Ben-David, 2018). What we do not know is the impact of individual differences, due to varying EI abilities, on outcomes.

Cherniss (2010) highlights that "the ability-based theory of emotional intelligence is based on three premises: (a) Individuals differ in their ability to perceive, understand, use and manage emotions; (b) Emotions play an important role in life; (c) These differences affect life outcomes differently, including the workplace" (p. 111). The proponents of EI theory promise that EI will assist with "the ability to carry out accurate reasoning about emotions and the ability to use emotions and emotional knowledge to enhance thought" (Mayer et al., 2008, p. 206). By doing so, they created a field of research and a group of scholars whose interest lies in discovering if this ability can enhance our prediction and understanding of life outcomes, especially the work performance of organisation members.

Given the unanswered question regarding the predictive validity of the ability-based EI construct, the primary aim of this study was to examine the relationship between EI and work performance and whether this relationship was moderated by context. The research question was: What is the role of emotional intelligence in terms of work performance in the SME credit risk assessment environment? Hence, the hypotheses, as summarised below, were developed to align to the research question and the identified variables.

Hypothesis 1 was developed to test the relationship between the EI branches. This foundational test is important because it is the combined integrative functioning of the branches that predicts the various outcomes.

Hypotheses 2 to 5 were developed to test whether the EI branches (Emotion Perception, Emotion Facilitation, Emotion Understanding and Emotion Regulation) individually predicted the work performance variables of delinquency and charge off.

Hypotheses 6a to 6d were developed to test whether the context (SME credit risk assessment measured using the risk grade) moderated the relationship between EI and the work performance variables of delinquency and charge off.

Hypothesis 7 was developed to test whether the EI branches acting together, moderated by the context (risk grade), predicted the work performance outcomes of delinquency and charge off.

In conclusion, the empirical results, according to extant literature, have been mediocre (Côté, 2014; O'Boyle et al., 2011). Given that the construct is strong, the model sound and the measurement tool appropriate, there have been numerous calls for a different approach to the linear research model for studying EI and its outcomes. The literature indicates that, in such instances, the introduction of a moderator variable can serve to ignite different relationships between the independent variable and outcome variable (Baron & Kenny, 1986; Muller et al., 2005; Namazi & Namazi, 2016). This study introduces a moderator (contextual variable) in the relationship between the independent and dependent variables. The application of the situation-specific research model ensures that the findings represent more than repetitions of past outcomes but instead start to show emerging phenomena and new knowledge.

3 CHAPTER 3 – METHODOLOGY

This chapter outlines the research paradigm, research design, research type, sampling procedure, unit of analysis, unit of observation and approach to data collection which were selected for this research. Thereafter, it comprehensively discusses the analytical approach, assumption checks, exploration of the data and inferential statistics. The chapter ends with a discussion of quality assurance and the approach to ethics adopted.

3.1 RESEARCH PARADIGM

According to Creswell (2013), “philosophy means the use of abstract ideas and beliefs that inform our research” (p. 16). He adds that the research paradigm “guides the researcher in philosophical assumptions about the research and in the selection of tools, instruments, participants, and methods used in the study” (p. 12). The research paradigm therefore reflects the assumptions as well as the distinct methods or procedures that the researcher chooses to follow. Clearly, it is a perspective that researchers carry into their research, which is both rooted in their training and reinforced by the scholarly community in which they work (Aliyu et al., 2014; Mackenzie & Knipe, 2006). It informs which research problems to study, how to go about studying these problems and how to add knowledge through the study. Consequently, the paradigm adopted in this study is reflective of my influences and philosophical assumptions as a researcher.

For the purposes of this study, I adopted a post-positivist research orientation. Aliyu et al. (2014) make a crucial distinction between positivism and post-positivism. Positivists believe in the traditional notion of the absolute truth of knowledge. They believe in strict cause and effect. This approach has been criticised for its inability to fully comprehend phenomena due to a reliance on independent realism. Post-positivists, in contrast, believe that the truth we obtain through scientific paradigms is our truth, and therefore we cannot claim to be positive when studying human behaviour and action (Scotland, 2012). In other words, truth remains tentative. In practice, however, the key elements of post-positivist research are reductionist, logical, empirical, cause-and-effect oriented and deterministic, based on a-priori theories (Aliyu et al., 2014; Mackenzie & Knipe, 2006). Hence, the problems studied by post-positivists reflect the need to identify and assess the causes that give rise to outcomes. This study therefore focused on the influence of emotional intelligence on work performance outcomes.

With this in mind, I researched observable and measurable latent variables. EI is a latent variable (MacCann, 2010). The intention, therefore, was to study a latent but not directly observable human ability. This is in keeping with intelligence tests and design protocols (Mayer, 2015). In conducting the study, I was of the view that an important epistemological foundation was causal adequacy. Thus, the focus of the study on EI's ability to influence work performance outcomes when work context is considered. The key requirements were objectivity, replicability and generalisability of the study.

3.2 RESEARCH DESIGN

The research design has been described as a blueprint for how the research will be conducted (Mackenzie & Knipe, 2006). It serves to answer the questions: What kind of study will be conducted? What type of study will best answer the question formulated? And what kind of evidence is required to address the research question adequately? Hence the research question: What is the role of emotional intelligence in terms of work performance in the SME credit risk assessment environment?

The research design adopted in a study is a culmination of the research philosophy, and research methods, which reflect either a quantitative or a qualitative approach (Mackenzie & Knipe, 2006). In part, this study tested an existing theory. The key issue of concern with this area of research was the unanswered questions relating to the outcomes or utility of the ability-based EI construct and its suitability for answering the outstanding questions about predictive and incremental validity (Grobelny et al., 2021; Miners et al., 2018). Based on the research problem, I made the call for a deductive approach. The research approach was suitable because the research procedure was guided by the EI theory that had already been developed (Mayer & Salovey, 1997). Accordingly, the variables specified in the conceptual model (section 2.8.4) were extracted from theory (sections 2.2 to 2.8) and the research question (section 1.4) and the hypotheses were related to the identified variables.

The overall research design for the study was quantitative. According to Quick and Hall (2015), "quantitative research is an approach for testing objective theories by examining relationships among variables" (p. 192). This approach was therefore deemed appropriate for this study. Hence, the independent variable (emotional intelligence) was measured using an existing instrument (MacCann et al., 2014). Additionally, the dependent variable (work performance) and the moderator variable (credit risk assessment) were measured using the bank's proprietary database, which was hard to obtain (required signing of an NDA – Appendix D) but adequate for measuring the work of loan officers (Campbell et al., 2019; Filomeni et al., 2016). Several precautions were built into the study, including: non-response error, non-response bias, controlling for alternative explanations, and ensuring that the results could be generalised and the findings replicated.

Quantitative research with a post-positivist worldview originated largely in psychology (Aliyu et al., 2014). This study follows in the footsteps of similar studies. Thus, the strategy of inquiry applicable to this study was correlational design. In this type of study, explains Creswell (2014), "investigators use the correlational statistic to describe and measure the degree or association (or relationship) between two or more variables or sets of scores" (p. 12). This study aimed to investigate the correlation between EI and work performance, moderated by a credit risk assessment context. The justification for the choice of technique for this study is provided in section 3.11.2 on regression methods.

3.3 RESEARCH TYPE

This was an explanatory study. An explanatory study sets out to explain a relationship between variables by subjecting the variables to statistical tests. Often the researcher has observed something, and they wish to develop a better understanding of it than what they have gleaned from existing theory. In this study, I sought to do the same. The study covered the period 2018–2019, prior to the advent of the global Covid pandemic in March 2020. This avoided any possible spurious effect on the results, given the distorting effect of the pandemic. Most studies looking at post-loan issuance performance are cross-sectional in nature and this study followed in those footsteps (Campbell et al., 2019; Filomeni et al., 2016).

3.4 POPULATION AND SAMPLING

3.4.1 Population

A study's research population influences the generalisability of research results to an applicable domain. The target population for this study was the 300 bankers or loan officers in a major bank in South Africa. These loan officers were selected as they were in the SME segment and, for the period of the study, were involved in the processing of loan applications. They directly engaged and interacted with borrowers in the segment and therefore collected impressionistic or ‘soft information’ about them (Campbell et al., 2019; Filomeni et al., 2016; Wilson, 2016). In assessing credit risk, they had to incorporate into the approval process information about the borrower other than hard, quantifiable information. The loan officers were based in all nine provinces in South Africa and were spread across the bank’s 600+ branches. Some were located in the branches, while others were in the suites with borrowers or customers who either walked in or made telephone contact to discuss their borrowing needs.

All the loan officers in the population were employed on a full-time basis by the bank. They were paid a basic salary and earned an annual bonus on the basis of how they had performed against targets, which were linked to volume as well as the performance of the loans. In terms of the bank’s organisational hierarchy, the loan officers were regarded as junior management staff who played a critical role in the growth of the bank’s loan book and therefore its profitability.

3.4.2 Sample Frame

A sample frame is defined as “…. a list of elements from which a sample may be drawn…” (Zikmund et al., 2009, p. 391). This study used a single organisation sample frame, which means that it focused on only one of the four major banks in South Africa. This was a pragmatic move considering the costs and hurdles associated with accessing employee (loan officer) and client (borrower) information in the wake of the Protection of Personal Information Act 4 of 2013 (POPIA). The sampling design for the population was single stage. According to Quick and Hall (2015, p. 193), “a single stage sampling procedure is one in which the researcher has access to names in the population and can sample the people (or other elements) directly”.

3.4.3 Sampling Procedure

Sampling can be defined as the process through which individuals or sampling units are selected from the sample frame (Martínez-Mesa et al., 2016). For this study, a complete list of the population was obtained and confirmed using the bank’s database. Owing to the manageable size of the population within one organisation and relatively low hurdles associated with reaching them, I adopted the census approach (Martínez-Mesa et al., 2016). As a result, all members of the population who met the criteria were invited to participate in the study. The criteria for participation related to the whether the member of the population was still occupying the position of loan officer at the time the study was conducted. This was necessary for the purpose of ensuring that data on the loan officer and borrowers linked to them could still be extracted from the bank source system. I did not use any form of stratified sampling because the study adopted the census approach, but for practical reasons I excluded those who were no longer in the role. This process delivered the target population of 300 loan officers.

Even though it was relatively easy to obtain the complete list of the population, it was nevertheless difficult to confirm the final list. This is because of the bank's continuous improvement efforts, which have resulted in people being moved around to different parts of the bank for personal growth and other, organisational reasons.

3.4.4 Sample Size

A study's sample size is important because it can affect the statistical tests, either by making them insensitive (with small sample sizes) or overly sensitive (with very large sample sizes) (Hair et al., 2014). However, the matter of the sample size estimation technique has become a much-debated topic in research, with many authors offering views on the heuristics thereof (Schoemann et al., 2017; Siddiqui, 2013). Morton et al. (2014) highlight that in the 21st century mere reporting on the response rate may not be enough to assess the validity and utility of studies. Instead, they argue that, accompanying the sample size discussion, researchers must elaborate on the study context and the key study elements, such as recruitment, insights on participants and non-participants, participants' interest in the study question and efforts made to raise the response rate, among others (Morton et al., 2014). In line with this guidance, in the paragraphs below I set out the context for the collection of the data and the process followed for the administration of the psychometric tests.

The context for the study was a high-pressure and high-stakes environment. The loan officers had a one-week window in a calendar month when they were not pursuing targets but performing their administrative tasks to ensure that the business came in on time. This left them with very little time to conduct the psychometric tests. Hence, this affected both the surveys received and the usable surveys received – the result of a high non-completion rate of the full battery of psychometric tests. Furthermore, the population was not accustomed to participating in research and completing psychometric tests. Even though this was considered in the design of the recruitment communication and at the meetings with the department leadership team to ensure a strong response rate, the factor clearly still had an adverse impact.

The administration of the tests (Appendix C) covered a period of three to four months and followed a four-step process: First, I sent a short introductory letter to all members of the population, explaining the purpose of the study with a question and answer (Q&A) section attached. Second, approximately three days later, I sent a follow-up letter to the population inviting them to participate, with a hyperlink to the tests. The letter provided the rules of participation and an explanation of each of the tests. Further, it outlined the rules regarding consent, anonymity and confidentiality. Third, after a slow response rate and, based on the advice of the senior management in the bank, I scheduled meetings with the middle managers of the loan officers to encourage participation. Despite taking this last step, approximately four weeks later the responses were still not satisfactory. Finally, I approached the executive management to ask for their help in encouraging the loan officers to participate. The executive management used the same email that was sent in step 2 above to encourage participation. This intervention worked as the number of responses increased to the minimum threshold required for the data analysis technique.

According to Siddiqui (2013), the sample size determination for regression analysis should be 15 to 20 observations for each predictor variable. This rule of thumb – as applied to this study – means that the sample size should be between 60 and 80 for the four EI problem-solving areas (branches). The sample size, shown in Table 1 below, was 70 – a reduction from the 106 surveys received due to some surveys being unusable as a result of incomplete data. Given that loan officers operate in a high-performance and high-stakes environment, together with the multiple attempts that were made to secure cooperation, the response rate of 35.3% is deemed appropriate. However, because of the sample size, the power tests could not be performed and the hypothetical structure of the conceptual model (Figure 12) could not be tested (Raykov & Marcoulides, 2008).

Table 1. Summary of population, sample size and response rate.

Survey Questionnaires	Respondents
Surveys sent out	300
Surveys received	106
Usable surveys received	70
Response rate	35.3%

3.5 UNIT OF ANALYSIS AND UNIT OF OBSERVATION

According to Sedgwick (2014, p.1), “The unit of observation sometimes referred to as the unit of measurement is defined statistically as the ‘who’ or ‘what’ for which data are measured or collected. The unit of analysis is defined statistically as the ‘who’ or ‘what’ for which information is analysed and conclusions are made”. This is set out below.

As the primary purpose of the study was to understand the EI of the loan officers and the relationship with work performance, the unit of analysis for the research was therefore the loan officers who, as described above, were at the time employed by the bank and participated in the SME credit risk assessment process. They were the ‘who’ for which information was analysed and conclusions were drawn (Sedgwick, 2014). The unit of observation, on the other hand, was the loans that were manually approved (that is, not approved via the automated scorecard system), which the loan officers were instrumental in guiding through the credit approval process. This was the ‘what’ for which data were measured or collected (Sedgwick, 2014). The loans that were automatically approved were excluded from the investigation as there would have been no opportunity for the loan officers to apply EI abilities.

3.6 DATA COLLECTION METHODS

To test the hypotheses and answer the research question, the data collection methods were aligned to the variables under investigation. The conceptual framework (see Figure 12) proposes three main variables: (a) Emotional intelligence as the independent variable; (b) Work performance, as measured by delinquency and charge off as a proxy for post-issuance loan performance, as the dependent variable; and (c) the SME credit risk assessment context, as measured by the risk grade score, as the moderating variable. Furthermore, the framework proposes the following demographic and non-demographic control variables: (a) demographic variables – age, gender, race and tenure; and (b) non-demographic variables – cognitive ability, personality traits and repeat lending. Both primary and secondary data sources were used for the study. I confined the analysis to those respondents for whom I had complete primary data records.

The next section outlines how the variables were operationalised.

3.7 OPERATIONALISATION OF VARIABLES

This section outlines how each of the main variables in the study was operationalised. Furthermore, the section provides a summary of the three main variables and the control variables, which illustrates how the variables and the data collection methods are linked.

3.7.1 Independent Variable – Emotional Intelligence

As motivated in the literature review, EI is best measured using ability or performance tests (Mayer et al., 2016; Miners et al., 2018). To reiterate, Carroll (1993) defines ability as "the possible variations over individuals in the liminal [threshold] levels of task difficulty ... at which, on any given occasion in which all conditions appear to be favorable, individuals perform successfully on a defined class of tasks" (p. 8). It follows, therefore, that the data on levels of EI problem-solving abilities were collected by asking the sample to participate in a performance test.

To measure the independent variable of EI, the Mayer–Salovey–Caruso Emotional Intelligence Test – MSCEIT V2.0 – was utilised because it has been endorsed by the majority of scholars as the most valid and reliable test of this construct (e.g., Dasborough, 2019; Legree et al., 2014; MacCann et al., 2014; Mattingly & Kraiger, 2018; Mayer, 2015; O'Boyle et al., 2011; Sanchez-Garcia et al., 2015). The scientific validity and reliability scores of the test point to an instrument that is meaningful and useful because of its reliability, so that inferences can be drawn from it (Mayer et al., 2012). Furthermore, it has been shown to have acceptable internal consistency. The test's internal consistency reliability (split-half), as indicated in the manual, is $\hat{r} = .93$ and this has been confirmed through empirical tests (Fiori et al., 2014, Miners et al., 2018). The test–retest reliability is $\hat{r} = .86$ (Brackett & Mayer, 2003). Finally, in one of the most comprehensive meta-analyses, O'Boyle et al. (2011) concluded that the instrument was suitable for measuring individual differences in relation to the ability-based EI construct. Importantly, although lower than stream 2 (self-report ability measure), it was relatively important as a predictor of job performance (Grobelny et al., 2021). Figure 13 below shows the four branches (problem-solving areas) of EI extracted from Brackett and Salovey (2006).

Table 2
The four-branches of emotional intelligence measured by the MSCEIT

Emotional Intelligence Measured by the MSCEIT			
Branch 1: (Perception of emotion)	**Branch 2: (Use of emotion to facilitate thinking)**	**Branch 3: (Understanding of emotion)**	**Branch 4: (Management of emotion)**
Task 1: Faces Participants view photographs of faces and identify the emotions in them	*Task 3: Sensation* Which tactile, taste, and color sensations are reminiscent of a specific emotion?	*Task 5: Blends* Which emotions might blend together to form a more complex feeling?	*Task 7: Emotion management* How effective alternative actions would be in achieving a certain outcome, in emotion-laden situations where individuals must regulate their feelings
Task 2: Pictures Participants view photographs of faces and artistic representations and identify the emotions in them	*Task 4: Facilitation* How moods enhance thinking, reasoning and other cognitive processes	*Task 6:Changes* How emotions progress and change from one state to another	*Task 8: Relationship management* Test-takers evaluate how effective different actions would be in achieving an emotion-laden outcome involving other people

Figure 13. MSCEIT four-branch model tasks (Source: Brackett & Salovey, 2006).

I obtained permission to use the test, which is copyright-protected intellectual property, from the test developer and owner, Multi-Health Systems (MHS), based in Canada. MHS, which owns the marketing and distribution rights, charged me a nominal research student fee of $6 for each completed test. MHS then referred me to the leading psychometric testing company in South Africa, JvR Psychometrics, to assist with the administration of the test.

The underlying MSCEIT factor structure has been the subject of much controversy in the scientific literature (Sanchez-Garcia et al., 2015). Despite the ongoing debate, the full battery was administered. The MSCEIT V2.0 tool was structured to measure all four factors. Sanchez-Garcia et al. (2015, p. 2) point out that “in general the MSCEIT yields 15 scores: a total score, two area scores (experiential and strategic), four branch scores (corresponding to the four-branch model), and eight task scores”. However, for data analysis purposes, the study used a single-factor score representative of an overall EI score and a four-factor score for each of the four branches. A total of five scores were used (see the structure in Figure 14 below).

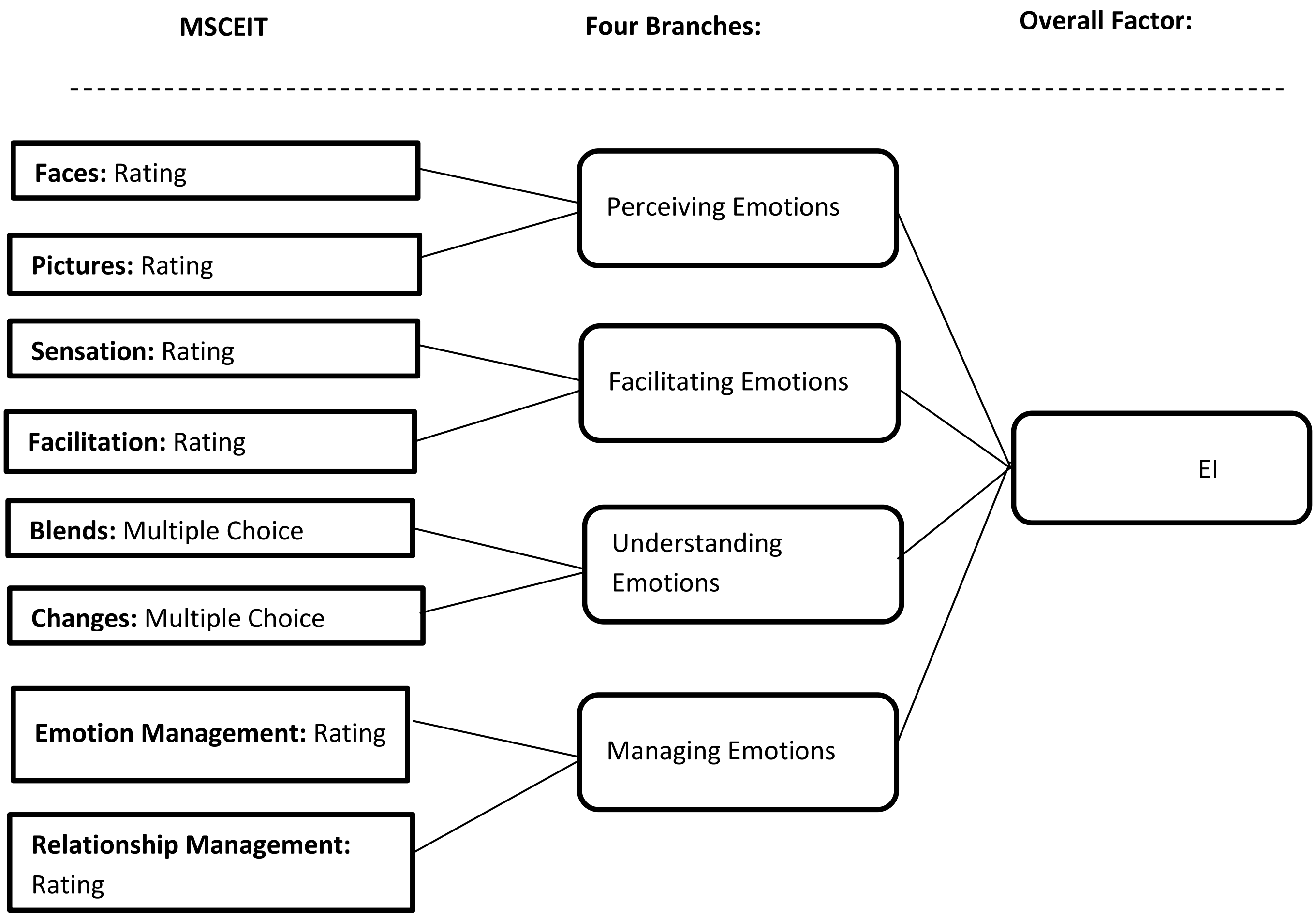

Figure 14. MSCEIT structure (Source: Adapted from Sanchez-Garcia, Extremera & Fernandez-Berrocal, 2015).

The eight sub-tests measuring Emotion Perception, Emotion Facilitation, Emotion Understanding and Emotion Management are described in more detail in Appendix B (MSCEIT V2.0 Questionnaire). The full test battery had 141 items, with six of the sub-tests using a Likert-type rating scale ranging from 1 (not at all present/effective) to 5 (very much present/effective) and the other two using a multiple-choice format.

The MSCEIT was developed specifically to address criticisms that it did not match other intelligence tests that use right or wrong answers. As a result, it uses an objective-style test with right or wrong answers, as in a traditional intelligence test. In terms of the scoring rubric, there are two options: consensus and expert. Prior studies have shown that the two scoring methods are highly correlated: $\hat{r}$ = .96 to .98, respectively (Mayer et al., 2008; Mayer et al., 2012). As previous studies supported the use of consensus scoring, this study used consensus scores, both for theoretical and empirical reasons, in addition to other alternative scoring methods (MacCann et al., 2014). Consensus scores reflect the proportion of people in the normative sample (over 5000 people from various parts of the world) who endorsed each MSCEIT test item (Brackett & Salovey, 2006; MacCann et al., 2014).

This test, plus the other two psychometric tests of cognitive intelligence and personality, were administered under the supervision of Dr Nicola Taylor, Director: Data Enablement at JVR Psychometrics, who is a qualified psychometrist with the Health Professions Council of South Africa (registration number PMT0073679). I disseminated the test electronically using an email with Dr Taylor's signature. The test was then self-administered by the respondents, which removed any possibility of bias and obviated the need for physical collection.

3.7.2 Dependent Variable – Work Performance

As discussed earlier, the dependent or outcome variable was work performance. In line with Grobelny et al. (2021), work performance referred to task performance, was outcome related instead of behavioural and used an objective measure. To measure it, this study used post-issuance loan performance, as measured by delinquency and charge off, as a proxy for work performance (Campbell et al., 2019). To reiterate, post-issuance loan performance or loan quality is a critical, adverse indicator of the outcome of the credit risk assessment performed on the borrower at the time the loan is granted (Brown et al., 2020; Campbell et al., 2019; Filomeni et al., 2016). Charge-off measures relate to whether a loan has been charged off during the period under review, while delinquency measures relate to whether the borrower has defaulted on the loan (Campbell et al., 2019; Chen et al., 2015; Filomeni et al., 2016). As has already been established, these measures have a very strong association with the quality of the loan officers' decisions or their work performance. The loan officers, when motivating for the approval of credit, have no certainty about the outcomes of these measures, yet they understand that they are important for post-issuance loan performance.

The data for the dependent variable were collected using the bank's proprietary systems and quality checked by the Head of Data Governance. The data covered borrowers linked to the loan officers and were therefore confidential. I signed a non-disclosure agreement (see example in Appendix D), approved by the bank's executive management, head of compliance and data privacy structure, to gain access to the borrower and loan officer data and to use them only for the purposes agreed. Owing to the confidential nature of the bank data, they were anonymised and aggregated before given to me and JVR Psychometrics. I had undertaken to handle the data with due care and diligence. See Appendix D in which the bank confirmed its willingness to make the data available and to assist in their compilation so that the requirements of the study could be met.

This study followed earlier studies which measured post-issuance loan performance using these proxies. Such studies showed that loan quality is best measured by a loan's adverse post-issuance performance (Agarwal & Hauswald, 2010; Brown et al., 2020; Campbell et al., 2019; Filomeni et al., 2016). The two loan quality measures, as explained, were delinquency and charge off. According to the bank's credit policy, a loan is defined as charged off when payment has been outstanding for 180 days (six months) and the matter has been transferred to the legal department for collection. Delinquency, on the other hand, according to the bank's policy, is when a borrower has fallen behind on their payment for a single day after the agreed payment date. Essentially, it is any instance in which a loan is one day past its repayment due date – irrespective of whether the loan has not been paid in full or has been partially paid.

The moderating variable data for the loan applications being investigated were extracted from the bank's systems. The scores were calculated using Excel and then the R software for loan applications that were approved manually. In other words, for these applications straight-through processing did not occur; instead, the loan officers were required to put forward a recommendation for the credit to be approved. Furthermore, the approved loan application should have been taken up by the borrower for it to be in the loan officer's portfolio. For the individual applications that qualified, I assigned to each loan officer a score reflecting their post-loan issuance performance as a proxy for their work performance. It was hypothesised that the mean delinquency and charge-off scores for borrowers in the portfolio or linked to a loan officer constituted individual differences that were significant and could be explained by the differences in their EI scores.

3.7.3 Moderating Variable – Credit Risk Assessment

I argued in section 2.8.1 on credit risk assessment for SMEs that loan officers face significant asymmetry of information when performing credit risk assessments for the SME lending market (Agarwal & Ben-David, 2018; Filomeni et al., 2016). Credit markets for SME lending require much more than hard information to come to the right decision; they require soft information which is hard to obtain and expensive to collect (Agarwal & Ben-David, 2018; Campbell et al., 2019; Filomeni et al., 2016). They are expected to avoid both Type I errors (where the loan officer rejects high-quality loans) and Type II errors (where the loan officer approves low-quality loans), even though there is incomplete information. The assessment of risk in this context requires that much more reliance is placed on the borrower characteristics than on the enterprise's hard information. Loan officers are expected to accurately interpret and reflect soft information (Campbell et al., 2019; Chen et al., 2015). I further argued that the lack of hard information creates uncertainty about the outcome of the post-issuance loan performance until it is confirmed ex-post facto using loan quality measures. Hence, the risk grade score is an early indication of the probable post-issuance loan quality of the borrower.

This study classified the risk grade score as a moderator. Individually this variable is not a predictor of EI. From a methodological perspective, Ro (2012) states that "the moderator is a third variable which could affect the amount of correlation and/or change the direction of the dependent and independent variables" (p. 957). In other words, this variable affects the potency or strength of the relationship between the independent and dependent variables. More importantly, the moderator in this study was conceptualised as a contextual variable, which means that the mediating process between EI and work performance varies as a function of the loan officers' credit risk assessment (Muller et al., 2005). Because it was also an individual difference variable, the work performance outcome was meant to be different for loan officers who differed on this contextual variable.

As stated above, the risk grade score is an algorithmic score based on the borrower's historical financial behaviour and is meant to alert the bank as to the creditworthiness of the borrower. The borrowers were assigned scores between 1 and 5, with 5 being the riskiest category of borrower. Each assigned score considered the borrower's income statement and balance sheet ratios, including data points like repayment history. In describing the score, Filomeni et al. (2016, p. 3) point out: "The outcome is summarized in a numerical score/rating that typically reflects a firm's probability of defaulting over a given time span". It is not possible for loan officers to change the overall risk grade rating or score. However, they can challenge it where they have information that clarifies any discrepancies or better explains the reasons for the score. An acceptable risk grade score is not a guarantee that the borrower will automatically be approved for the loan, as there may be other requirements that must be fulfilled before a loan can be approved. However, a bad score will almost certainly require further motivation.

The moderating variable data for the loan applications under investigation were extracted from the bank's systems. The risk grade score of the borrowers in the loan officers' portfolio of customers was calculated on the basis of the mean score for all the applications that qualified. It was hypothesised that the mean risk grade score for customers in the portfolio or linked to loan officers was an area of significant individual difference and could be explained by the difference in their EI scores. However, the lack of variability in the data limited this statistical analysis and the insights that could be gained.

All the data collection methods applied in this study, as outlined in the conceptual model (excluding the control variables), are highlighted in Table 2 below. The key variables were carefully linked to the data collection methods to ensure conceptual model parsimony.

Table 2. Summary of the variables, hypotheses and data collection method (Source: Author).

Analysis Type	Hypothesis	Data Collection Method
Mediation Analysis	**H1**	• Refer to Task 1, Faces and Task 2, pictures of the MSCEIT sub-scales. • Refer to Task 3, Sensations and Task 4, Facilitation of the MSCEIT sub-scales. • Refer to Task 5, Blends and Task 6, changes in the MSCEIT sub-scales. • Refer to Task 7, Emotion Management and Task 8, relationship management of the MSCEIT sub-scales and bank database.
	H2	• Refer to Task 1, Faces and Task 2, pictures of the MSCEIT sub-scales and bank database (delinquency and charge off).
	H3	• Refer to Task 3, Sensations and Task 4, Facilitation of the MSCEIT sub-scales and bank database (delinquency and charge off).

Analysis Type	Hypothesis	Data Collection Method
	H4	• Refer to Task 5, Blends and Task 6, changes in the MSCEIT sub-scales and bank database (delinquency and charge off).
	H5	• Refer to Task 7, Emotion Management and Task 8, relationship management of the MSCEIT sub-scales and bank database (delinquency and charge off).
Moderation Analysis	**H6a, b, c, d**	• Refer to Tasks 1, 2, 3, 4, 5, 6, 7 and 8 of the MSCEIT sub-scales and bank database for risk grade score (overdraft and term loan)
Moderation Model Analysis	**H7**	• Refer to Tasks 1, 2, 3, 4, 5, 6, 7 and 8 of the MSCEIT sub-scales and bank database for risk grade (overdraft and term loan) and for work performance (charge off and delinquency).

3.7.4 Control Variables

Control variables that are not taken care of or are omitted could possibly become a source of bias, thus confounding the validity of the study. The objective behind the inclusion of control variables in the study was to eliminate alternative explanations for the results (Chen et al., 2015; Filomeni et al., 2016; Mayer, 2015; Ro, 2012). Côté (2014) highlights the best practice for control variables to be included in ability-based EI academic studies as: cognitive intelligence, the Big Five personality traits (neuroticism, extraversion, conscientiousness, openness and agreeableness) and demographic factors. Furthermore, Côté (2014) encourages researchers to look for more relevant control variables which are specific to the context and criterion of interest in a study and to measure them. In line with this guidance, I identified further control variables unique to the SME credit risk assessment context. The key question that emerges is whether EI remains a statistically significant predictor of outcomes after controlling for the specified variables.

Some studies have found differences in EI attributable to gender (Dasborough, 2019; MacCann, 2010; Mattingly & Kraiger, 2018) and others have measured racial differences (Joseph & Newman, 2010). Accordingly, this study controlled for the following demographic variables: age, gender and race. An additional demographic variable that was included, which was unique to the current study context of credit risk assessment, is job tenure or experience (Agarwal & Ben-David, 2014; Beck et al., 2013; Bellucci et al., 2010).

In other loan officer studies, a non-demographic variable that was included, and that was relevant to the criterion of interest, was repeat lending (Campbell et al., 2019). This is a loan or firm-specific variable that distinguishes between existing and new relationships between the loan officers and borrowers and is worthy of measuring because it may capture the degree of accessibility and transmission of soft information which is uncoded (Chen et al., 2015; Filomeni et al., 2016). This study-specific variable has been found to be relevant because of higher information asymmetry problems for the loan officer between new and existing borrowers (Chen et al., 2015). On its own it is not a known predictor of work performance but if not controlled for it could affect the results. The EI-specific, non-demographic control variables that were measured are cognitive intelligence and personality traits. It is crucial that both these variables are controlled for because individually they have been found to be relevant predictors of work performance (O'Boyle et al., 2011; Sanchez-Garcia et al., 2015).

To measure cognitive intelligence, a short but appropriate test was used in the study – the Matrigma, which comprises 30 items and takes about 20 minutes to complete (Côté & Miners, 2006). The test score for internal reliability is good at $\hat{r} = .74$ and shows a high correlation with other cognitive intelligence tests, for instance $\hat{r} = .74$ with the Weschler Adult Intelligence Scale and $\hat{r} = .74$ with the General Aptitude Test Battery.

The results of a previous study showed that the Big Five traits and MSCEIT scores were not significantly related; neuroticism ($\hat{r} = -.17$), extraversion and conscientiousness ($\hat{r} = .12$) and openness ($\hat{r} = .18$), with only agreeableness ($\hat{r} = .25$) moderately associated (Mayer et al., 2016). In a ground-breaking study, Joseph et al. (2015) found that mixed-EI measures, due to their use of heterogeneous domain sampling, were a significant predictor of work outcomes. Hence, there was a need to control for these traits. The current study used the Basic Traits Inventory (BTI) test to measure personality traits.

Like the MSCEIT V2.0, the instruments measuring cognitive ability and personality traits were administered under the supervision of JvR Psychometrics. The latter company also did the scoring and generated the results under their licence.

The data collection methods for the control variables that were applied in this study, as outlined in the conceptual model, are highlighted in Table 3 below. The control variables were carefully linked to the data collection methods to ensure that confounding explanations were eliminated.

Table 3. Summary of data collection methods used for control variables (Source: Author).

Control Variable Name	Data Collection Method
Demographic variables: • Age (in years) • Gender • Race • Tenure (in years)	Data collected as part of the completion of the main test, the MSCEIT V2.0 battery
Cognitive intelligence	Refer to survey instrument – Matrigma
Personality traits (Big Five)	Refer to survey instrument – BTI
Repeat lending	Data obtained from the bank's internal systems

3.8 ANALYSIS

This section discusses the analytical approach applied to the collected data and the statistical tools employed. Before the data analysis design was finalised, I sought input from an expert statistician for some of the design and implementation aspects.

3.8.1 Software

All analyses were performed using R (R Core Team, 2021), an open-source programming language often used for statistical analysis. The reason for choosing R over other commercial statistical packages (e.g., SPSS) was that R allowed for much finer control over the steps involved in the analytical process and was more capable of producing detailed outputs and visualisations. R also facilitated the data-cleaning stages of the analysis by allowing repetitive tasks to be automated. The added benefit was that the cleaning processes were documented in scripts for reproducibility.

3.8.2 Data Preparation

Given the confidentiality of the research and the multiple parties involved in the data collection process, the data preparation and editing involved several steps:

1. The data for the demographic, moderating (risk grade) and dependent variables (delinquency and charge off) were extracted from the bank's source systems and transferred onto an Excel spreadsheet by the bank's management information (MI) team.

2. The same team assigned to each loan officer at an individual borrower level in their loan book portfolio the relevant scores for the period under review. This step entailed a significant amount of cleaning up and checking of the data for accuracy.

3. The completed Excel spreadsheet, which did not show borrower identifiers but did show loan officer identifiers, was then transmitted by the bank's MI team directly to JVR Psychometrics.

4. Upon receipt of the Excel spreadsheet, JVR assigned psychometric scores to each loan officer where they had completed a test by matching their name and surname from the psychometric test results to the Excel spreadsheet. This step involved a significant amount of cleaning up as sometimes the official name and surname in the bank's system were not the same as those used by the respondent in the psychometric test. In a few instances, the human resources function of the bank had to get involved to confirm the accuracy of the information.

5. It became clear during the JVR data-matching and assignment process that out of the approximately 106 initial respondents, not all had completed all three psychometric tests in full. Some had completed one or two out of the three tests.

6. Thus, from the initial 106 records, 70 respondents had a full set of psychometric test results. A full data analysis was conducted on these records and is the basis for the results reported in Chapter 4.

3.8.3 Coding of Variables

All data were coded and converted to the appropriate data types prior to the analysis. This typically involved: (a) assigning numeric values to categorical variables; (b) ensuring numeric values were indeed stored as integer and float values, where required; and (c) ensuring null values were correctly set to represent the absence of a value.

3.8.4 Confirmatory Factor Analysis

Raykov and Marcoulides (2008, p. 279) highlight that, "in CFA, one is not concerned with 'discovering' or 'disclosing' factors as in EFA, but instead with quantifying, testing and confirming an a priori proposed (preconceived) or hypothetical structure of the relationship among a set of considered measures". This study used the well-established MSCEIT V2.0 instrument to collect the independent variable data. The MSCEIT's factor structure has been well tested and there was no need to test it here (Gignac, 2005; O'Boyle et al., 2011; Rossen et al., 2008; Sanchez-Garcia et al., 2015). Furthermore, due to the sample size, the hypothetical structure of the conceptual model (Figure 12) was not tested (Raykov & Marcoulides, 2008).

3.8.5 Statistical Methods

Many of the common analytical methods employed in research methodologies fall under the branch of parametric statistics, like Student's t-tests. Such methods rely heavily on a set of assumptions regarding the shape of the distributions in the underlying populations and the form of the assumed distributions which, if violated, can result in inaccurate estimates in the statistical processes. These assumptions are generally not satisfied in practice, resulting in a serious practical problem that renders these conventional methods unsatisfactory.

There are, however, more modern, robust methods of analysis (not to be confused with non-parametric procedures) that have substantially greater statistical power and yield more accurate estimates than traditional approaches (Wilcox, 2017). The issues that plague conventional methods, such as violations in normality and the presence of significant outliers, for example, impact robust estimates significantly less than their parametric counterparts (Wilcox, 2017).

Therefore, all parametric assumptions were checked, prior to any statistical methods being performed, to inform which methods would be best to apply in the light of the objective. Such assumption checks generally involve a series of hypothesis tests. The results from these tests are reported on in their respective sections in Chapter 4.

3.8.6 Post Hoc Procedures

Post hoc procedures were generally employed where necessary to control for the familywise error rate, thus ensuring that the probability of one or more Type I errors was at most α when testing multiple hypotheses. It is common practice to apply a Bonferroni correction whereby each hypothesis test is performed at the α/N level, where N is the number of tests being performed. Although this technique is satisfactory, there are alternative approaches that provide higher statistical power. The Bonferroni method was avoided because power can often be poor, given that each hypothesis test is performed at a very small α level. Instead, I opted to use k-FWER procedures using Holm's (1979) method (Wilcox, 2017).

For the purposes of this study, *p*-value adjustments were made when the methods employed were from the same test family on the same sample set.

3.9 ASSUMPTION CHECKS

Many statistical techniques assume certain characteristics of a collection of data, and often it is necessary for these underlying assumptions to be checked. The two core assumptions that were checked in the present study were the assumption of no significant outliers within the data and the assumption of normality. Additional test-specific assumptions were also checked and are discussed in section 4.2.1 of this thesis.

3.9.1 Outliers

Careful consideration was given to strategies to remove outliers since approximately 34% of the sample was excluded after the data collection phase because of incomplete data. It was paramount that any outlier removal technique employed limited the number of records excluded. This was to prevent the overall sample size being reduced too much, thus limiting the loss of statistical power.

A common approach to tackling outlier removal is to apply the box plot rule which sets out when an outlier should be removed. However, this rule has been criticised for declaring too many points as outliers, especially when there is skewness (Wilcox, 2017). Instead, an adjusted box plot procedure, as proposed by Hubert and Vandervieren (2008), was used to determine which data points were outliers.

3.9.2 Normality

One primary assumption that underlies many parametric statistical procedures is that of normality. To test for this assumption, I used the Shapiro–Wilk (1965) test of normality in combination with visually examining the underlying distributions of the variables in this study.

The results are presented in section 4.2.2 and differ for each of the variables as follows: the BTI results showed normal distribution; for the MSCEIT, the distributions were normal except for Emotion Regulation; for Matrigma, the distributions were non-normal; for work performance and for credit risk assessment, the distributions were non-normal.

3.10 EXPLORING THE DATA

The biographical data and independent/dependent variables were all explored prior to the inferential statistics to gain a general overview. The sections that follow describe the techniques used for this exploration.

3.10.1 Descriptives

A series of descriptive statistics were computed to gain an overview of the different variables in the study. Robust estimates for measures of location and scale were computed in addition to standard descriptive metrics that are commonly reported.

Standard arithmetic can suffer from non-normally distributed data, specifically when the tails of said distributions dominate their value (Wilcox, 2017). Outlying data points can often shift the mean, giving an inaccurate representation of where the central tendency may lie. To overcome this challenge, winsorised means were instead employed along with winsorised variances. This method deals with the problem of significant outliers affecting the estimates by giving less weight to the values in the tails and instead giving more focus to values nearer the centre of the distribution (Wilcox, 2017).

In addition to the robust descriptive metrics mentioned above, the min, max, range, skewness and kurtosis were calculated for each variable. Skewness and kurtosis values were interpreted as usual.

3.10.2 Internal Consistency

The reliability of the psychometric tools was examined using common internal consistency metrics, specifically Cronbach's (1951) coefficient alpha ($\boldsymbol{\alpha}$) and McDonald's (1999) coefficient omega ($\boldsymbol{\omega}$). As shown in the results (section 4.2.2), the assumption of normality was not always upheld for some variables in the study; thus, I wanted to ensure that this assumption violation did not interfere with the internal consistency calculations.

To this end, I employed Zhang and Yuan's (2016) robust method for computing alpha and omega, which has been demonstrated to provide better reliability estimates than conventional non-robust methods under non-normality and non-tau equivalence. This method involved computing correlational analysis directly by scaling robust estimates of the covariance matrices before estimating the reliability coefficients for the psychometric assessments.

3.11 INFERENTIAL STATISTICS

3.11.1 Correlations

Tests of associations were performed using Kendall's tau to directly test whether the correlations being estimated were statistically different from zero (refer to section 4.4.2). Kendall's tau is used for non-metric rank-order data (Hair et al., 2014). All tests applied *p*-value adjustments, as explained in section 3.8.6 on Post Hoc Procedures.

3.11.2 Regressions

In a causal system model, narrow abilities influence each other directly in sometimes complex networks of association (Schneider et al., 2016). The EI branches operate individually and together to predict outcomes. To improve the EI predictive and incremental validity credentials, the literature highlights the need to move beyond bivariate models towards multivariate analysis models (Côté, 2014) – hence the conceptual framework in Figure 12.

Using the guidelines suggested by Baron and Kenny (1986) and Ro (2012), the conceptual framework for this study can be classified as a moderation model. Ro (2012) points out: "In such a model the moderator variable is a third variable which could affect the amount of the correlation and/or change the direction of the dependent and independent variables" (p. 953). Ro (2012) adds that in such an instance, the researcher's main interest is the independent variable, as opposed to the moderator. In other words, the independent variable's association with the outcome variable is stronger or weaker at the different levels of the moderator variable. These models are particularly useful when the relationship between the dependent and independent variables is inexplicably weak, which is the case in the ability-based EI literature (Joseph & Newman, 2015; O'Boyle, 2011). Therefore, the inclusion of the moderator, though secondary to the study, is to generate a more precise explanation of the relationship between the dependent and independent variables.

In line with the literature, this study relied on multivariate analysis techniques. Multivariate analysis, according to Hair et al. (2014, p. 4), "refers to all statistical techniques that simultaneously analyse multiple measurements on individuals or objects under investigation". These techniques are an extension of the univariate (using one dependent measure) and bivariate (simple correlation between two sets of variables) analysis techniques. There are several examples of dependence techniques, such as multiple regression, discrimination analysis and conjoint analysis. They can generally be categorised according to (1) the number of dependent variables and (2) the type of measurement scale employed by the variables (Hair et al., 2014).

In an authoritative study, Namazi and Namazi (2016) and Ro (2012) motivated for the use of hierarchical multiple regression (HMR) where the independent and dependent variables were continuous variables. This study mimicked Côté and Miners (2006) and Farh et al. (2012), because of both studies' similarities to the current study, where HMR was applied and where the impact of contextual variables, as moderators of the relationship between the dependent and independent variables, was investigated. Historically, the use of moderation and mediation was prevalent in individual differences research or basic and applied psychology research (Dasborough, 2019; Edwards & Lambert, 2007).

The choice of HMR in this study was motivated by a number of factors (Ro, 2012): (a) the nature of the research question relates to a few variables, (b) the independent variable is multi-level in nature, and (c) all the variables (independent, dependent and moderator) are continuous variables. One of the other key advantages of HMR is that there is no constraint on sample size.

The general approach taken in the regression analyses was to first test the model with only the independent variable/s and dependent variables, and then to add the control variables and revaluate the model. The final step was to add the moderating variable with the interaction term/s to test the moderation effect. This was done for each set of regression models constructed to answer the research hypotheses. Diagnostic plots were also produced for every model to provide a richer interpretation of the results of the regression.

3.11.3 Group Differences

It was decided that group differences should be explored to determine whether there were significant differences in participants' work performance variables when grouped according to their EI scores. The performance of group difference checks is common in individual difference research (EI research) (O'Boyle et al., 2011). It is logical to assume that participants with higher levels of EI would in essence have better work performance variables (i.e., they would make better loan decisions) (Newman et al., 2010).

If participants in the different EI groups did have statistically significant differences in their work performance variables, then this would justify performing an additional regression model at this group level, in the hope that the models would perform better (Joseph & Newman, 2010).

The common student's *t*-test was avoided owing to some practical concerns, the most pressing concern being that it can have limited power when there are slight departures from normality, as is the case with the current study (Wilcox, 2017). Instead, the natural and reasonable approach was to compare the variable distributions using robust measures of location and scale (refer to section 4.4.3). The method chosen to do this was to compare trimmed sample means using the Yuen-Welch method (see Wilcox, 2017 for an overview of this method).

Respondents were partitioned according to their EI results. The easiest approach was to group respondents into low scores and high scores, respectively. Low scores were classified as less than 85, whereas high scores were classified as 85 and above.

3.12 QUALITY ASSURANCE AND ETHICS

Ethical issues can occur at any stage during a study, from design to analysis and reporting of results. Research involves collecting data from people, about people. Therefore, ethical issues in research have been commanding increasing attention (Babbie, 2015). Owing to the potentially intrusive nature of this study, especially when it came to the collection of primary data, the possibility of several ethical issues arising needed to be contemplated.

The collection of data using psychological instruments required that the professional code of ethics for educational and psychological testing be observed. In this regard, the study relied heavily on JVR Psychometrics, a registered and accredited organisation in South Africa which provided assistance and support to ensure that ethics protocols were adhered to. Additionally, the person supervising the collection of primary data was a qualified and licensed psychometrist (see section 3.7.1).

Furthermore, to gain access to the participants for the study, the necessary permissions were sought from the bank's governance structures and an NDA (see example in Appendix D) was signed by me (the researcher), the bank and the psychometric testing company. The research instrument was sent to the participants electronically, accompanied by a letter that specified the objectives, the time involved, the potential impact and the outcomes of the research. The principles of voluntary participation, anonymity and confidentiality and the no-harm principle were highlighted and strictly adhered to. It was emphasised that I would not get the individual participant results but rather the aggregated outputs for the purpose of conducting the analysis. The participants' consent was sought prior to the psychometric assessments (see Appendix C). Participants were informed that the results from the psychometric tests would be made available to them upon request, at their expense.

Because of the potential interest that the results of this study may generate and their possible publication, the authorship of such publication was outlined in advance for all the contributors, including the bank. The bank requested that it remain anonymous in the report or in future publications, and the request was acceded to.

I employed the services of an experienced statistician to conduct the model for the data analysis. Furthermore, because the research process required that the individual participant results (from the psychometric instruments measuring the independent variable and controlling for confounding effects) be matched with the moderator variable and the dependent variable, the anonymity of respondents and borrowers was ensured in the exchange of data between me, the bank and JVR Psychometrics.

All the psychometric raw data remained with the instrument owners who were accredited to hold it. The loan officer and borrower raw data remained with the bank, and I received anonymised data only. The keeping of all other data adhered to the ethical requirements outlined by the Gordon Institute of Business Science (GIBS) Ethics Committee.

3.13 SUMMARY OF THE CHAPTER

This chapter provided an overview of the study's research design and methodology. The research paradigm was post-positivist, while the research design was quantitative in nature. The strategy of inquiry was correlational and the research type was explanatory. The description of the research process included the conceptual model and the hypotheses, the unit of analysis, and the data collection and data analysis methods. Additionally, the ethical considerations were outlined and the importance of maintaining the quality of the study highlighted.

The main thrust of the study was testing an existing theory in a different context or setting, thereby contributing to new knowledge (Miners et al., 2018). The question addressed was: Does the methodology, as described, provide answers to the stated research problem? The research problem, in turn, was: Can the ability-based EI construct predict work outcomes more precisely when context is taken into consideration? In this regard, I ensured that the research design, the description of the variables, the operationalisation of the variables, the data collection and the data analysis were specifically designed to provide a more precise explanation. In other words, the study was structured in such a way as to provide answers to the research question.

Distinguishing loan officers by their EI abilities, their role in credit risk assessments (determining the probability of default by borrowers) and linking these to the adverse post-issuance loan quality measures served to enhance our understanding of how these factors interact to predict work performance. According to the literature, loan officers' interpretive interactions, judgements and processing of soft information in the informationally opaque SME context are important dimensions related to their performance (Lipshitz & Shulimovitz, 2007; Wilson, 2016). Moreover, the introduction of the moderator variable increased our understanding of the magnitude and nature of the relationship (Ro, 2012).

Lastly, the study enabled us to "assign numbers to behavioural and financial phenomena which will in turn allow for relationships to be tested, categorisations to be made and predictions to be considered" (Ybarra et al., 2014, p. 99). Previously, EI research has been criticised for assigning numbers to behavioural factors without giving due consideration to context (Ybarra et al., 2014). This study, because of the way in which it was designed, enabled attention to be given to context, offering further insight into the predictions made. As described above, several steps, including practical ones, were taken to ensure that the study's findings and conclusions were believable.

4 CHAPTER 4 – RESULTS

This chapter reports on the results of the analyses conducted in this study. The chapter commences with a description of the sample and then provides the descriptive statistics that were estimated for all the demographic variables collected. In addition, general descriptive statistics for all independent and dependent variables are provided and discussed. Thereafter, the results of the standard assumption checks are presented and interpreted. Additional assumption checks, which are test specific, are provided and discussed in conjunction with the tests to which they relate. These are followed by the results from the inferential analyses, specifically the correlation findings and regression models. Finally, the chapter concludes with a summary of the research results.

4.1 DESCRIPTIVE TESTING

This study used descriptive statistics to assist in summarising key variables in the data. The sub-sections that follow are dedicated to presenting these descriptive metrics and providing interpretations that will facilitate the discussion later on.

4.1.1 Sample Overview

A total of 300 loan officers were approached during the period August 2021–October 2021 and invited to participate in this study. Of these, only 106 individuals responded and were thus included in the sample. This means that there was a response rate of 35.33%. However, not all these respondents met the requirements for inclusion in the final sample as some provided incomplete data. Respondents were required to complete the main psychometric test for the independent variable (MSCEIT) and the two other psychometric tests for the control variables (Matrigma and BTI). In addition, there were data on them (on the bank's systems) pertaining to the moderating variable (risk grade) and dependent variable (delinquency and charge off).

Therefore, for practical reasons, some respondents were excluded from the initial sample, resulting in the final sample comprising 70 participants. An overview of the primary demographics of the sample is provided in Table 4 below.

Table 4. Descriptive statistics for the sample's demographic variables.

Demographic Variable	*N*	%
Gender		
Female	45	64.29
Male	25	35.71
	70	**100.00**
Ethnicity		
Black African	15	21.43
Caucasian (White)	33	47.14
Indian	1	1.71
Mixed ethnic origin	21	30.00
	70	**100.00**
Repeat lending		
Existing	3 709	98.36
New	62	1.64
	3 771	**100**

Note. N: Frequency of participants belonging to the demographic classification. %: Proportion of the sample in respect of the demographic classification.

It is clear that representation across the different demographic categories was not equal. For example, there were substantially more female participants ($N = 45$) than male participants ($N = 25$). Similarly, most participants were classified as Caucasian ($N = 33$) in contrast to the other ethnicities ($N = 15, N = 1 \; and \; N = 21$ for Black African, Indian and mixed ethnic origin, respectively). It is also evident that the loan officers primarily worked on loans for existing clients ($N = 3\,709$) as opposed to new clients ($N = 62$). The imbalance in these groups meant that some analyses might have been limited if analyses were performed at the different group levels. However, this was not a concern in this study as the respondents were not categorised according to any of these demographic variables.

The age of the respondents was examined using a density plot. This approach was more visually appealing and easier to interpret than that of categorising participants into age groups and computing frequencies. This age distribution is shown in Figure 15.

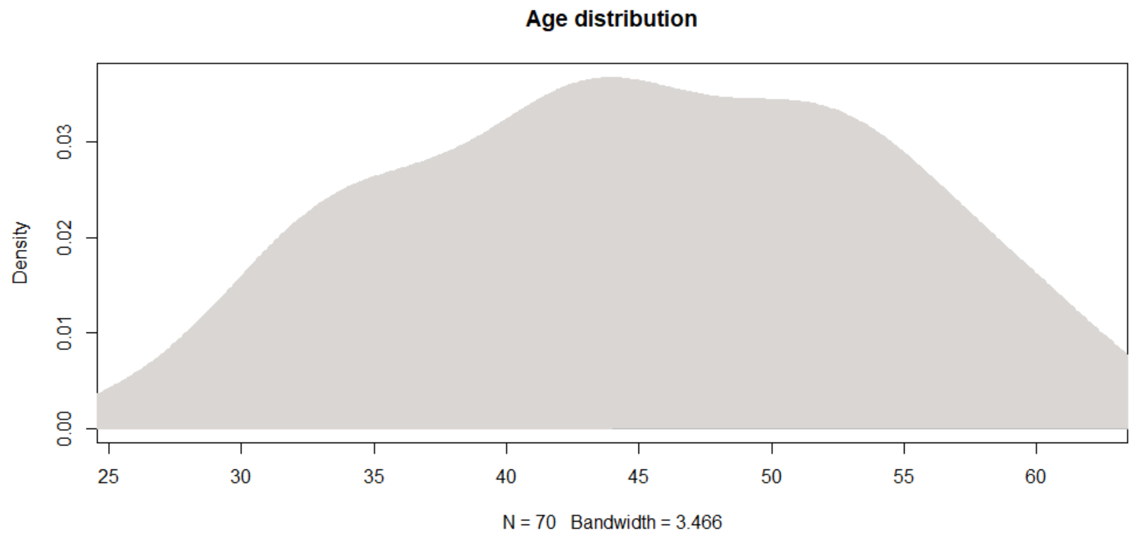

Figure 15. Age distribution of the participants.

The distribution appears to resemble a normal distribution, suggesting that the sample had a good representation of respondents of varying ages. Moreover, the minimum and maximum ages for the sample were 26 and 62 respectively.

The tenure (years in service) of respondents was also graphed using a density plot. This is shown in Figure 16.

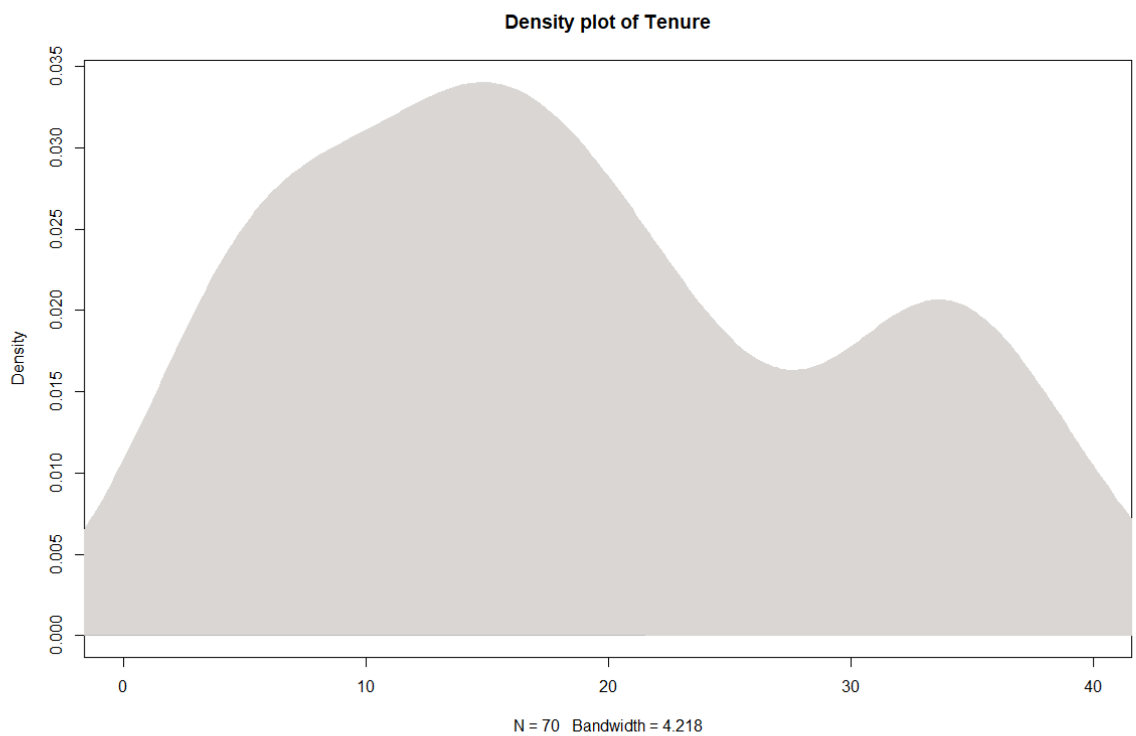

Figure 16. Distribution of tenure (years in service).

4.1.2 Psychometric Assessments Overview

Three internationally recognised psychometric tools, which had been shown to be statistically reliable and valid, were used to collect psychological data from the sample. For the independent variable the MSCEIT was used and for the control variable the BTI and Matrigma were used. The results of these assessments were represented by scale/facet scores and total scores, depending on how the assessment was structured and interpreted. The sub-sections that follow summarise the descriptive statistics for these assessments.

4.1.2.1 BTI

Descriptive statistics were computed for the five factors in the BTI, namely: (a) Extraversion; (b) Agreeableness; (c) Conscientiousness; (d) Openness to experience; and (e) Neuroticism. These are shown in Table 5 below.

Table 5. Descriptive statistics for the BTI.

Factors	$\hat{X}_w$	s_w^2	Min	Max	Range	Skew	Kurt
Extraversion	46.86	60.01	27	78	51	.52	2.64
Agreeableness	51.96	87.11	25	79	54	.07	2.15
Conscientiousness	49.44	75.29	25	75	50	- .18	2.06
Openness to experience	46.23	82.24	25	79	54	.28	2.18
Neuroticism	49.67	81.50	25	80	55	.07	2.29

Notes: $\hat{X}_w$: Winsorised mean. s_w^2: Winsorised variance. *Min*: Minimum value. *Max*: Maximum value. *Range*: Range of variable given by subtracting the minimum value from the maximum value. *Skew*: Skewness metric. *Kurt*: Kurtosis metric.

Generally speaking, the percentile scores for the BTI factors were between 46.23 and 51.96, as indicated by the winsorised mean values. Moreover, the skewness estimates all suggest that the distributions were fairly symmetrical to moderately skewed, since their absolute value was smaller than 1.00 (i.e., $|Skew| < 1.00$). The amount of skewing was, however, not enough to declare the distributions to be non-normal, given that the normality results in Table 5 were all non-significant. The kurtosis values were all less than 3, suggesting that the distributions were fairly mesokurtic (i.e., resembled a normal distribution).

4.1.2.2 MSCEIT

The MSCEIT branches and total score are summarised in Table 6. On average, participants obtained branch scores ranging from approximately 80.56 to 89.93 for the different psychological domains respectively. The skewness estimates appear to report reasonable amounts of skewing, with Emotion Perception showing the largest amount of skewing. However, the skewness estimates suggest that the distributions were to some extent symmetrical since they were all between -1.00 and 1.00. The kurtosis values were also all within the acceptable ranges (i.e., $|Kurt - 3| < 1$), which suggests the distributions were mesokurtic.

Table 6. Descriptive statistics for the MSCEIT.

Scale	$\widehat{X}_w$	s_w^2	Min	Max	Range	Skew	Kurt
Emotion Perception	86.39	154.20	29.67	130.03	100.36	- .53	3.34
Emotion Facilitation	83.12	189.68	47.51	123.89	76.38	.06	2.02
Emotion Understanding	83.40	52.08	53.41	111.83	58.43	- .13	3.02
Emotion Regulation	89.93	142.43	54.54	117.34	62.79	- .45	2.22
Total score	80.56	155.72	36.28	111.63	75.35	- .24	2.40

Note. $\hat{X}_w$: *Winsorised mean.* s_w^2*:* Winsorised variance. *Min*: Minimum value. *Max*: Maximum value. *Range*: Range of variable given by subtracting the minimum value from the maximum value. *Skew*: Skewness metric. *Kurt*: Kurtosis metric.

4.1.2.3 Matrigma

The descriptive statistics for the Matrigma are presented in Table 7. The variance for the total score was large given the range of values, suggesting that the data were somewhat spread out. In support of this claim, the kurtosis metric was significantly smaller than 3, suggesting that the distribution was platykurtic. This means that the tails of the distributions were thinner, and the peak was generally flatter than the normal distribution.

Table 7. Descriptive statistics for the Matrigma.

Scale	$\hat{X}_w$	s_w^2	Min	Max	Range	Skew	Kurt
Total score	2.86	2.44	0	6	6	.04	1.76

Note. $\hat{X}_w$: *Winsorised mean.* s_w^2*:* Winsorised variance. *Min*: Minimum value. *Max*: Maximum value. *Range*: Range of variable given by subtracting the minimum value from the maximum value. *Skew*: Skewness metric. *Kurt*: Kurtosis metric.

4.1.3 Work Performance Overview

Work performance was measured using delinquency and charge off scores. The descriptives of these two variables are shown in Table 8 below.

Table 8. Descriptive statistics for work performance.

Scale	$\hat{X}_w$	s_w^2	Min	Max	Range	Skew	Kurt
Charge off	.02	< .001	0	.12	.12	1.21	3.71
Delinquency	.03	< .001	0	.24	.24	2.29	10.05

Note. $\hat{X}_w$: *Winsorised mean.* s_w^2*:* Winsorised variance. *Min*: Minimum value. *Max*: Maximum value. *Range*: Range of variable given by subtracting the minimum value from the maximum value. *Skew*: Skewness metric. *Kurt*: Kurtosis metric.

It is clear that the magnitude of the delinquency and charge off values is extremely small, with the variables being (at most) .24 and .12, respectively. In addition, the variance is extremely small, meaning that there is not a lot of spread within the data and, instead, data points tend to be close to the winsorised mean $\hat{X}_w$. Lastly, a very large kurtosis estimate for delinquency is evident. This is an indication of heavier tails in the distribution. These distributions are explored in more detail in section 4.2 where the results of the assumption checks are discussed.

4.1.4 Credit Risk Assessment Overview

The descriptive statistics for both risk grade variable scores (overdraft and term loan) are presented in Table 9. The Winsorised averages for both risk grade variables were identical. There is no theoretical justification for why this would be the case and thus is purely coincidental. The skewness and kurtosis metrics fell within their acceptable ranges. Based on these values, it is expected that the distribution for risk grade TL would have slightly heavier tails than risk grade

OD (overdraft). However, looking at the density plots of these two variables in Figure 22 his difference appears to be negligible.

Table 9. Descriptive statistics for credit risk.

Scale	$\hat{X}_w$	s_w^2	Min	Max	Range	Skew	Kurt
Risk grade OD	1.93	.78	0	5	5	.29	2.54
Risk grade TL	1.90	1.46	0	8	8	.66	3.98

Note. $\hat{X}_w$: *Winsorised mean.* s_w^2*:* Winsorised variance. *Min*: Minimum value. *Max*: Maximum value. *Range*: Range of variable given by subtracting the minimum value from the maximum value. *Skew*: Skewness metric. *Kurt*: Kurtosis metric.

4.2 ASSUMPTION TESTING

4.2.1 Outliers

Outliers were identified using the adjusted box plot rule. Figure 17 depicts the box plots constructed for each primary variable in the study. Visually one can see that the Emotion Perception and Emotion Understanding branches in the MSCEIT and both risk grade variables (overdraft and term loan) had outlying observations. Specifically, a total of eight outliers were detected using the adjusted box plot rule and were thus removed from the analyses to prevent their having any influence on the estimates.

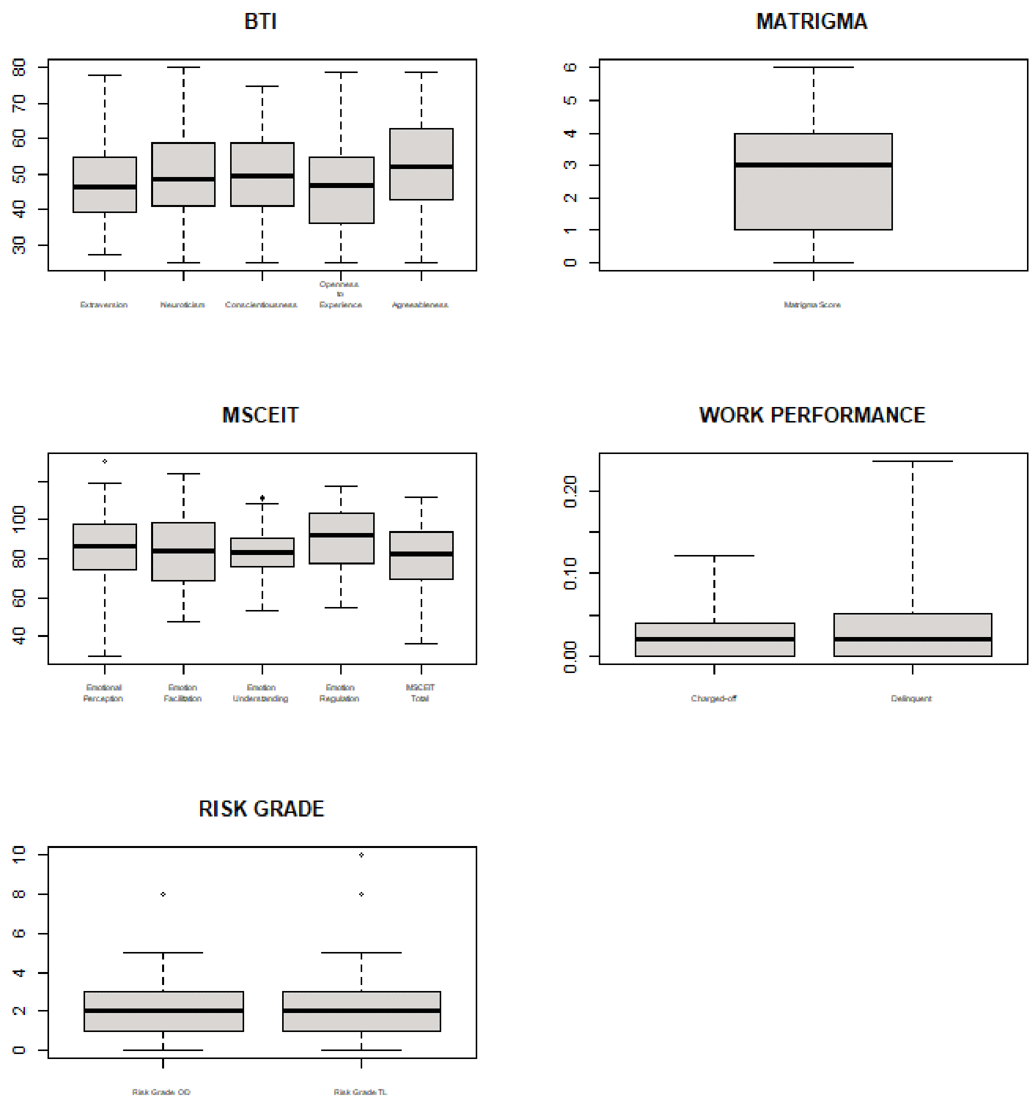

Figure 17. Box plots for the different variables in the study.

4.2.2 Normality

Both density plots and Shapiro-Wilk (1965) tests were used to assess the normality of the underlying distributions of the variables. These findings are presented in the sections that follow. It should be noted that all *p*-values for the Shapiro-Wilk tests of normality were adjusted to account for the familywise error rate.

4.2.2.1 *BTI*

The density plots of the distributions of the BTI factors can be seen in Figure 18. Visually, the distributions all appear to be normal, but a slight skewing can be seen in some of the plots. Additionally, there appear to be multiple peaks (i.e., multimodal distributions) for Neuroticism, Conscientiousness and Openness to experience.

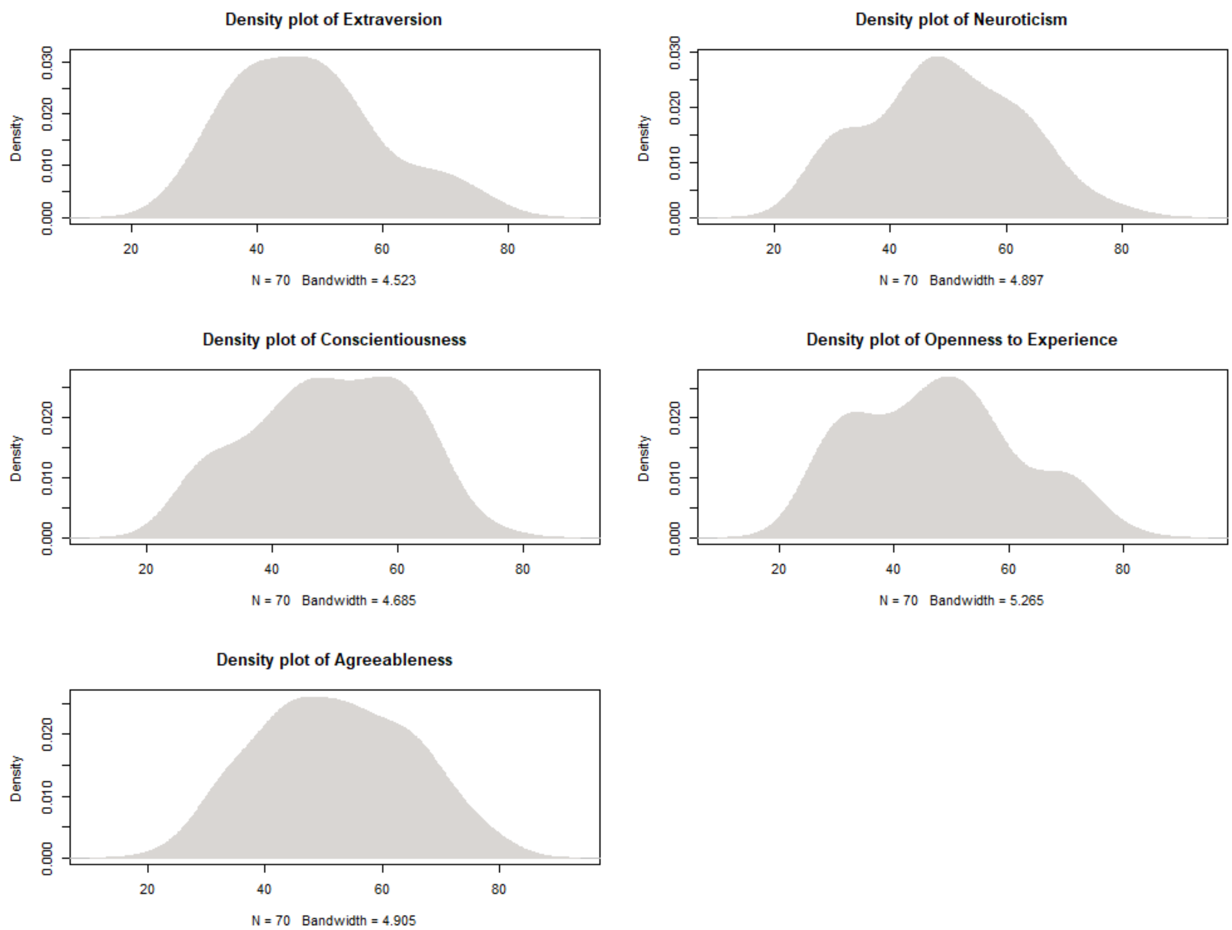

Figure 18. Density plots for the BTI scales.

The results of the Shapiro-Wilk tests in Table 10 all demonstrate that the distributions are normal, as indicated by the non-significant *p*-values. One can confidently say that the assumption of normality holds for the BTI factors.

Table 10. Shapiro-Wilk normality test results for the BTI.

Scale	$\hat{w}$	p_{adj}
Extraversion	.97	.32
Neuroticism	.98	.60
Conscientiousness	.97	.32
Openness To experience	.96	.10
Agreeableness	.98	.60

Note. $\hat{w}$: Test statistic. p_{adj}: Adjusted *p*-value.

4.2.2.2 MSCEIT

The density plots for the MSCIET are shown in Figure 19. There appear to be signs of non-normality, with the most prominent observation being that both Emotion Facilitation and the MSCEIT total score appear to be bimodal distributions. It is also evident that Emotion Regulation has a slightly negatively skewed distribution.

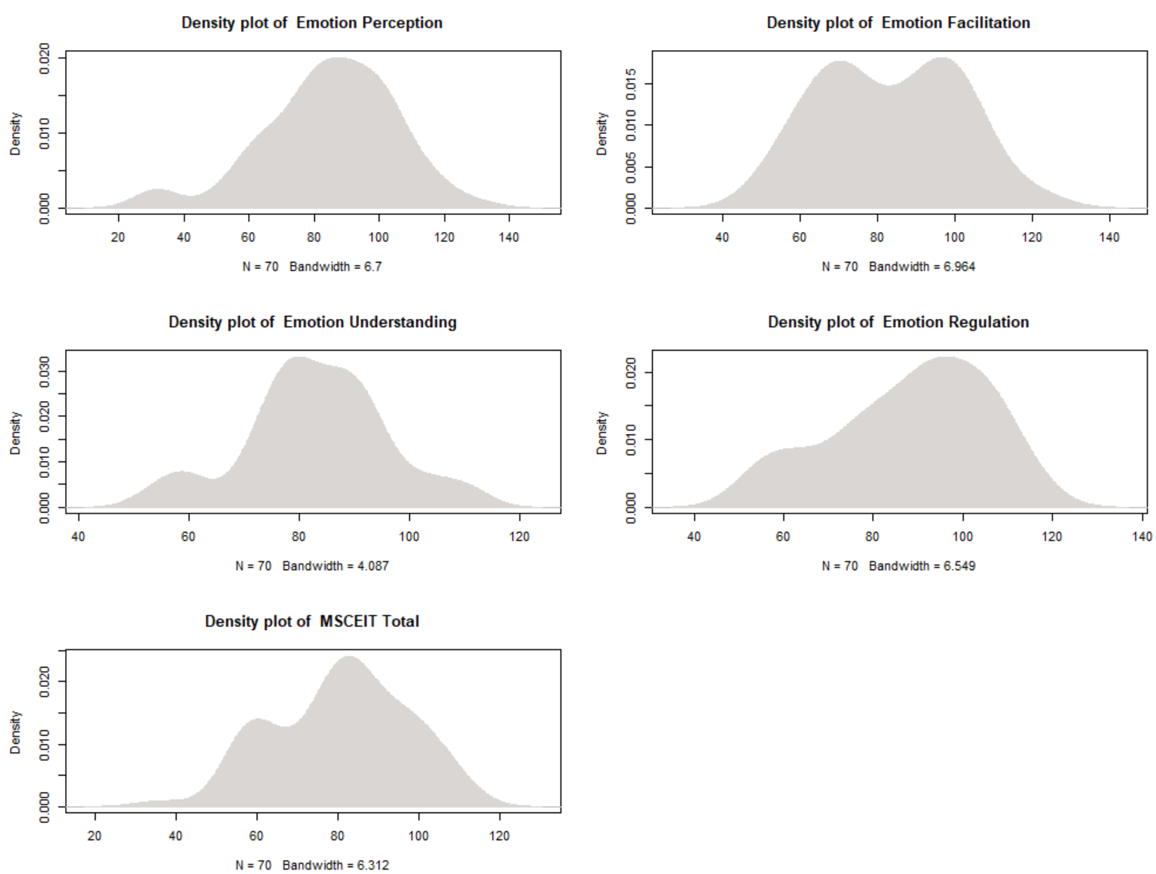

Figure 19. Density plots for the scales in the MSCEIT.

The Shapiro-Wilk test results in Table 11 indicate that only the Emotion Regulation distribution is non-normal ($p = .04$). Given this finding in combination with the skewness metrics and density plots, one can conclude that all except the Emotion Regulation have normal distributions. The MSCEIT test factor scores could therefore be used in the analysis.

Table 11. Shapiro-Wilk normality test results for the MSCEIT.

Scale	$\hat{w}$	p_{adj}
Emotion Perception	.92	.48
Emotion Facilitation	.97	.48
Emotion Understanding	.98	.48
Emotion Regulation	.95	**.04**
Total score	.97	.48

Note. $\hat{w}$: Test statistic. p_{adj}: Adjusted *p*-value.

4.2.2.3 Matrigma

In the density plot for the Matrigma total score in Figure 20, there appear to be three distinct peaks in the distribution. Furthermore, the three peaks seem to have similar densities and, if these three separate peaks are treated as one, the 'peak' appears to be somewhat flat and spread out. The kurtosis metric that was estimated for the Matrigma score in Table 12 was 1.76, which also suggests that the overall distribution is platykurtic.

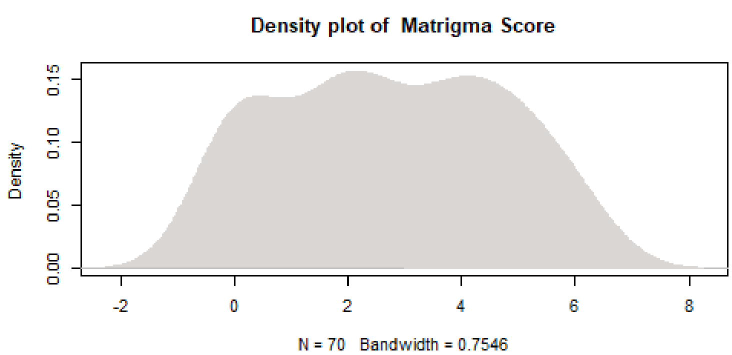

Figure 20. Density plots for the Matrigma.

The results of the Shapiro-Wilk normality test in Table 12 were significant ($p < .001$), which is an indication that the distribution deviates from normality. Taken together, it is inferred that the distribution of the Matrigma score variable is non-normal. The test result scores show that a noticeable number of the participants scored zero and there were no higher scores than six out of the possible 10. The absence of normality in the data invited the use of robust statistical techniques.

Table 12. Shapiro-Wilk normality test results for the Matrigma.

Scale	$\hat{w}$	p_{adj}
Total score	.92	**< .001**

Note. $\hat{w}$: Test statistic. p_{adj}: Adjusted *p*-value.

4.2.2.4 Work Performance

The density plots of charge off and delinquency are presented in Figure 21. Both distributions appear to be non-normal. They are also positively skewed and have long tails on the right of their distributions. The kurtosis metrics estimated in Table 13 are 10.05 and 3.71 for delinquency and charge off respectively. This suggests that both distributions are leptokurtic, which does seem to be true in the density plots. The differences in the magnitudes of the kurtosis metrics are also evident in the plot, with delinquency having a much sharper and higher peak than that of the charge off variable.

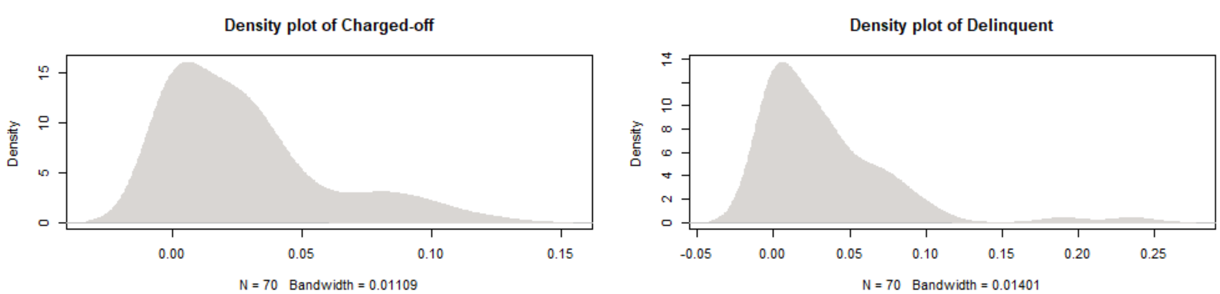

Figure 21. Density plots for work performance.

The Shapiro-Wilk tests in Table 13 point to the conclusion that the underlying distributions of the work performance variables are indeed non-normal. The non-normality and low variability in the scores of the loan officers for both these work performance variables mean that the prediction of a constant was very difficult.

Table 13. Shapiro-Wilk normality test results for work performance.

Scale	$\hat{w}$	p_{adj}
Delinquency	.74	**< .001**
Charge off	.84	**< .001**

Note. $\hat{w}$: Test statistic. p_{adj}: Adjusted *p*-value.

4.2.2.5 Credit Risk Assessment

The density plots in Figure 22 appear to substantially deviate from the normal distribution. Both plots are asymmetrical in that the right tail is thinner and longer than the left tail. This pattern is to be expected since respondents tended to have scores of less than 4, which means that the risk profile of the borrower was less risky.

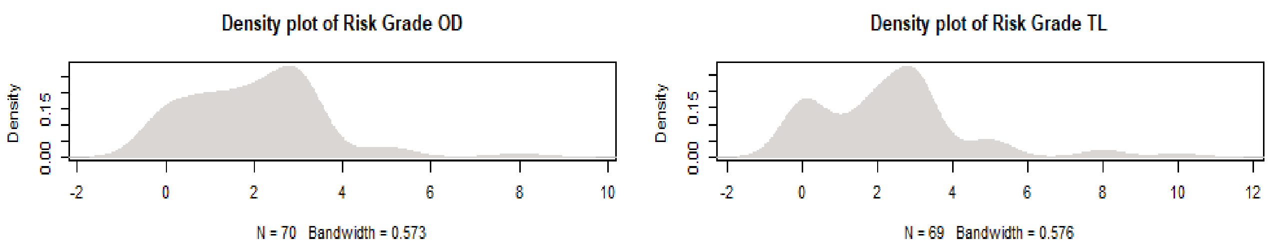

Figure 22. Density plots for credit risk assessment.

As expected, the Shapiro-Wilk tests of normality were both statistically significant, signalling that both distributions were indeed not normal. These results can be seen in Table 14 below. The non-normality and low variability in the scores of the loan officers for both these credit risk assessment variables mean that the prediction of a constant was very difficult.

Table 14. Shapiro-Wilk normality test results for credit risk assessment.

Scale	$\hat{w}$	p_{adj}
Risk grade OD	.87	**< .001**
Risk grade TL	.84	**< .001**

Note. $\hat{w}$: Test statistic. p_{adj}: Adjusted *p*-value.

4.3 INTERNAL CONSISTENCY

The internal consistency of the instruments was examined using Cronbach's (1951) coefficient alpha (α) and McDonald's (1999) coefficient omega (ω). The results of these analyses are presented in the sections that follow.

4.3.1 BTI

The structure of the BTI comprises the Big 5 personality factors which in turn are made up of a set of individual facets. Internal consistency estimates were computed at both the factor and facet levels using the sample responses. These results are shown in Table 15 and Table 16 below.

Table 15. Internal consistency estimates for the BTI factors.

Factor	N_{items}	$\hat{\alpha}$	$\hat{\omega}$
Extraversion	36	.90	.91
Neuroticism	34	.97	.97
Conscientiousness	41	.97	.97
Openness to experience	32	.94	.95
Agreeableness	37	.95	.96

Note. N_{items}: Number of items in factor. $\hat{\alpha}$: Estimated Cronbach's alpha coefficient. $\hat{\omega}$: Estimated McDonald's omega coefficient.

Table 16. Internal consistency estimates for the BTI facets.

Facet	N_{items}	$\hat{\alpha}$	$\hat{\omega}$
Ascendance	7	.74	.75
Liveliness	8	.74	.75
Positive affectivity	6	.89	.89
Gregariousness	7	.91	.91
Excitement-seeking	8	.84	.85
Affective Instability	8	.93	.93
Depression	9	.93	.94
Self-consciousness	9	.91	.91
Anxiety	8	.95	.95

Facet	N_{items}	$\hat{\alpha}$	$\hat{\omega}$
Effort	8	.91	.92
Order	10	.94	.95
Dutifulness	9	.93	.93
Prudence	6	.90	.90
Self-discipline	8	.93	.93
Aesthetics	7	.91	.92
Ideas	6	.86	.86
Actions	7	.90	.90
Values	6	.72	.75
Imagination	6	.91	.92
Straightforwardness	8	.83	.84
Compliance	8	.81	.83
Prosocial tendencies	8	.87	.88
Modesty	7	.78	.80
Tendermindedness	7	.94	.94

Note. N_{items}: Number of items in facet. $\hat{\alpha}$: Estimated Cronbach's alpha coefficient. $\hat{\omega}$: Estimated McDonald's omega coefficient.

The reliability estimates at both factor and facet levels were well within the acceptable ranges, demonstrating that the BTI is a reliable measure of personality. As a result, one could rely on the BTI psychometric test results for analytical purposes. At the factor level, all estimates were above $.90$, with Neuroticism and Conscientiousness having the greatest internal consistency. At the facet level, the average estimates were $\bar{X}_{\hat{\alpha}} = .87$ and $\bar{X}_{\hat{\omega}} = .88$. Anxiety ($\hat{\alpha} = .95$ and $\hat{\omega} = .95$) and Order ($\hat{\alpha} = .94$ and $\hat{\omega} = .95$) had the highest estimates, while Values ($\hat{\alpha} = .72$ and $\hat{\omega} = .75$) was found to have the lowest internal consistency. The analysis used the factor scores instead of the facet scores.

4.3.2 MSCEIT

The estimates for Cronbach's coefficient alpha and McDonald's coefficient omega are presented in Table 17.

Table 17. Internal consistency estimates for the MSCEIT.

Scale	N_{items}	$\hat{\alpha}$	$\hat{\omega}$
Total score	141	.95	.96
Branches			
Emotion Perception	50	.94	.94
Emotion Facilitation	30	.85	.86
Emotion Understanding	32	.83	.84
Emotion Regulation	29	.90	.91
Tasks			
Faces	20	.89	.90
Sensation	15	.79	.81
Changes	20	.76	.76
Emotional management	20	.85	.86
Pictures	30	.94	.94
Facilitation	15	.80	.81
Blends	12	.69	.69
Emotional relations	9	.81	.83

Note. N_{items}: Number of items in facet. $\hat{\alpha}$: Estimated Cronbach's alpha coefficient. $\hat{\omega}$: Estimated McDonald's omega coefficient.

The estimates above suggest that the MSCEIT has acceptable internal consistency and therefore it could be relied upon for analytical purposes. At the highest level, the total score, internal consistency was found to be $\hat{\alpha} = .95$ and $\hat{\omega} = .96$, which is indicative of very good reliability. At the branch level, the average estimates were $\bar{X}_{\hat{\alpha}} = .88$ and $\bar{X}_{\hat{\omega}} = .89$. The Emotion Understanding branch had the lowest internal consistency. However, it was still above the acceptable cut-off points. Finally, at the task level, the average internal consistency was estimated to be $\bar{X}_{\hat{\alpha}} = .82$ and $\bar{X}_{\hat{\omega}} = .83$ respectively. The Blends task had the lowest internal consistency at $\hat{\alpha} = .69$ and $\hat{\omega} = .69$. This is below the acceptable cut-off point that would typically be used for psychometric tools like the MSCEIT. This is not a concern for the present study since the assessment is not interpreted at the task level but at the branch level. Furthermore, since both the total score and the four branches had good internal consistency scores, one can conclude that the MSCEIT had good reliability overall (Côté, 2014; Roberts et al., 2016).

4.3.3 Matrigma

It was not possible to compute internal consistency estimates for the Matrigma from the data collected in this study because gaining access to the item-level data was not feasible. Although unfortunate, the Matrigma’s psychometric properties have previously been established in South Africa and have been shown to be acceptable. Cronbach’s alpha has been found to be .98 and .98 for both Form A and B of the Matrigma for Africa and South Africa, respectively (Taylor & De Bruin, 2017). These internal consistencies are acceptable, meaning that the Matrigma is a reliable instrument in the South African setting and was thus a suitable instrument to use in the present study.

4.4 INFERENTIAL STATISTICS

4.4.1 Correlations

This study was reliant on correlations to test both the research hypotheses directly, as in the case of hypothesis 1, and to aid the regression analyses by examining the extent to which the different variables relate to one another before the models were run. To begin with, it should be noted that hypothesis 1 in essence comprises separate questions as it is concerned with establishing sequential relationships between the different MSCEIT dimensions. Thus, two separate tests of associations were performed to determine the significance of these relationships. These are presented in Table 18 and the corresponding scatterplots are depicted in Figure 23.

Table 18. Correlations between MSCEIT branches.

X	Y	$\hat{\tau}$	$\hat{Z}$	p
Emotion Perception	Emotion Understanding	.27	3.21	**.001**
Emotion Facilitation	Emotion Understanding	.39	4.52	**< .001**
Emotion Understanding	Emotion Regulation	.39	4.48	**< .001**

Note. $\hat{\tau}$: Kendall's Tau estimate*.* $\hat{Z}$: Test statistic. p: *p*-value.

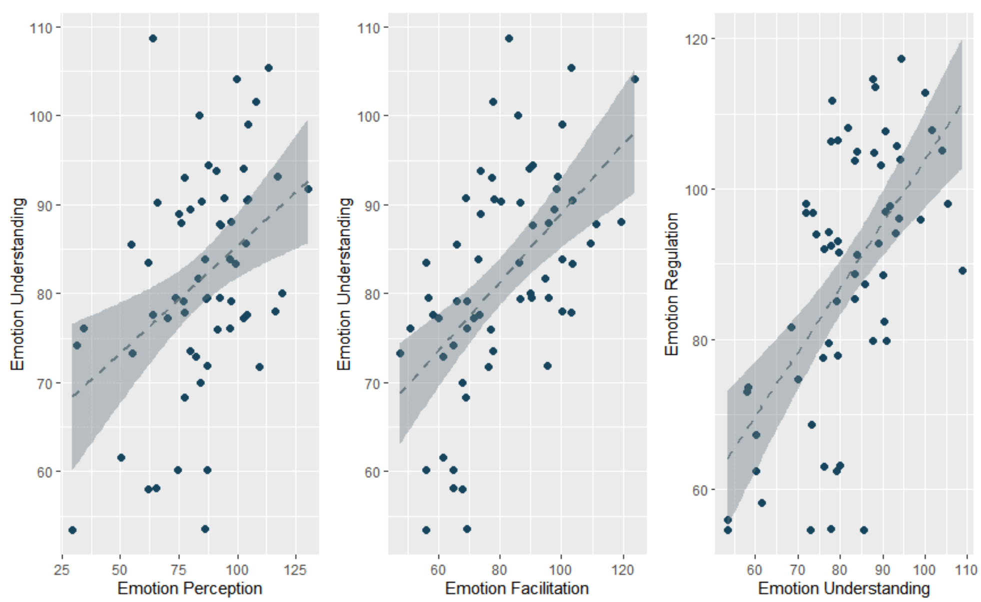

Figure 23. Scatter plots between the MSCEIT branches.

All the tests of associations were significant ($p \leq .001$), meaning that the correlations were found to be statistically significant from zero. All relationships were also moderate and positive. Given these findings, one can conclude that there is statistical evidence that supports the predictions made in hypothesis 1.

The next step involved establishing the nature of the different relationships between the input and output variables in the regression models. The results of the tests of association are presented in Table 19 and the corresponding scatter plots are depicted Figure 24.

Table 19. Correlations between MSCEIT branches and work performance variables.

X	Y	$\hat{\tau}$	$\hat{Z}$	p
Emotion Perception	Delinquency	.04	.47	1.00
Emotion Perception	Charge off	.06	.54	1.00
Emotion Facilitation	Delinquency	.11	1.18	1.00
Emotion Facilitation	Charge off	.05	.57	1.00
Emotion Understanding	Delinquency	-.01	-.13	1.00
Emotion Understanding	Charge off	-.07	-.80	1.00
Emotion Regulation	Delinquency	.06	.62	1.00
Emotion Regulation	Charge off	-.01	-.12	1.00

Note. $\hat{\tau}$: Kendall's Tau estimate. $\hat{Z}$: Test statistic. p: *p*-value.

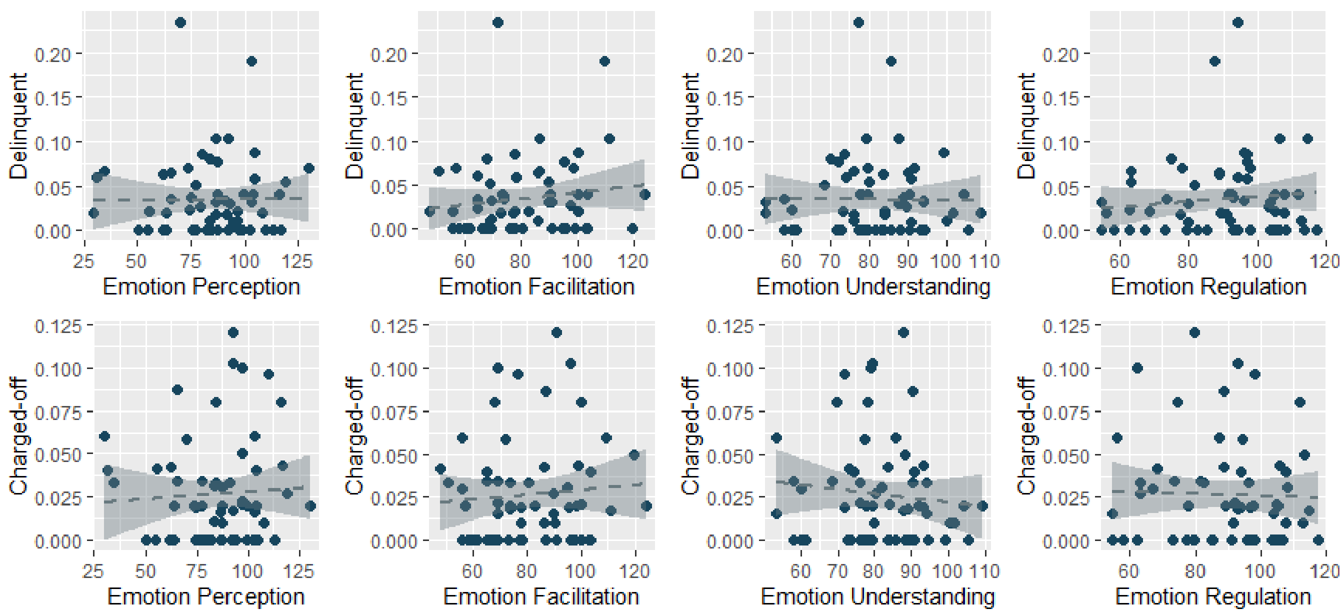

Figure 24. Scatter plots between the branches of the MSCEIT and the work performance variables.

All tests were non-significant, meaning that no correlation was found to be statistically different from zero. In addition, the actual correlation estimates are weak since they fall within the range of [- .10, .10]. These findings have implications for the regression models. Since there appears to be no linear association between the input and output variables in the regression model, one would expect that any linear regression model built including these variables would be non-significant.

The scatter plots in Figure 24 suggest that multiple participants obtained zeros for charge off and delinquency. This may be related to the data from the bank's systems. This influences the correlation analyses as it distorts any potential association that may exist.

4.4.2 Regressions

Multiple regression analyses were conducted to test the different hypotheses outlined in sections 2.7 and 2.8 of the literature review. The sections that follow report on the results of each individual hypothesis.

4.4.2.1 Emotion Perception does not predict work performance

Hierarchical multiple regression was conducted to directly test hypothesis 2 which was concerned with examining whether Emotion Perception is a good predictor of work performance, as measured by charge off and delinquency. The work performance variables were analysed separately.

For the first step in the model, Emotion Perception was specified as the independent variable and charge off as the dependent variable (see Table 20). The diagnostic plots in Figure 25 were created to check that the model met the assumptions of linear regression. First, it should be noted that in the Residual vs Fitted plot the red line is not horizontal, indicating that the assumption of a linear relationship between the independent and dependent variables was violated. In other words, there are signs of non-linearity in the data. This finding is not surprising given the correlation results.

In the Normal Q-Q plot, the data points are deviating from the diagonal straight line, meaning that there is an absence of normality in the data. Furthermore, the Scale–Location plot shows if the residuals are equally spread along the ranges of independent variables. Ideally there should be a horizontal line with the data points equally spread, which arguably can be seen in the plot, which is an indication of constant variance. This was confirmed using the non-constant error variance test (hereafter referred to as the NVC test) which was found to be non-significant ($\hat{\chi}^2 = 1.04, p = .31$). This means that there is enough evidence of constant variance among the data.

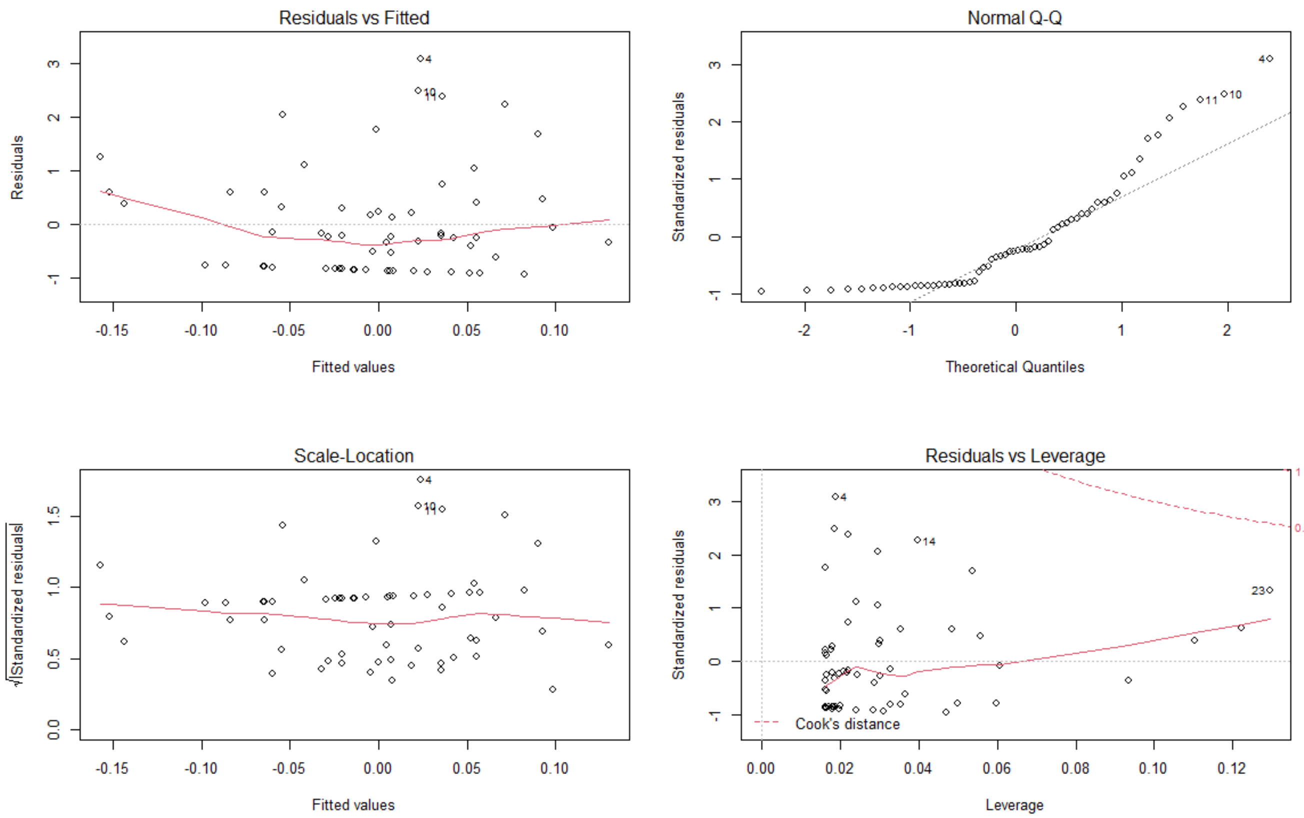

Figure 25. Regression diagnostic plots.

The results of the first step in the regression analysis revealed the model to be not statistically significant, with $R^2 = -.01$, $F(1,60) = .22, p = .64$. The R^2 value associated with this model suggests that Emotion Perception accounts for 1% of the variation in charge off, meaning 99% of the variation in charge off cannot be explained by Emotion Perception alone. The R^2 value is also negative, which is an indication that the model fits the data poorly.

For the second step of the analysis, the control variables in Table 20 were added as predictors to the model. Again, diagnostic plots were created, which are presented in Figure 26 to check that the model met the assumptions of linear regression. It is again evident that the red line in the Residual vs Fitted plot is not horizontal, indicating that the assumption of a linear relationship between the independent and dependent variables was violated. Furthermore, the data points resemble a funnel shape, a sign of heteroskedasticity. In the Normal Q-Q plot, the data points are deviating from the diagonal straight line, meaning that there is an absence of normality in the data. Moreover, the Scale–Location plot suggests that the variability of the residual points increases with the value of the fitted outcome variable, suggesting heteroskedasticity. This was confirmed using the NVC test which was found to be significant ($\hat{\chi}^2 = 6.95, p = .01$). This means that there is not constant variance among the data.

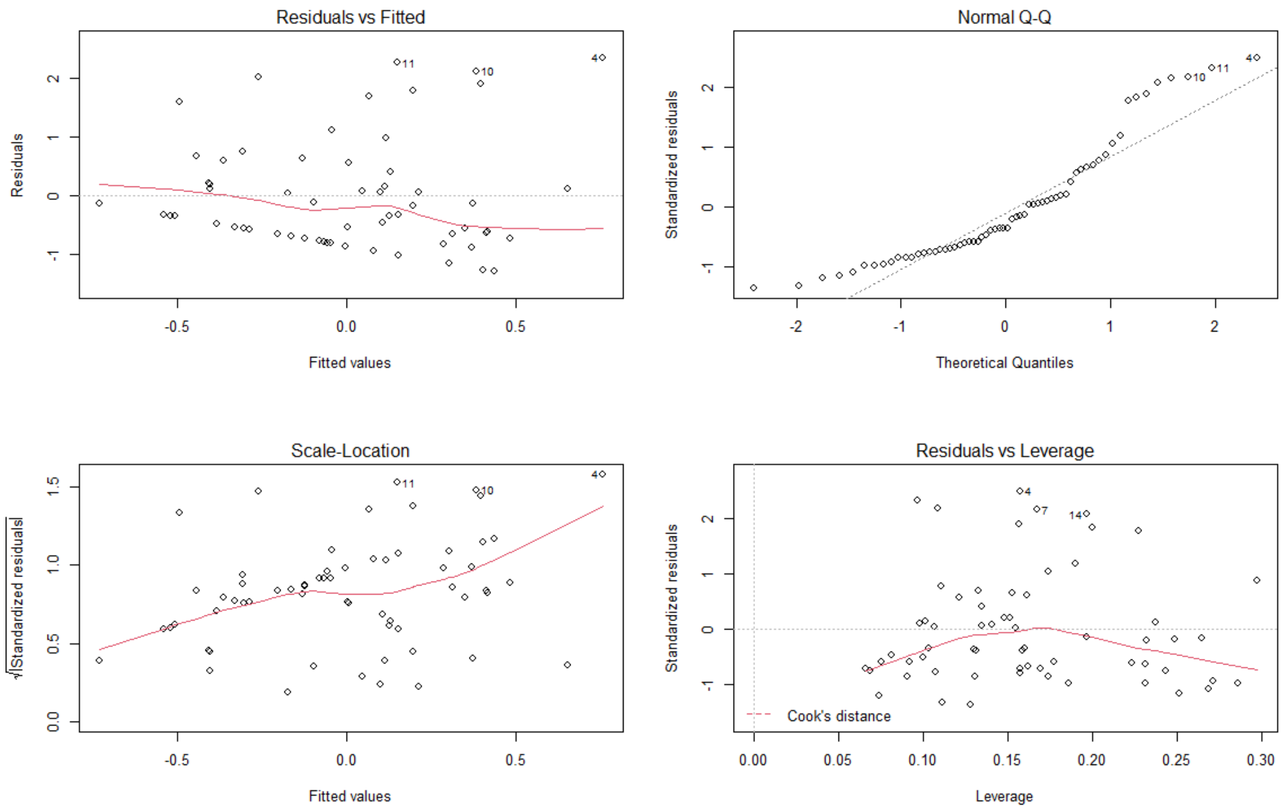

Figure 26. Regression diagnostic plots.

The results of the second step of the analysis revealed the model to also be statistically non-significant, with $R^2 = -.05$, $F(9,52) = .69, p = .72$. The R^2 value is again negative but with a slightly greater magnitude, suggesting that the model again fits the data poorly.

Table 20. Regression results with charge off as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	<.001	.13	.00	1.00
Emotion Perception	.06	.13	.46	.64
Step 2				
(Intercept)	<.001	.13	.00	1.00
Emotion Perception	.07	.15	.49	.63
Extraversion	-.13	.07	-.74	.46
Neuroticism	-.03	.14	-.20	.84
Conscientiousness	-.20	.22	-.88	.38
Openness to experience	-.20	.18	1.07	.29
Agreeableness	.34	.21	1.57	.12
Matrigma score	.06	.14	.45	.65
Gender	.15	.16	.94	.35
Age	.03	.14	.19	.85

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

Another regression analysis was performed which was identical to the previous model, except that the dependent variable was not specified as delinquency. The diagnostic plots can be seen in Figure 27. One can see that there is a slight parabolic pattern in the Residual vs Fitted plot, but as a whole the red line remains close to the dotted line. The plot also shows that some outliers may exist and that there may be signs of some heteroskedasticity. In the Normal Q-Q plot, the data points are deviating from the diagonal straight line, meaning that there is an absence of normality in the data. Furthermore, the Scale–Location plot suggests that there is constant variance. This was confirmed by the NCV test which was non-significant ($\hat{\chi}^2 = .06, p = .81$).

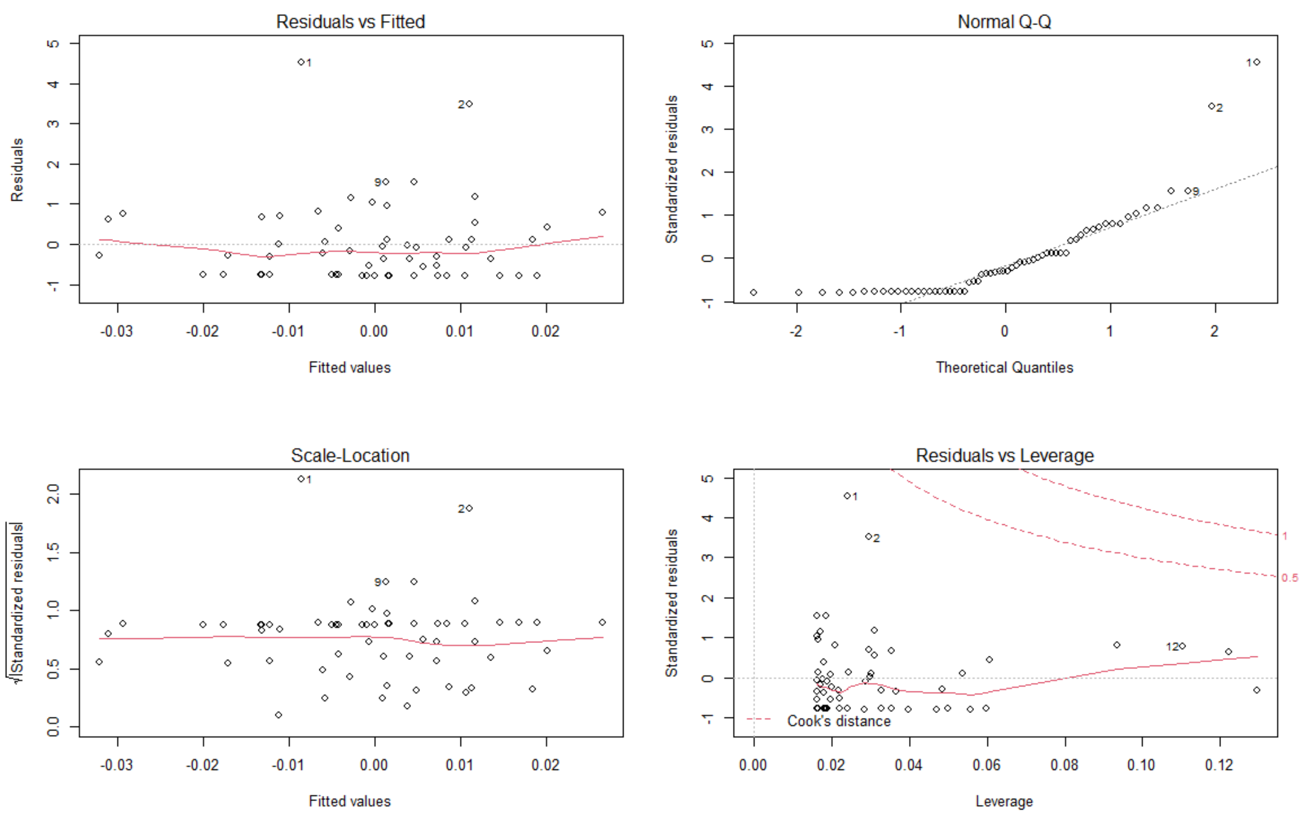

Figure 27. Regression diagnostic plots.

The first step in the analysis revealed a non-significant model, with $R^2 = -.02,\ F(1,60) = .01, p = .93$. The R^2 value suggests that Emotion Perception accounts for 2% of the variation in delinquency, meaning that 98% of the variation in delinquency cannot be explained by Emotion Perception alone. Again the R^2 value is negative, which is an indication that the model fits the data poorly.

For the second step, the control variables in Table 21 were added as predictors to the model. The diagnostic plots for this model are shown in Figure 28. There are clear signs of heteroskedasticity when looking at the Residuals vs Fitter plot, most notably by the visible funnel pattern. This claim is further corroborated by the Scale–Location plot and by the significant NCV test results, with $\hat{\chi}^2 = 27.99, p < .001$.

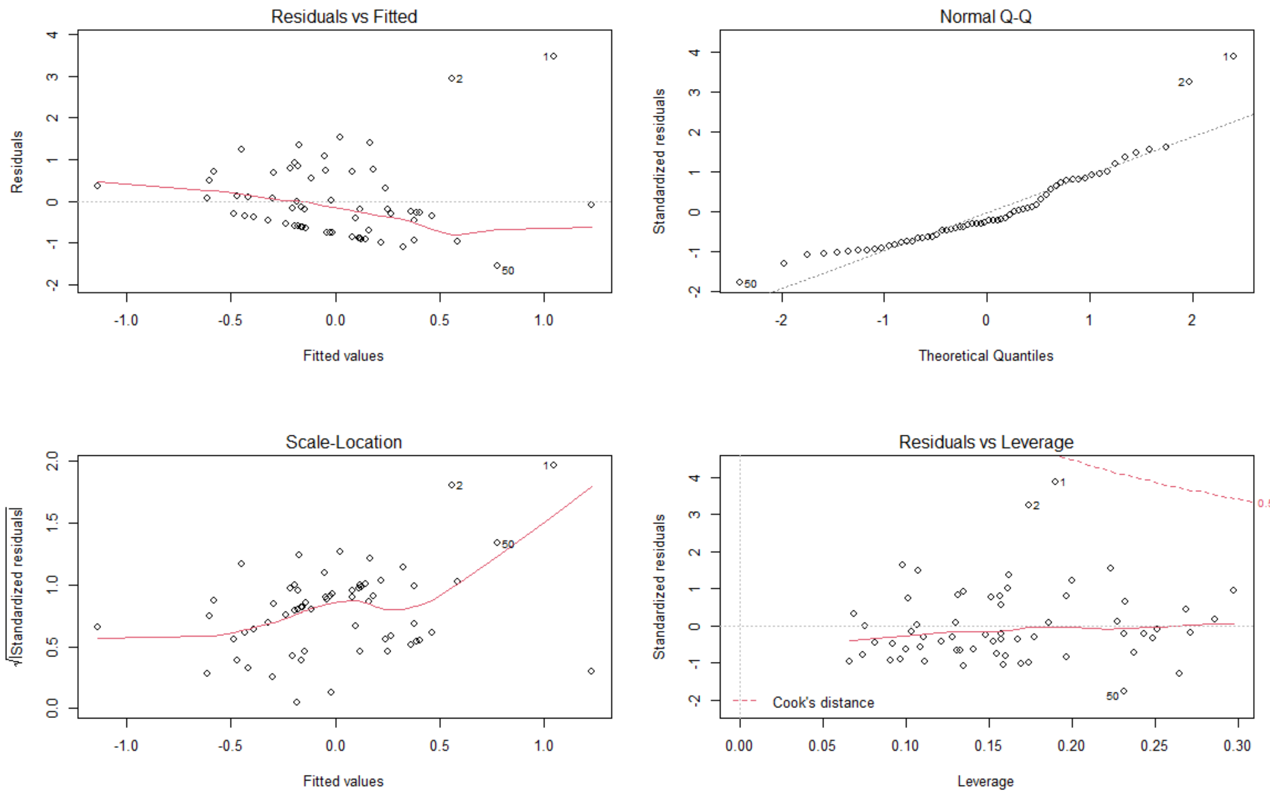

Figure 28. Regression diagnostic plots.

The results of the second step in the analysis revealed a model to also be statistically non-significant, with $R^2 = .01,\ F(9{,}52) = 1.10, p = .39$. The R^2 value suggests that 1% of the variation in delinquency is explained by Emotion Perception.

Table 21. Regression results with delinquency as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Perception	.01	.13	.09	.92
Step 2				
(Intercept)	.00	.13	.00	1.00
Emotion Perception	-.05	.15	-.33	.74
Extraversion	-.21	.17	-1.29	.20
Neuroticism	-.31	.14	-2.25	.03
Conscientiousness	.15	.21	.70	.49
Openness to experience	-.01	.18	-.03	.98
Agreeableness	-.08	.21	-.36	.72
Matrigma score	-.21	.13	-1.58	.12
Gender	-.15	.15	-.94	.35
Age	.09	.14	.65	.52

Note. $\hat{\beta}$: Estimated beta coefficients. Std. Error: Standard error. t-statistic: Test statistic. p: p-value.

Overall, the results from the regression analyses suggest that Emotion Perception is not a good predictor of work performance, both when controlling for and not controlling for personality and cognitive factors, gender and age. This means that hypothesis 2 is rejected and the null hypothesis is accepted.

Another aspect that was investigated was whether respondents' credit risk assessments moderated the relationship between Emotion Perception and work performance. The results of the regressions were statistically non-significant for both charge off ($R^2 = .07,\ F(13{,}47) = 1.33, p = .23$) and delinquency ($R^2 = .85,\ F(13{,}47) =, p = 61$). This means that hypothesis 6a is rejected and the null hypothesis is accepted.

4.4.2.2 *Emotion Facilitation does not predict work performance*

Hypothesis 3 was concerned with examining whether Emotion Facilitation is a good predictor of work performance, as measured by charge off and delinquency. The work performance variables were analysed separately.

For the first step in Table 22 of the model, Emotion Facilitation was specified as the independent variable and charge-off as the dependent variable. The diagnostic plots can be seen in Figure 29 below. The red line in the Residual vs Fitted plot is somewhat horizontal. However, there is some spread of data near the centre of the plot. Additionally, the Scale–Location plot has a red line which is horizontal. The NCV test was found to be non-significant ($\hat{\chi}^2 = .33, p = .56$). Taken together, these results suggest that there is evidence that heteroskedasticity was not a problem. In the Normal Q-Q plot, the data points are deviating from the diagonal straight line, meaning that there is an absence of normality in the data.

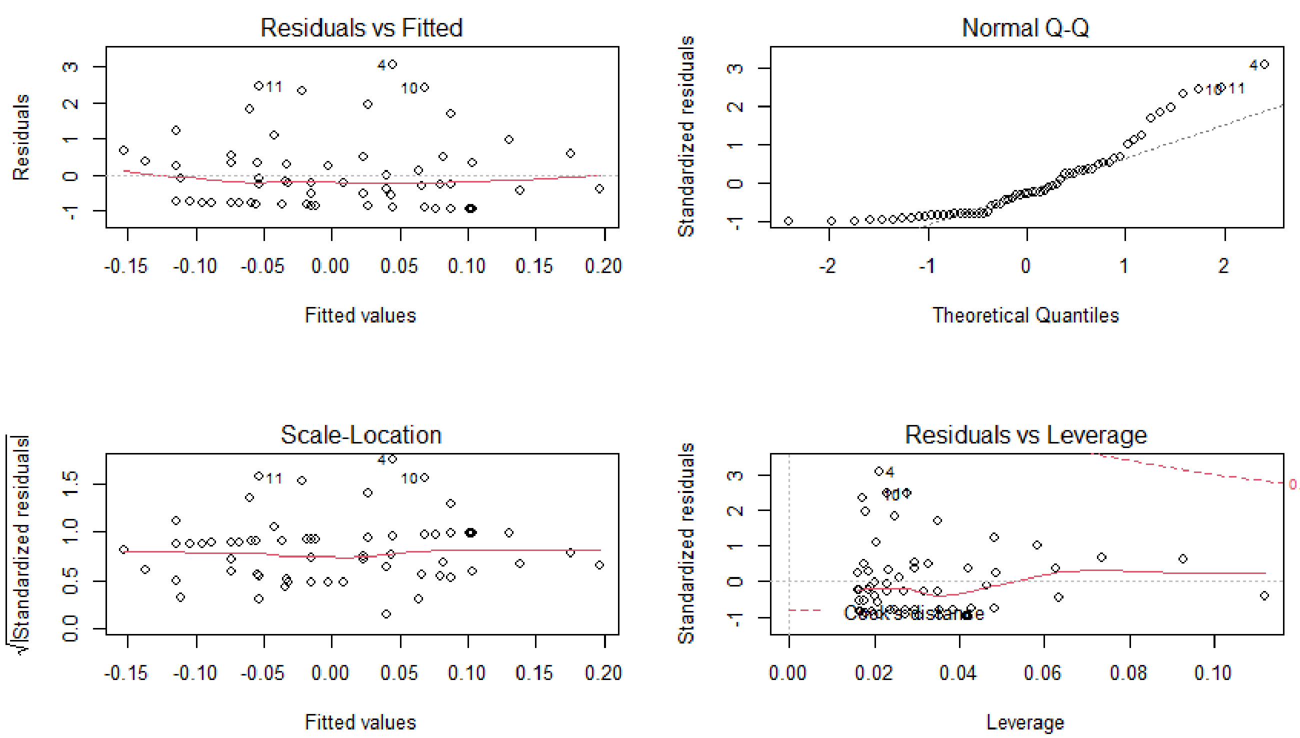

Figure 29. Regression diagnostic plots.

The results of the first step of the analysis revealed that the model was not statistically significant, with $R^2 = -.01,\ F(1{,}60) = .40, p = .53$. The R^2 value associated with this model suggests that Emotion Facilitation accounts for 1% of the variation in charge off, meaning that 99% of the variation in charge off cannot be explained by Emotion Facilitation alone. The R^2 value is also negative, which is an indication that the model fits the data poorly.

For the second step in Table 22, the control variables were added as predictors to the model. The diagnostic plots are presented in Figure 30. There are signs of heteroskedasticity, confirmed by the NVC test ($\hat{\chi}^2 = 7.48, p < .01$). Also visible are elements of non-normality based one the Normal Q-Q plot.

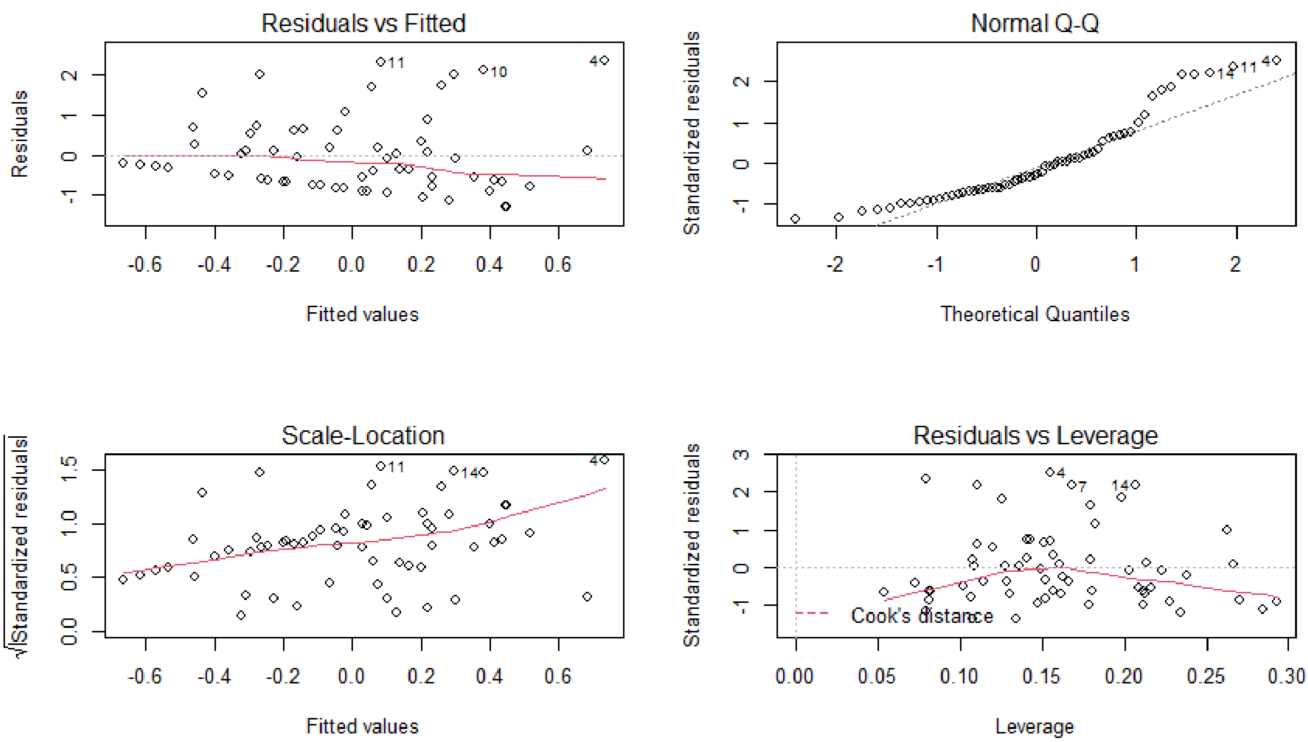

Figure 30. Regression diagnostic plots.

The results of the second step revealed a model to also be statistically non-significant, with $R^2 = -.05,\ F(9{,}52) = .68, p = .72$. Again, the R^2 value was negative, suggesting that the model fits the data poorly.

Table 22. Regression results with charge off as the dependent variable.

	$\hat{\boldsymbol{\beta}}$	***Std. Error***	***t-statistic***	$\boldsymbol{p}$
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Facilitation	.08	.13	.63	.53
Step 2				
(Intercept)	.00	.13	.00	1.00
Emotion Facilitation	-.07	.16	.44	.66
Extraversion	-.14	.17	-.83	.41
Neuroticism	-.03	.14	-.20	.84
Conscientiousness	-.17	.21	-.83	.41
Openness to experience	.20	.18	1.11	.27
Agreeableness	.32	.21	1.54	.13
Matrigma score	.05	.14	.36	.72
Gender	.15	.16	.93	.36
Age	.04	.15	.28	.78

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

Another regression analysis was performed which was identical to the previous model, except that the dependent variable was not specified as delinquency. The diagnostic plots for the first step of the analysis are shown in Figure 31. The red line in both the Residual vs Fitted plot and the Scale–Location plot is horizontal, with a slight downward trend on the right side of the plot. The Scale–Location plot also has a somewhat horizontal line. The NCV test was also found to be non-significant ($\hat{\chi}^2 = 1.41, p = .24$), leading to the conclusion that the variance of the residuals was constant. Again, there are signs of non-normality in the Normal Q-Q plot.

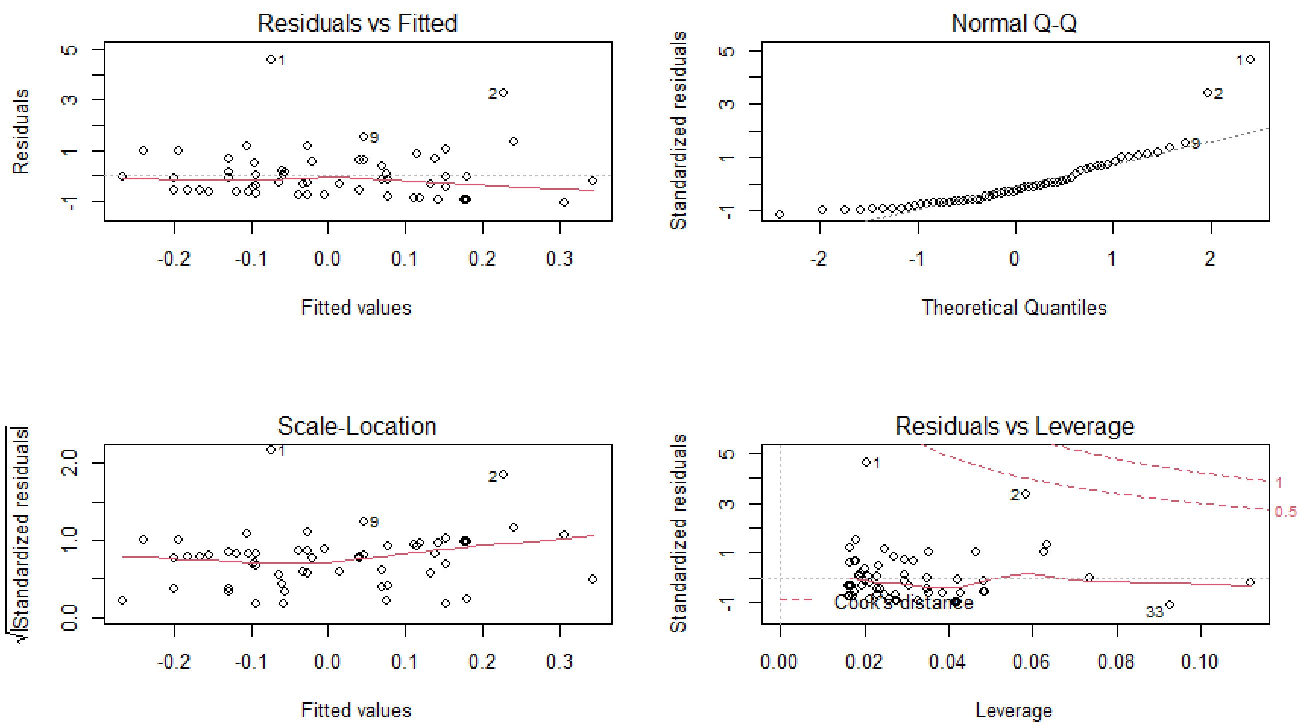

Figure 31. Regression diagnostic plots.

The first step in the analysis revealed a non-significant model, with $R^2 < .01$, $F(1{,}60) = 1.24, p = .27$. The R^2 value suggests that Emotion Facilitation accounts for less than 1% of the variation in delinquency. It is also evident that the R^2 value is negative, which is an indication that the model fits the data poorly.

For the second step in Table 23, the control variables were added as predictors to the model. In the diagnostic plots in Figure 32 there are signs of heteroskedasticity, confirmed by the NVC test ($\hat{\chi}^2 = 24.60, p < .001$), and of non-normality.

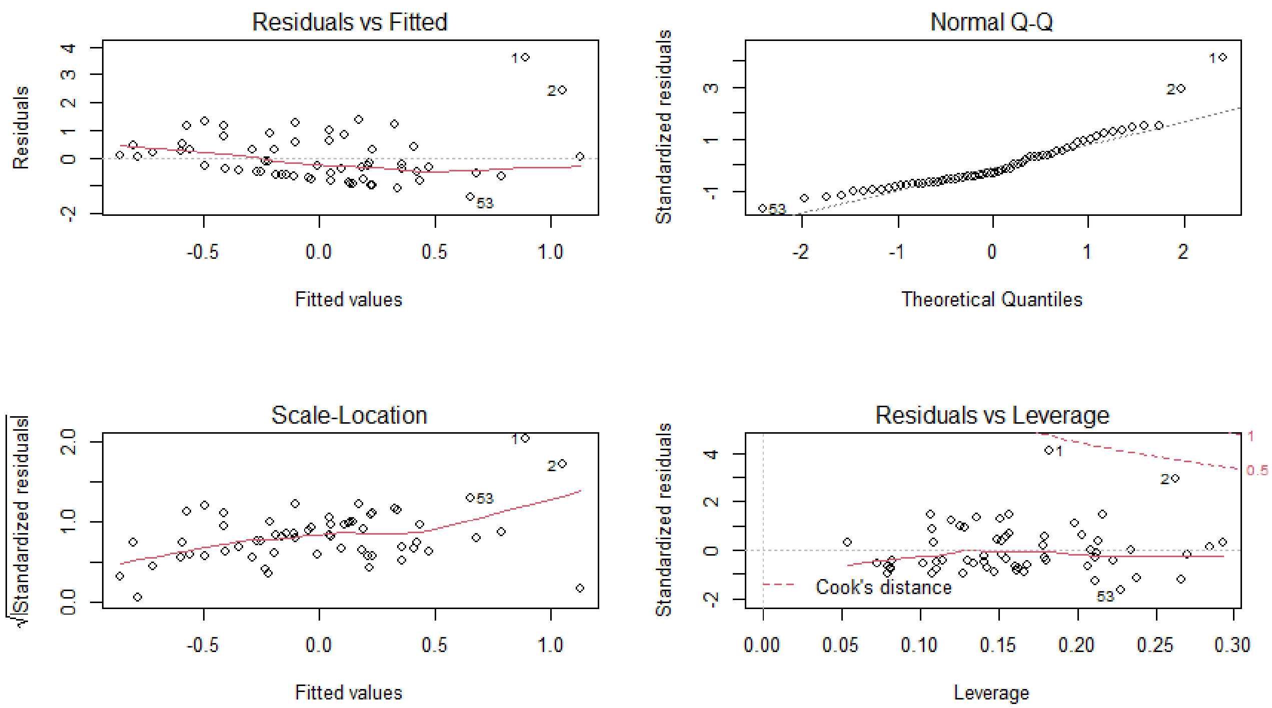

Figure 32. Regression diagnostic plots.

The results of the second step revealed a model to also be statistically non-significant, with $R^2 = .06$, $F(9,52) = 1.41, p = .21$. The R^2 value suggests that 6% of the variation in delinquency is explained by Emotion Facilitation.

Table 23. Regression results with delinquency as the dependent variable.

	$\hat{\boldsymbol{\beta}}$	***Std. Error***	***t-statistic***	$\boldsymbol{p}$
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Facilitation	.14	.13	1.11	.27
Step 2				
(Intercept)	.00	.12	.00	1.00
Emotion Facilitation	.24	.15	1.59	.12
Extraversion	-.20	.16	-1.27	.21
Neuroticism	-.31	.13	-2.31	**.02**
Conscientiousness	.05	.20	.26	.80
Openness to experience	.00	.17	.01	.99
Agreeableness	-.03	.20	-.14	.89
Matrigma score	-.29	.14	-2.08	**.04**
Gender	-.05	.15	-.31	.76
Age	.17	.14	1.17	.25

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

Overall, the results from the regression analyses suggest that Emotion Facilitation is not a good predictor of work performance, both when controlling for and not controlling for personality and cognitive factors, gender and age. This means that hypothesis 3 is rejected and the null hypothesis is accepted.

In addition, an attempt was made to investigate whether respondents' credit risk assessments moderated the relationship between Emotion Facilitation and work performance. The results of the regressions were statistically non-significant for both charge off ($R^2 = -.05,\ F(13,47) = .80, p = .66$) and delinquency ($R^2 = .09,\ F(13,47) = 1.45, p = .17$). This means that hypothesis 6b is rejected and the null hypothesis is accepted.

4.4.2.3 *Emotion Understanding does not predict work performance*

Hypothesis 4 was concerned with examining whether Emotion Understanding is a good predictor of work performance, as measured by charge off and delinquency. The work performance variables were analysed separately.

For the first step in Table 24 of the model, Emotion Understanding was specified as the independent variable and charge off as the dependent variable. The diagnostic plots can be seen in Figure 33 below. The red line in the Residual vs Fitted plot is somewhat horizontal. However, there is a large spread of data near the centre of the plot. Additionally, the Scale–Location plot has a parabolic-like pattern to it. These signs hint at the possibility of heteroskedasticity, but the NCV test was found to be non-significant ($\hat{\chi}^2 = 1.04, p = .31$). Rather, this means that there is evidence that heteroskedasticity is not a problem in this case. In the Normal Q-Q plot, the data points are deviating from the diagonal straight line, meaning that there is an absence of normality in the data.

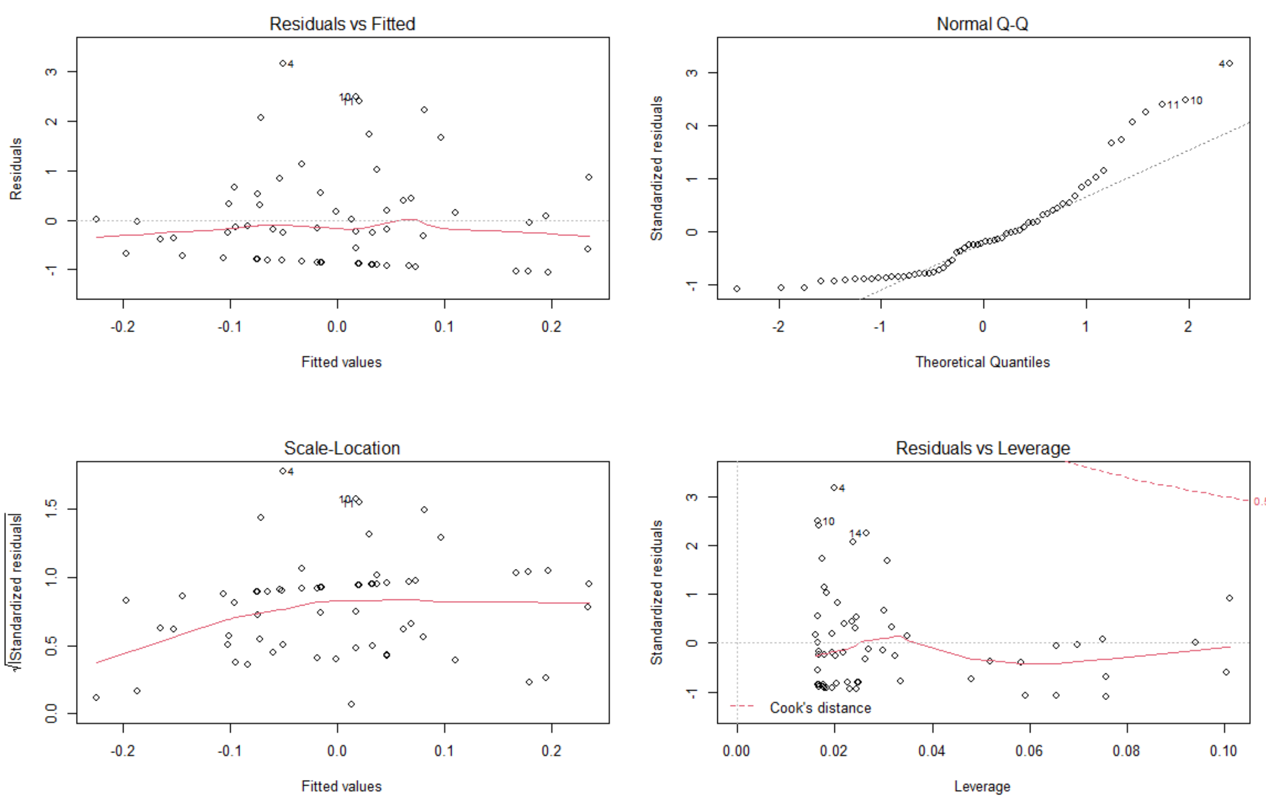

Figure 33. Regression diagnostic plots.

The results of the first step of the analysis revealed that the model was not statistically significant, with $R^2 = -.01,\ F(1{,}60) = .64, p = .43$. The R^2 value associated with this model suggests that Emotion Understanding accounts for 1% of the variation in charge off, meaning that 99% of the variation in charge off cannot be explained by Emotion Understanding alone. The R^2 value is also negative, which is an indication that the model fits the data poorly.

For the second step in Table 24, the control variables were added as predictors to the model. The diagnostic plots are presented in Figure 34. Again, one sees signs of heteroskedasticity, confirmed by the NVC test ($\hat{\chi}^2 = 9.27, p < .01$), and of non-normality.

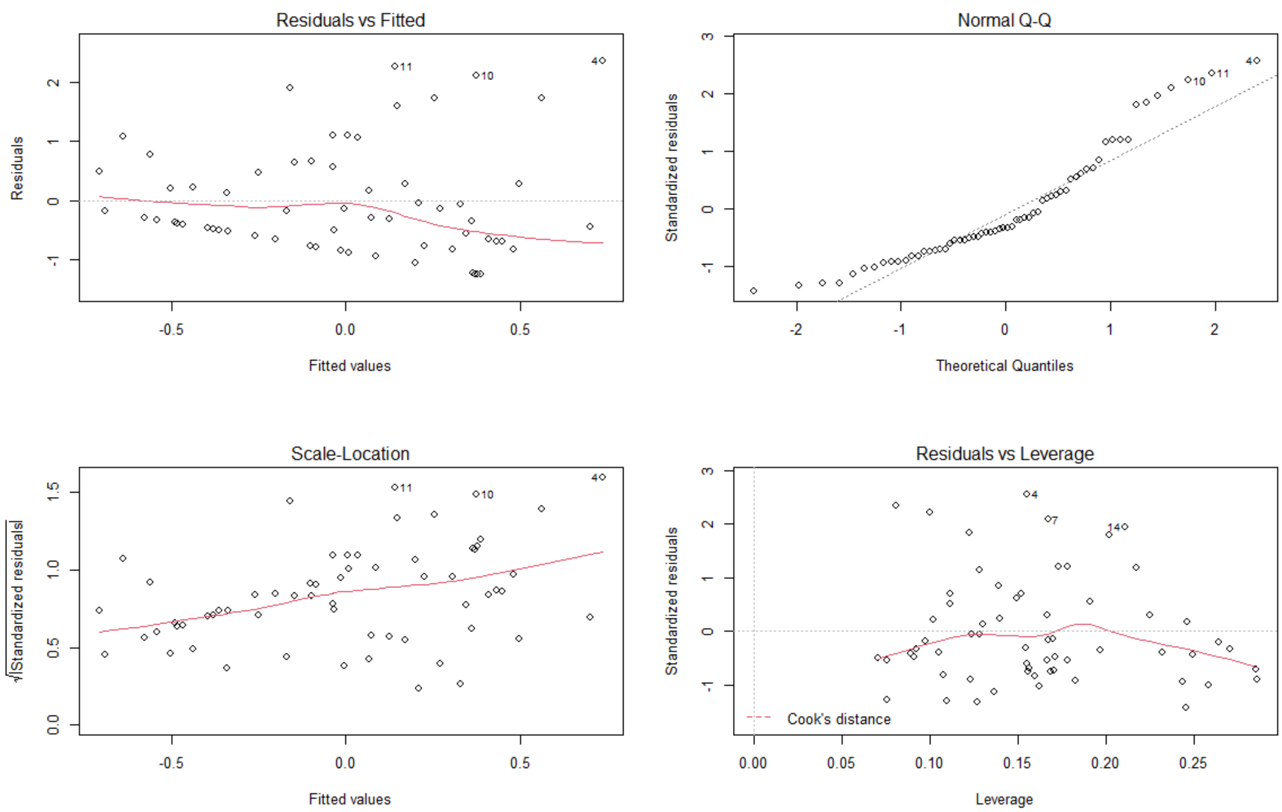

Figure 34. Regression diagnostic plots.

The results of the second step revealed a model to also be statistically non-significant, with $R^2 = -.01,\ F(9{,}52) = .92, p = .52$. Again, the R^2 value is negative, suggesting that the model fits the data poorly.

Table 24. Regression results with charge off as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Understanding	-.10	.13	-.80	.43
Step 2				
(Intercept)	.00	.13	.00	1.00
Emotion Understanding	-.21	.15	-1.44	.16
Extraversion	-.17	.17	-1.03	.31
Neuroticism	-.03	.14	-.18	.86
Conscientiousness	-.09	.20	-.44	.66
Openness to experience	.23	.18	1.28	.20
Agreeableness	.28	.21	1.38	.17
Matrigma score	.15	.15	1.01	.32
Gender	.13	.15	.88	.38
Age	.02	.14	.13	.90

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

Another regression analysis was performed which was identical to the previous model, except that the dependent variable was not specified as delinquency. The diagnostic plots for the first step of the analysis are shown in Figure 35. The red line in the Residual vs Fitted plot is horizontal. The same holds for the Scale–Location plot. The NCV test was also found to be non-significant ($\hat{\chi}^2 = .09, p = .78$), leading to the conclusion that the variance of the residuals was constant. Again, there are signs of non-normality in the Normal Q-Q plot.

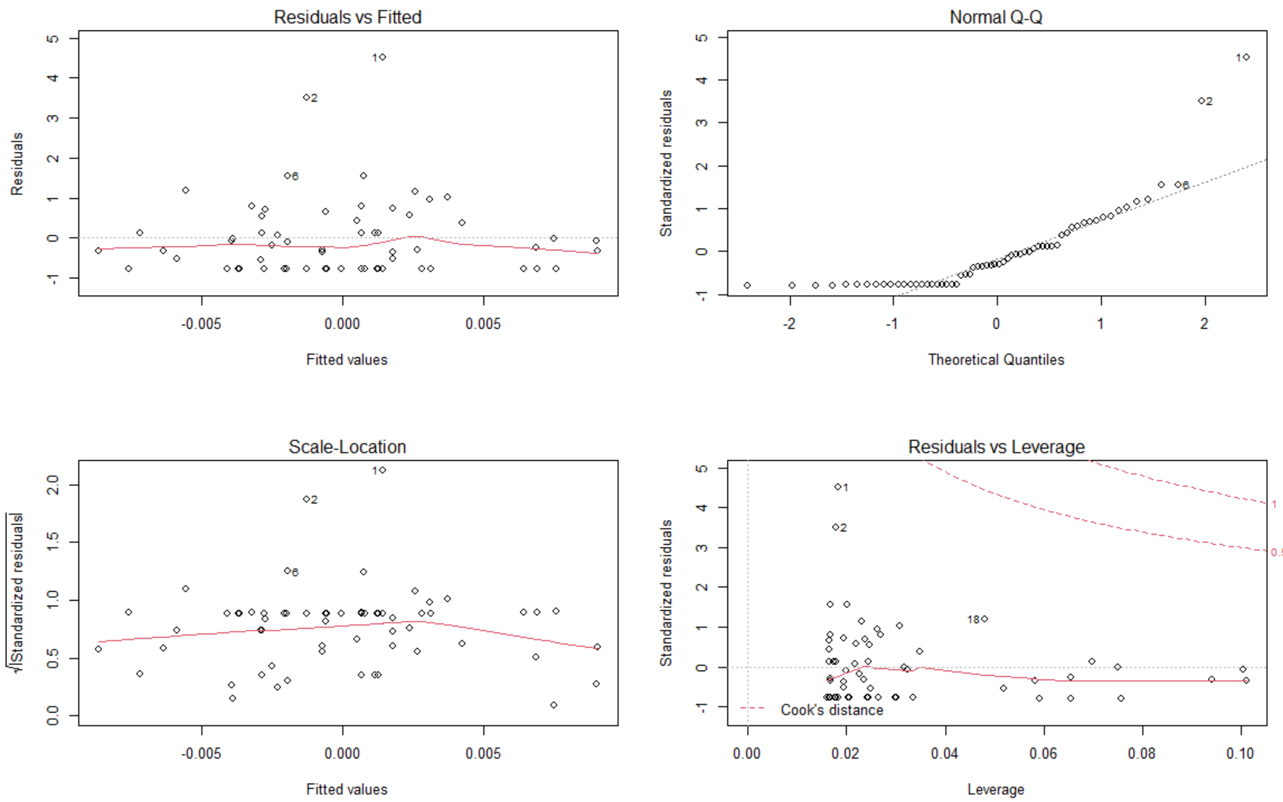

Figure 35. Regression diagnostic plots.

The first step in the analysis revealed a non-significant model, with $R^2 = -.02$, $F(1{,}60) = .001, p = .98$. The R^2 value suggests that Emotion Understanding accounts for 2% of the variation in delinquency, meaning that 98% of the variation in delinquency cannot be explained by Emotion Understanding alone. Again, the R^2 value is negative, which is an indication that the model fits the data poorly.

For the second step in Table 25, the control variables were added as predictors to the model. In the diagnostic plots in Figure 36, there are again signs of heteroskedasticity, confirmed by the NVC test ($\hat{\chi}^2 = 27.04, p < .001$), and of non-normality.

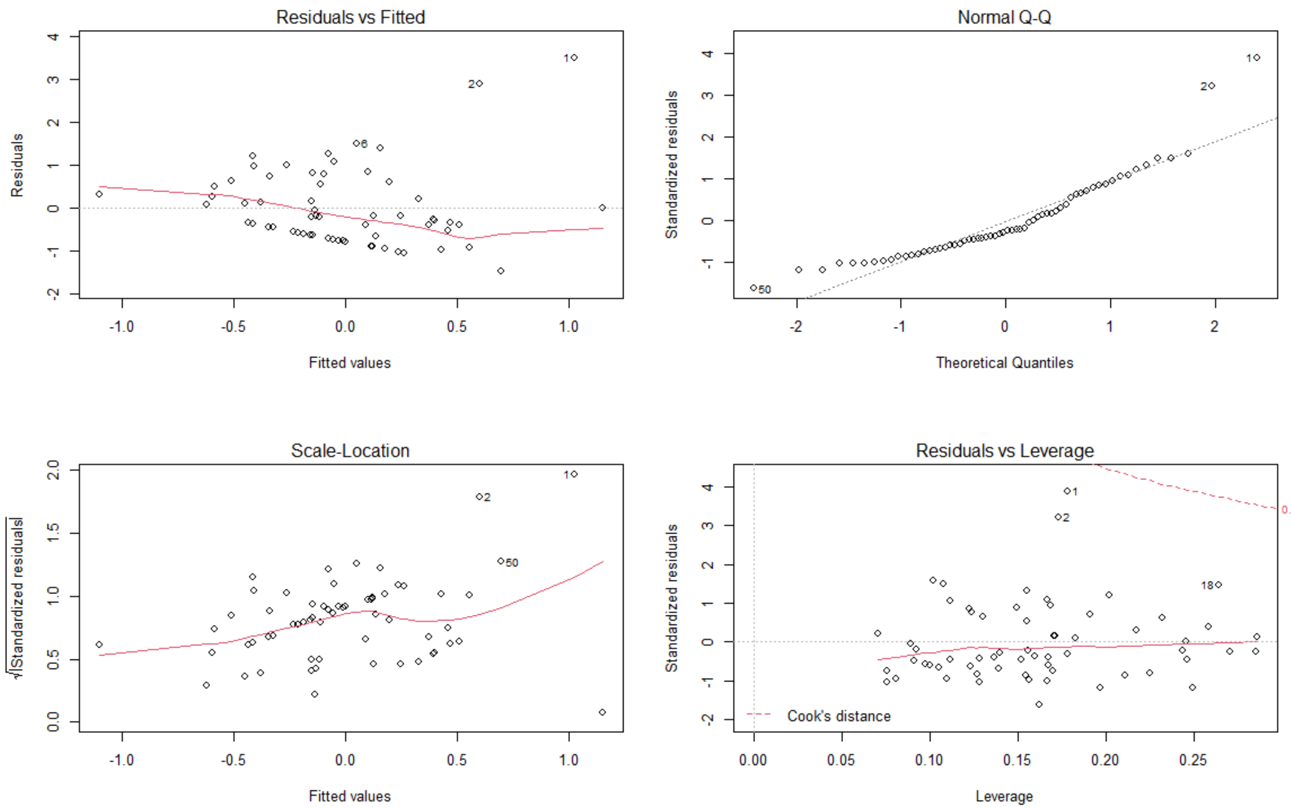

Figure 36. Regression diagnostic plots.

The results of the second step revealed a model to also be statistically non-significant, with $R^2 = .01,\ F(9,52) = 1.10, p = .39$. The R^2 value suggests that 1% of the variation in delinquency is explained by Emotion Understanding.

Table 25. Regression results with delinquency as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Understanding	.00	.13	-.03	.98
Step 2				
(Intercept)	.00	.13	.00	1.00
Emotion Understanding	.05	.15	.31	.76
Extraversion	-.20	.17	-1.20	.24
Neuroticism	-.31	.14	-2.26	**.03**
Conscientiousness	.11	.20	.54	.59
Openness to experience	-.01	.18	-.08	.94
Agreeableness	-.05	.20	-.26	.79
Matrigma score	-.24	.14	-1.63	.11
Gender	-.13	.15	-.89	.38
Age	.09	.14	.69	.50

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

Overall, the results from the regression analyses suggest that Emotion Understanding is not a good predictor of work performance, both when controlling for and not controlling for personality and cognitive factors, gender and age. This means that hypothesis 4 is rejected and the null hypothesis is accepted.

An attempt was also made to investigate whether respondents' credit risk assessments moderated the relationship between Emotion Understanding and work performance. The results of the regressions were statistically non-significant for both charge off ($R^2 = -.05,\ F(13,47) = .79, p = .67$) and delinquency ($R^2 = -.01,\ F(13,47) = .96, p = .51$). This means that hypothesis 6c is rejected and the null hypothesis is accepted.

4.4.2.4 Emotion Regulation does not predict work performance

Hypothesis 5 was concerned with examining whether Emotion Regulation is a good predictor of work performance, as measured by charge off and delinquency. The work performance variables were analysed separately.

For the first step in Table 26 of the model, Emotion Regulation was specified as the independent variable and charge off as the dependent variable. The diagnostic plots are presented in Figure 37. The red line in the Residual vs Fitted plot and Scale–Location plot is somewhat horizontal, and the NCV test was found to be non-significant ($\hat{\chi}^2 = .79, p = .37$). These observations suggest that heteroskedasticity is not a problem. In the Normal Q-Q plot, the data points are deviating from the diagonal straight line, meaning that there is an absence of normality in the data.

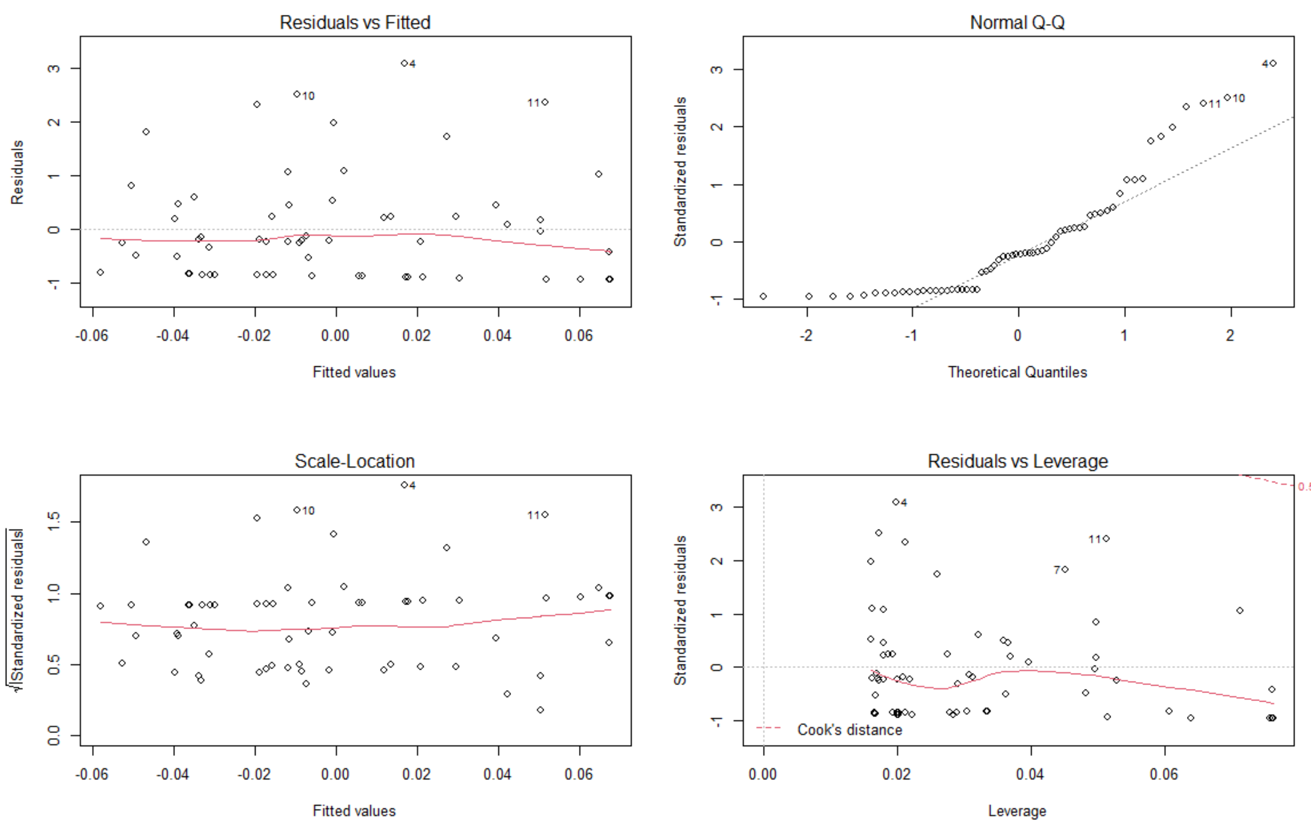

Figure 37. Regression diagnostic plots.

The results of this step revealed a model not to be statistically significant, with $R^2 = -.002$ $F(1,60) = .07, p = .90$. The R^2 value associated with this model suggests that Emotion

Regulation accounts for .2% of the variation in charge off. The R^2 value is also negative, which is an indication that the model fits the data poorly.

For the second step in Table 26, the control variables were added as predictors to the model. The diagnostic plots in Figure 38 suggest that variance of the residuals is unequal. This is most visible in the Residuals vs Fitted and Scale–Location plots. Furthermore, the NCV test was found to be statistically significant, with $\hat{\chi}^2 = 6.29, p = .01$. Therefore, the assumption of homogeneity of variances was violated.

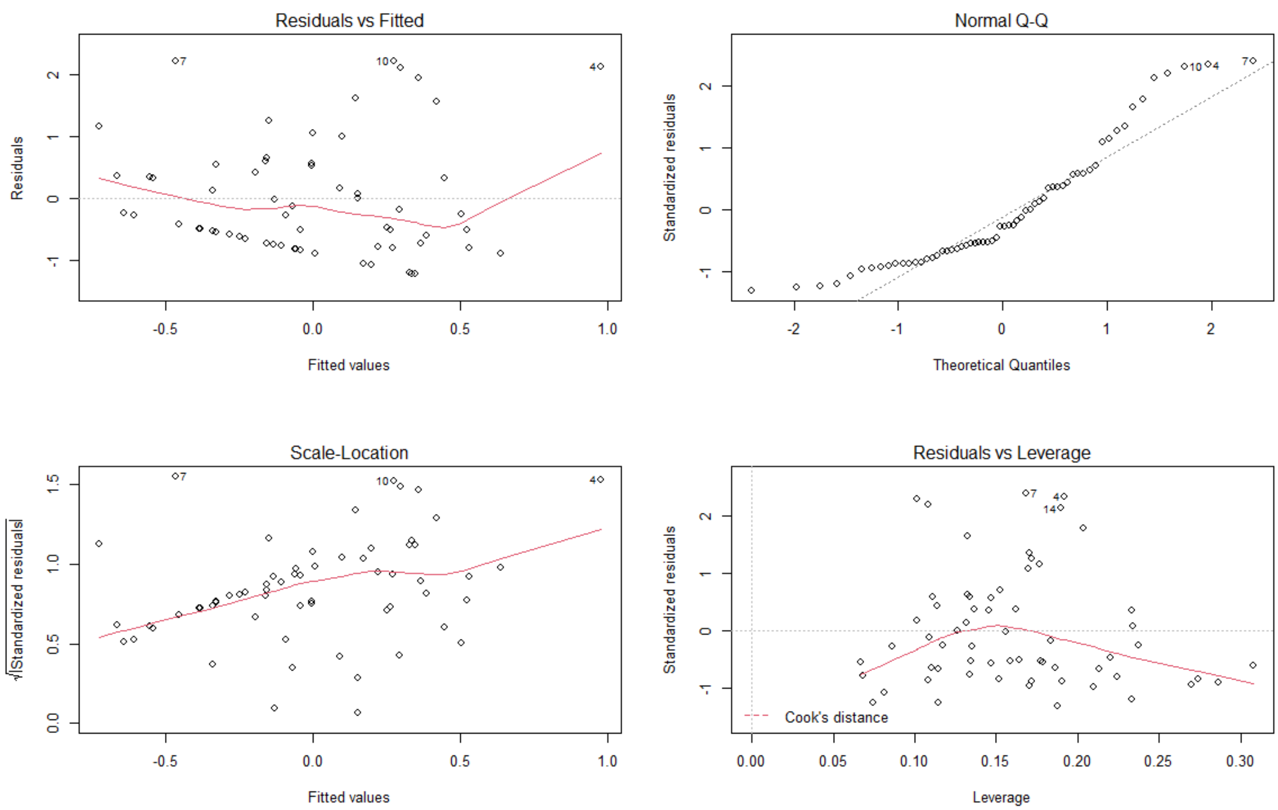

Figure 38. Regression diagnostic plots.

The results of the second step revealed a model to also be statistically non-significant, with $R^2 = -.02,\ F(9,52) = .86, p = .57$. The R^2 value suggests that Emotion Regulation accounts for 2% of the variation in charge off, meaning that 98% is unexplained by Emotion Regulation alone. Again the R^2 value is negative, which is an indication that the model fits the data poorly.

Table 26. Regression results with charge off as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Regulation	-.04	.13	-.27	.79
Step 2				
(Intercept)	.00	.13	.00	1.00
Emotion Regulation	-.22	.17	-1.25	.22
Extraversion	-.18	.17	-1.06	.29
Neuroticism	-.02	.14	-.16	.87
Conscientiousness	-.04	.22	-.20	.84
Openness to experience	.18	.18	.98	.33
Agreeableness	.34	.21	1.66	.10
Matrigma score	.13	.14	.90	.37
Gender	.09	.15	.58	.56
Age	.00	.14	-.03	.97

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

Another regression analysis was performed which was identical to the previous model, except that the dependent variable was not specified as delinquency. The diagnostic plots for the first stage of the analysis suggested that the assumption of homogeneity of variances was not violated, which was further corroborated by the non-significant NCV test, with $\hat{\chi}^2 = 1.83, p = .18$.

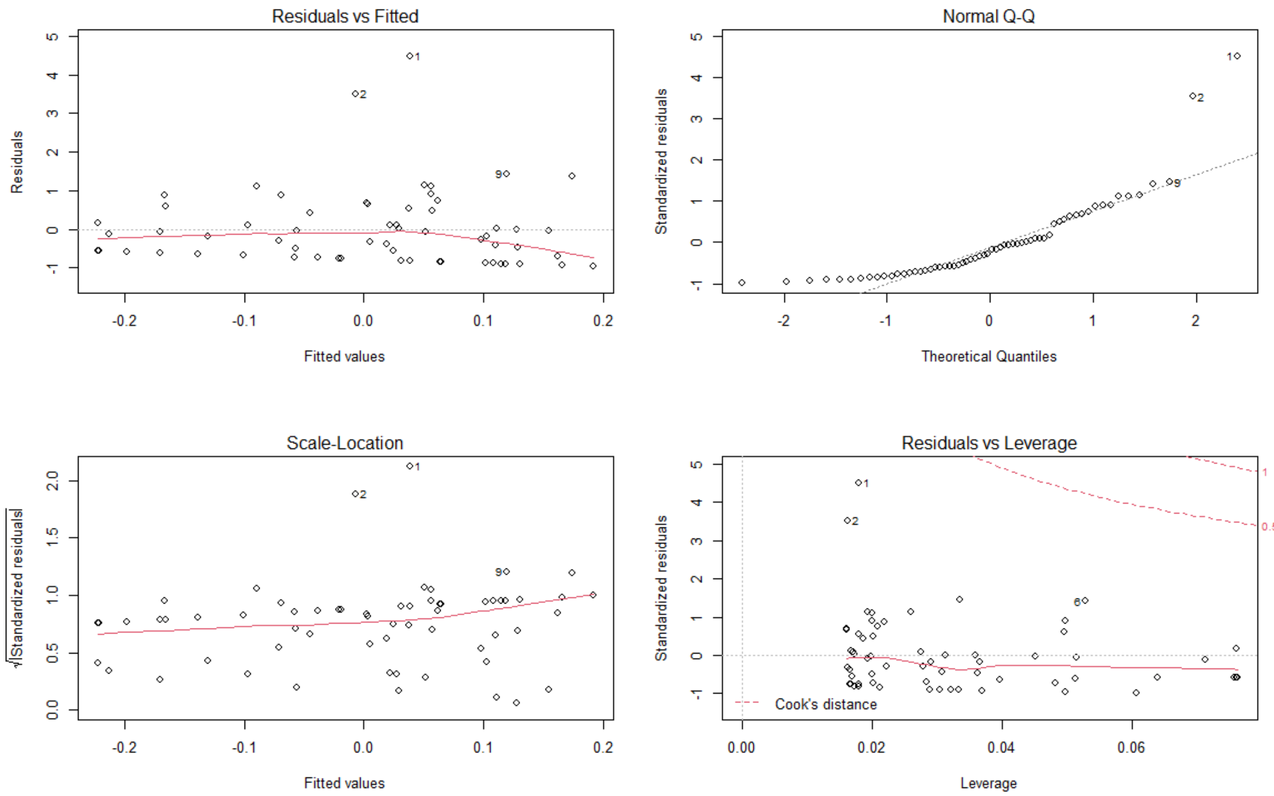

Figure 39. Regression diagnostic plots.

The first step in the analysis revealed a non-significant model, with $R^2 = -.002\ \ F(1{,}60) = .82, p = .37$. The R^2 value associated with this model suggests that Emotion Regulation accounts for .2% of the variation in delinquency. The R^2 value is also negative, which is an indication that the model fits the data poorly.

For the second step in Table 27, the control variables were added as predictors to the model. In the Residuals vs Fitted plot and Scale–Location plot, there is a funnel-like pattern and a parabolic horizontal red line respectively. The NVC test was also found to be significant, with $\hat{\chi}^2 = 24.62, p < .001$.

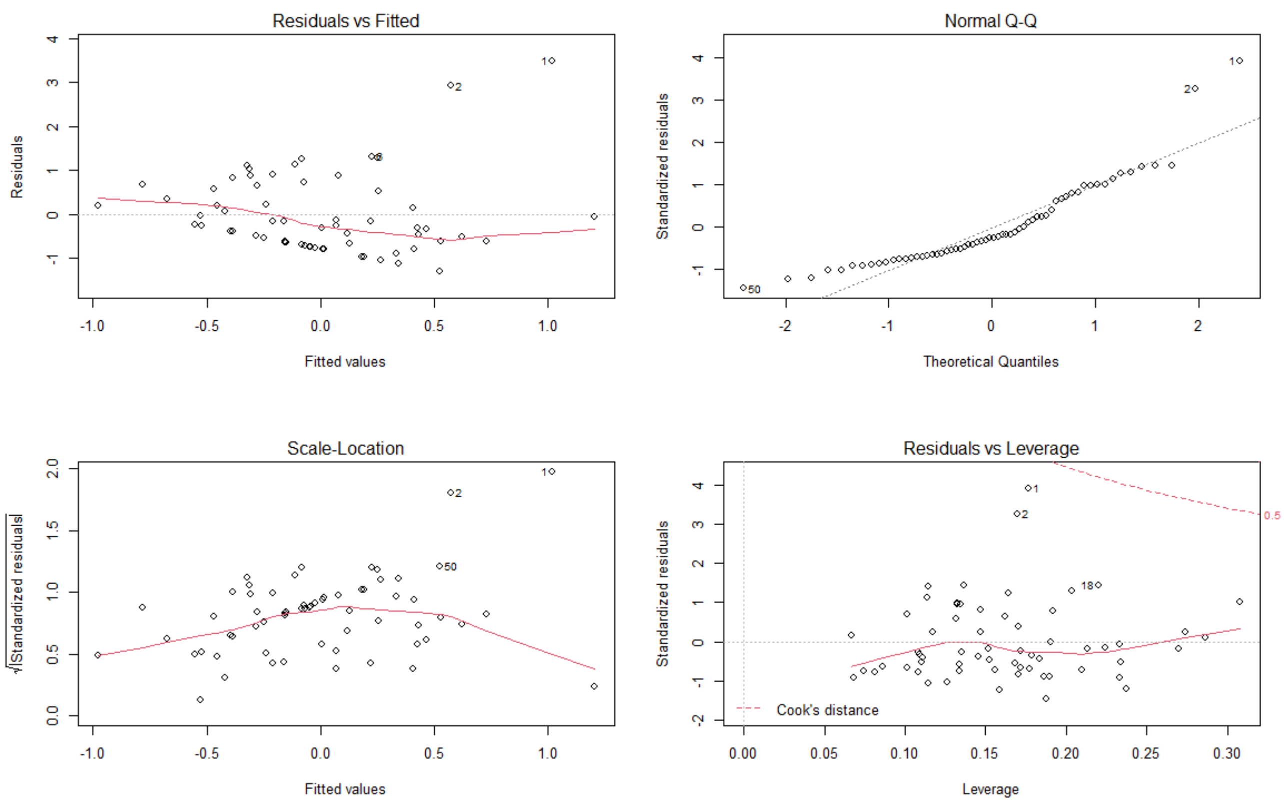

Figure 40. Regression diagnostic plots.

The results of the second step revealed a model to also be statistically non-significant, with $R^2 = .03,\ F(9,52) = 1.21, p = .31$. The R^2 value suggests that Emotion Regulation accounts for 3% of the variation in delinquency, meaning that 97% is unexplained by Emotion Regulation alone.

Table 27. Regression results with delinquency as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Regulation	.12	.13	.91	.37
Step 2				
(Intercept)	.00	.13	.00	1.00
Emotion Regulation	.17	.17	1.02	.31
Extraversion	-.17	.17	-1.05	.30
Neuroticism	-.32	.14	-2.31	**.03**
Conscientiousness	.04	.21	.17	.87
Openness to experience	.01	.18	.06	.95
Agreeableness	-.08	.20	-.42	.68
Matrigma score	-.26	.14	-1.89	.06
Gender	-.10	.15	-.68	.50
Age	.11	.14	.83	.41

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

Overall, the results from the regression analyses suggest that Emotion Regulation is not a good predictor of work performance, both when controlling for and not controlling for personality and cognitive factors, gender and age. This means that hypothesis 5 is rejected and the null hypothesis is accepted.

Another aspect that was investigated was whether respondents' credit risk assessments moderated the relationship between Emotion Regulation and work performance. The results of the regressions were statistically non-significant for both charge off ($R^2 = .01,\ F(13{,}47) = 1.04, p = .42$) and delinquency ($R^2 = .01,\ F(13{,}47) = 1.01, p = .41$). This means that hypothesis 6d is rejected and the null hypothesis is accepted.

4.4.2.5 *Emotional intelligence abilities do not predict work performance*

Hypothesis 7 was concerned with examining whether EI abilities are together good predictors of work performance, as measured by charge off and delinquency, with credit risk assessment acting as a moderating variable. The work performance variables were analysed separately.

For the first step in Table 28 of the model, Emotion Perception, Emotion Facilitation, Emotion Understanding and Emotion Regulation were specified as the independent variable and charge off as the dependent variable. In the diagnostic plots in Figure 41, both the Residuals vs Fitted plot and the Scale–Location plot appear to have funnel patterns. Moreover, the NCV test was significant, with $\hat{\chi}^2 = 4.26, p = .04$.

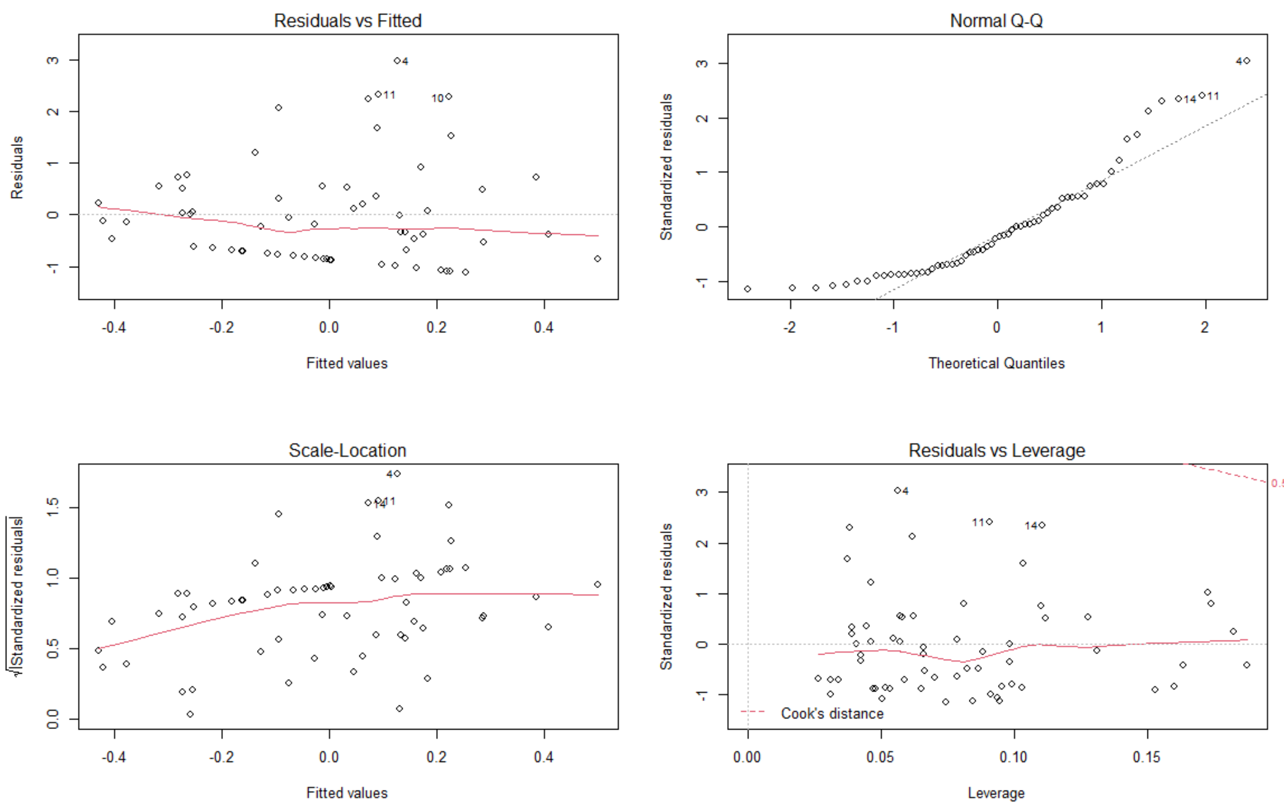

Figure 41. Regression diagnostic plots.

The results of this step revealed a model not to be statistically significant, with $R^2 = -.02, F(4{,}57) = .469\ p = .60$. The R^2 value associated with this model suggests that EI abilities account for 2% of the variation in charge off. The R^2 value is also negative, which is an indication that the model fits the data poorly.

For the second step in Table 28, the control variables were added as predictors to the model. The diagnostic plots again suggest that the assumption of homogeneity of variances, the assumption of linearity and the assumption of normality were all violated. Moreover, the NCV test was statistically significant, with $\hat{\chi}^2 = 9.24, p < .01$.

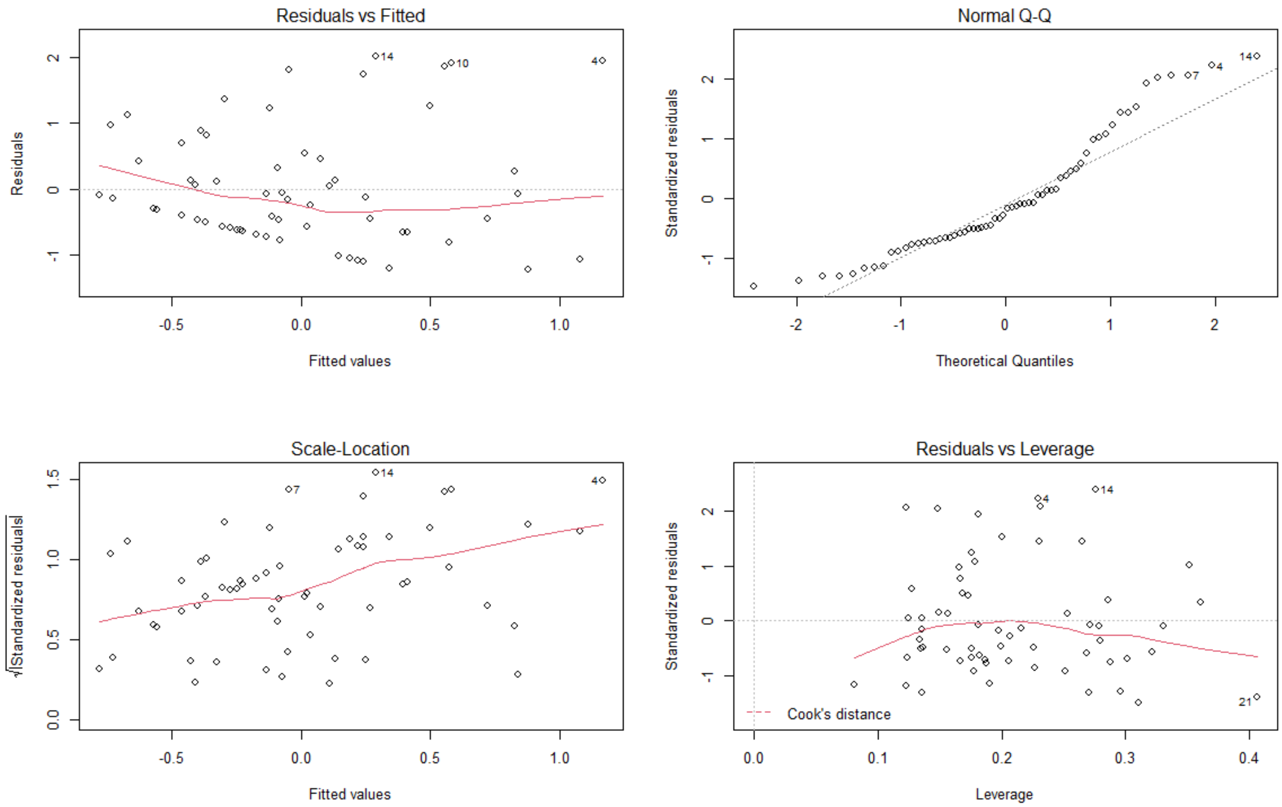

Figure 42. Regression diagnostic plots.

The results of the second step showed a model to also be statistically non-significant, with $R^2 = .02, F(12,49) = 1.8, p = .40$. The R^2 value associated with this model suggests that EI abilities account for 2% of the variation in charge off.

Another regression analysis was performed which was identical to the previous model, except that the dependent variable was not specified as delinquency. The diagnostic plots are shown in Figure 43 which suggest that the assumption of linearity, the assumption of homogeneity of variances and the assumption normality were violated. The NCV test was statistically significant, with $\hat{\chi}^2 = 6.20, p = .01$.

Table 28. Regression results with charge off as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Perception	.05	.16	.32	.75
Emotion Facilitation	.24	.21	1.18	.24
Emotion Understanding	-.18	.17	-1.10	.28
Emotion Regulation	-.12	.20	-.62	.54
Step 2				
(Intercept)	.00	.13	.00	1.00
Emotion Perception	.04	.17	.25	.80
Emotion Facilitation	.41	.28	1.74	.09
Emotion Understanding	-.25	.18	-1.37	.18
Emotion Regulation	-.37	.24	-1.51	.14
Extraversion	-.23	.17	-1.35	.18
Neuroticism	-.02	.14	-.13	.90
Conscientiousness	-.04	.23	-.17	.86
Openness to experience	.21	.18	1.16	.25
Agreeableness	.40	.21	1.86	.07
Matrigma score	.14	.15	.97	.34
Gender	.23	.16	1.38	.17
Age	.10	.15	.68	.50

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

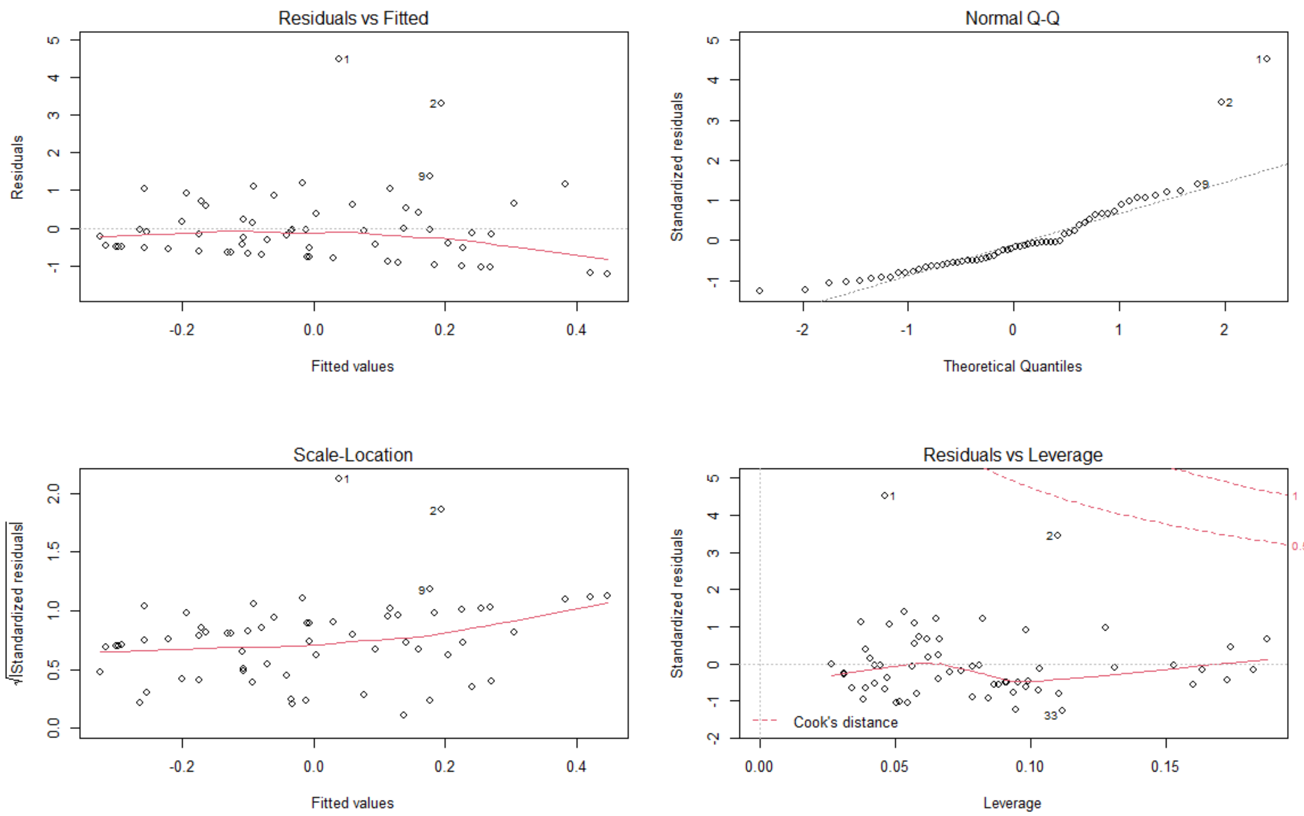

Figure 43. Regression diagnostic plots.

The first step in the analysis revealed a non-significant model, with $R^2 = -.03, F(4, 57) = .58, p = .68$. The R^2 value associated with this model suggests that EI abilities account for .3% of the variation in delinquency. The R^2 value is also negative, which is an indication that the model fits the data poorly.

For the second step in Table 29, the control variables were added as predictors to the model. The diagnostic plots are shown in Figure 44, which suggests that the assumption of linearity, the assumption of homogeneity of variances and the assumption normality were violated. The NCV test was also found to be statistically significant, with $\hat{\chi}^2 = 26.88, p < .001$.

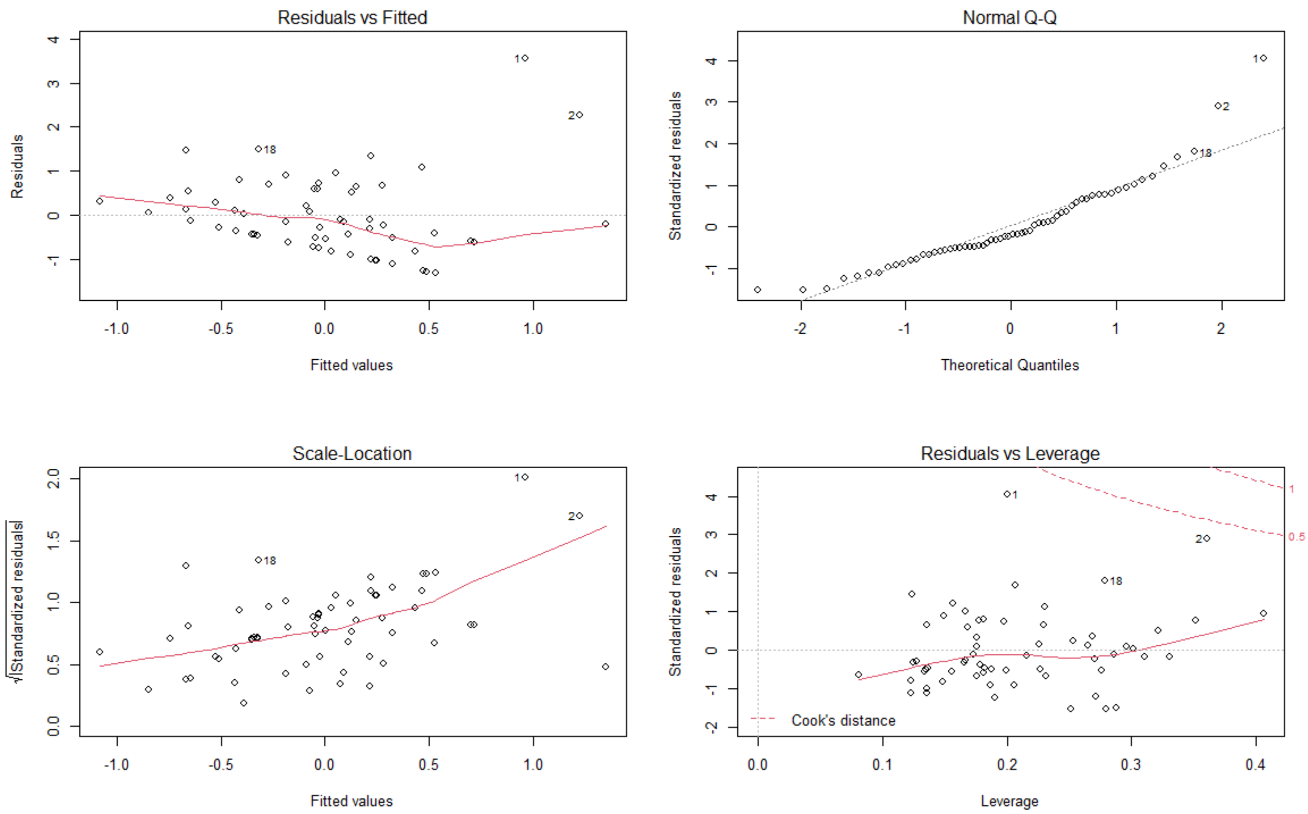

Figure 44. Regression diagnostic plots.

The results of the second step revealed a model to also be statistically non-significant, with $R^2 = .04,\ F(12, 49) = 1.19, p = .32$. The R^2 value associated with this model is extremely small, meaning that EI abilities account for less than .01% of the variation in delinquency.

Overall, the results from the regression analyses suggest that EI abilities are not a good predictor of work performance, both when controlling for and not controlling for personality and cognitive factors, gender and age.

Table 29. Regression results with delinquency as the dependent variable.

	$\hat{\beta}$	*Std. Error*	*t-statistic*	p
Step 1				
(Intercept)	.00	.13	.00	1.00
Emotion Perception	-.09	.16	-.57	.57
Emotion Facilitation	.20	.21	.97	.33
Emotion Understanding	-.13	.17	-.80	.43
Emotion Regulation	.09	.20	.46	.65
Step 2				
(Intercept)	.00	.12	.00	1.00
Emotion Perception	-.21	.17	-1.22	.23
Emotion Facilitation	.40	.24	1.68	.10
Emotion Understanding	-.08	.18	-.47	.64
Emotion Regulation	.00	.24	.01	.99
Extraversion	-.25	.17	-1.48	.15
Neuroticism	-.31	.14	-2.27	.03
Conscientiousness	.15	.23	.67	.51
Openness to experience	.03	.18	.17	.86
Agreeableness	-.09	.21	-.42	.68
Matrigma score	-.27	.14	-1.90	.06
Gender	-.06	.16	-.34	.73
Age	.19	.15	1.31	.19

Note. $\hat{\beta}$: Estimated beta coefficients. *Std. Error*: Standard error. *t-statistic*: Test statistic. p: *p*-value.

An attempt was also made to investigate whether respondents' credit risk assessments moderated the relationship between EI abilities and work performance. The results of the regressions were statistically non-significant for both charge off ($R^2 = .13,\ F(22{,}38) = 1.40, p = .18$) and delinquency ($R^2 = .10,\ F(22, 38) = 1.32, p = .22$). This means that hypothesis 7 is rejected and the null hypothesis is accepted.

4.4.3 Group Differences

Given the non-significant regression models, it was decided that it may be beneficial to partition the sample between low and high EI scores and then to re-run the regression analyses. The reasoning here is that one would expect individuals with higher EI scores to make good loan decisions, in contrast to those with lower EI scores. Before proceeding with this approach, however, I investigated whether there were significant differences in individuals' work performance and risk grade assessment scores when grouped according to their EI scores.

The results for the comparison of the trimmed means for the work performance variables (charge off and delinquency) using the Yuen-Welch method are presented in Table 30 below.

Table 30. Group differences between the work performance variables.

Variable	$\lvert\hat{X}_{t1} - \hat{X}_{t2}\rvert$	$\hat{T}_y$	$\hat{v}_y$	$Crit$	p	SE	$\hat{\xi}$
Charge off	<.01	.25	29.45	2.04	1.00	<.01	.09
Delinquent	<.01	.24	27.80	2.05	1.00	.01	.07

Note. $\lvert\hat{X}_{t1} - \hat{X}_{t2}\rvert$: Absolute difference between trimmed mean estimates. $\hat{T}_y$: Test statistic. $\hat{v}_y$: Degrees of freedom. $Crit$: Critical value. p: *p*-value. SE: Standard error. $\hat{\xi}$: Estimated explanatory effect size.

It is evident that both tests were non-significant, with $p > .05$. This means that no statistically significant differences in respondents' charge off and delinquency scores existed when they were grouped according to their EI results.

The results for the comparison of the trimmed means for the credit risk assessment or risk grade variables (overdraft and term loan) using the Yuen-Welch method are presented in Table 31 below.

Table 31. Group differences between risk grade assessment variables.

Variable	$\lvert\hat{X}_{t1} - \hat{X}_{t2}\rvert$	$\hat{T}_y$	$\hat{v}_y$	$Crit$	p	SE	$\hat{\xi}$
Risk grade OD	<.01	.25	29.45	2.04	1.00	<.01	.09
Risk grade TL	<.01	.24	27.80	2.05	1.00	.01	.07

Note. $\lvert\hat{X}_{t1} - \hat{X}_{t2}\rvert$: Absolute difference between trimmed mean estimates. $\hat{T}_y$: Test statistic. $\hat{v}_y$: Degrees of freedom. $Crit$: Critical value. p: *p*-value. SE: Standard error. $\hat{\xi}$: Estimated explanatory effect size.

Just as before, with the work performance variables, both tests were found to be non-significant, with $p > .05$. This, too, is an indication that respondents did not differ in their risk grade assessment scores once partitioned according to their EI scores.

Looking at the results of the group differences holistically, it can be concluded that respondents with higher EI scores did not appear to make better loan decisions than those respondents with lower EI scores. Instead, their work performance and risk grade assessment scores appear to be very similar, which is especially noticeable by the absolute difference between the trimmed mean estimates between the groups, which were extremely small. Given these results, it was decided not to perform the regression analyses at different group levels as this would likely have yielded similar results, while also having reduced statistical power to detect meaningful effects.

4.4.4 Summary of Results

Chapter 4 was dedicated to presenting the findings from the study. Table 32 below provides a summary of the outcomes of the hypotheses that were tested.

Table 32. Summary of the results for the hypotheses tested (Source: Author).

Hypothesis	Result
H1: Emotion Perception correlates with Emotion Understanding which in turn correlates with Emotion Regulation.	Support
H2: Emotion Perception predicts work performance.	No support
H3: Emotion Facilitation predicts work performance.	No support
H4: Emotion Understanding predicts work performance.	No support
H5: Emotion Regulation predicts work performance.	No support
H6a: Context (risk grade) moderates the relationship between Emotion Perception and work performance (delinquency and charge off).	No support
H6b: Context (risk grade) moderates the relationship between Emotion Facilitation and work performance (delinquency and charge off).	No support
H6c: Context (risk grade) moderates the relationship between Emotion Understanding and work performance (delinquency and charge off).	No support
H6d: Context (risk grade) moderates the relationship between Emotion Regulation and work performance (delinquency and charge off).	No support

Hypothesis	Result
H7: Emotional intelligence abilities (4 of the branches) together moderated by context (risk grade) predict work performance (delinquency and charge off).	No support

In summary, only one out of the seven hypotheses was supported by the results – that is, that the MSCEIT branches correlate with one another. The remaining hypotheses were not supported, with the regression models being a poor fit.

The sample, which comprised 70 participants, showed no unusual characteristics. In terms of the sample descriptives, the female and Caucasian groups were overrepresented. However, age and tenure were normally distributed in the sample. It was observed that the loan officers mostly worked on loans for existing rather than new borrowers and therefore would not have had to contend with information asymmetry, which is prevalent among new borrowers, probably inducing fewer emotions.

The psychometric tests used to collect data on the independent variable (emotional intelligence) and control variables (personality and cognitive intelligence) were found to be consistent measures and therefore could be relied upon. For the personality test (BTI), the scores were fairly symmetrical. However, the cognitive (Matrigma) test results did not come out as expected. There was a noticeable number of respondents who scored zero and many had low scores, which limited the ability to use the results for individual difference analysis, such as group difference analysis. The MSCEIT results, in contrast, came out as expected in that the distributions were normal except for the noticeable skewness of the Emotion Regulation branch. This outcome augured well for the testing of hypothesis 1 which posited a sequential relationship between the branches, which was supported.

The results for the dependent variable, work performance (delinquency and charge off), and the moderator variable, credit risk assessment (overdraft and term loan), were both non-normal. The violation of the assumption of normality meant that the standard parametric statistical methods could not be executed. More noticeably, the results for both variables showed extremely small variability. The lack of spread in the results impacted the ability to predict performance as it was difficult to measure individual differences.

At an early stage in the analysis, it became clear that there would be challenges with the running of the more complex statistical techniques. Besides the violation of normality by some variables in the conceptual model, the most fundamental assumption in the multivariate analysis, when conducting the tests of association between the independent and dependent variables, was that all the tests would come out as non-significant. The lack of linear association or strength in the relationship pointed to problems with the regression models.

As expected, the regression model testing for prediction by the individual branches (hypotheses H2 to H5) of the work performance variables came out as non-significant and the models fit the data poorly. Hence, hypotheses H2 to H5 were not supported. Equally, the regression model (H6a to H6d) testing for moderation of work context (credit risk assessment) of the independent and dependent variables came out as non-significant and the models fit the data poorly. Consequently, these hypotheses were not supported. Ultimately, hypothesis 7, which posited that all EI branches (together moderated by context) would predict the work performance variables, also came out as non-significant and the data fit the model poorly. Hypothesis 7 was therefore not supported.

Chapter 5 discusses the reported results in relation to the literature.

5 CHAPTER 5 – DISCUSSION OF FINDINGS

This chapter discusses and interprets the findings from the statistical analyses reported in Chapter 4 within the context of the literature review provided in Chapter 2. To reiterate the research question: What is the role of emotional intelligence in terms of work performance in the SME credit risk assessment environment? To test the utility of the ability-based EI model in predicting outcomes, the study was conducted in the informationally opaque SME credit risk assessment context. Except in the case of hypothesis 1, the results obtained do not support the extant literature from which the hypotheses were derived. Notwithstanding this outcome, the study contributes to the (albeit limited) ability-based EI research and literature on the relationship between EI and work performance when context is considered.

This chapter ends with a summarised discussion of the findings.

5.1 DISCUSSION OF THE DESCRIPTIVES FOR THE INDEPENDENT, MODERATING, CONTROL AND DEPENDENT VARIABLES

In EI research, the specification of variables is crucial for the type of research to be undertaken. In this section, the results of the descriptives of all the psychometric measures are discussed, including the control variables, the credit risk assessment variables and the work performance variables. Integrated into the discussion are the results from Chapter 4 and the extant literature in Chapter 2.

In section 2.7, I introduced the promise that the construct of emotional intelligence (EI) could contribute to our understanding of individual differences and could predict important life outcomes in the workplace, school and home settings (Côté, 2014). In the same seminal article, Côté (2014) aptly describes what research on ability-based EI is about as follows: “Research on emotional intelligence investigates whether a set of abilities about emotions and emotional information enhances our prediction and understanding of the outcomes of organisation members such as their job performance and their effectiveness as leaders” (p. 460). This study used the specific-situation model to investigate what a few studies had investigated – that is, whether ability-based EI moderated by context can provide parsimonious and credible solutions to real-life problems (Joseph & Newman, 2010).

5.1.1 MSCEIT Descriptives

The 70 respondents in this study were recruited using an email message requesting them to complete the 141-item MSCEIT V2.0 test of emotional intelligence. The MSCEIT is a performance test and is regarded as the most accurate measure of ability as it relates to emotions (Libbrecht et al., 2014; Mayer et al., 2008; Mayer et al., 2016; Miners et al., 2018). Ability tests look for maximum performance from the test taker, where the expectation is that they will maximise both knowledge and speed as they deal with the emotional problems presented (Dasborough, 2019; O'Connor et al., 2019). The email communication to the respondents contained two embedded links, one for the MSCEIT and the other for the BTI and Matrigma combined. Furthermore, the communication discouraged the test taker from withdrawing from the test without completing it. Therefore, it was expected that the respondents would complete this test in one sitting and would put in maximum effort, knowing that they were being tested for the period in question.

In line with the tradition of performance-based tests, the administration of the MSCEIT test by JVR was done to ensure conditions conducive to maximum performance, objectivity, replicability and generalisability of the outcomes of the current study. Based on the results in Table 17, the MSCEIT test showed acceptable internal consistency for both the total score and the branch level scores, at $\hat{\alpha} = .95$ and $\hat{\omega} = .96$ for the total score and $\bar{X}_{\hat{\alpha}} = .88$ to $\bar{X}_{\hat{\omega}} = .89$ for the branch scores. It was therefore a reliable measure. These results are consistent with previous studies in this area, thus giving credence to the claims that the MSCEIT measures the outcomes consistently (Côté, 2014; Roberts et al., 2016).

Table 4 shows the demographic variables of the 70 participants. Previous studies on EI have shown gender and race differences in performance but there has been no definitive finding on the impact of the demographic differences on the scores for the different genders and races/ethnicities (Joseph & Newman, 2010; MacCann; 2010; Mattingly & Kraiger, 2018). This study did not focus on the role of gender or race differences as a differentiator except to control for them. Hence the study closely followed the best practice guide on EI research which calls for these measures to be controlled for (Côté, 2014). The two largest groups were females making up 64.29% and Caucasians making up 47.14% of the population respectively.

The descriptives for the MSCEIT are presented in Table 6 and the tests of normality are presented in Figure 19 using density plots. A number of key observations are worth noting from these data points. First, with regard to the MSCEIT (refer to Table 6), the participants obtained on average between 83.12 and 89.93 for the branch scores, while the mean for the total score was 80.56. In addition, the min and max for both the total score and the branches show that very few participants scored above the US norm average of 115. Extant literature revealed that South African scores on the MSCEIT are generally lower than US scores, and the test results for this study confirmed the previous finding (Combrie et al., 2009; Gallant, 2005). This is not necessarily a concern for the study as the results were in line with the expected South African norm.

Second, there was a challenge with the generally lower scores that emerged from the categorisation done in section 4.4.3. The purpose of the categorisation was to test sub-group differences with a view to understanding whether EI scores influenced performance on the credit risk assessment and work performance variables. The participants could not be grouped into high, medium or low scores because not many achieved high scores of 115 and above. Instead, the grouping was done according to high and low scores with the cut-off being 85, which is comparable to the SA norm. Third, the underlying distributions for the Emotion Facilitation and overall MSCEIT total score showed signs of non-normality and the Emotion Regulation branch was negatively skewed. However, overall, the skewness and kurtosis were in the symmetric range.

5.1.2 BTI Descriptives

Extant literature has confirmed the predictive value of personality factors with job performance (Côté, 2014; Joseph & Newman, 2010; Mayer et al., 2016; Miners et al., 2018). Some studies have focused on all five factors of personality (Big Five), whereas other studies have isolated the effect of Conscientiousness, Extraversion and Openness to experience as having the most potent predictive power (Joseph et al., 2015). This study applied all five factors using the long version of the basic trait inventory (BTI) test. The long version consists of 193 (including a 13-item social desirability scale) for the five factors and test takers completed the test online. The respondents used a 5-point Likert-type scale to respond to statements, with answers ranging from strongly disagree to strongly agree.

The BTI test is a self-report measure and not a performance-based one – unlike the two other psychometric tests, the MSCEIT and Matrigma – but this is in line with personality tests. It was designed by Taylor and De Bruin (2017) specifically for the South African population and is based on the Five-Factor Model (FFM). The rationale for its development was to close the gap in a South African trait-based personality inventory test. Hence, the test has been shown to have cross-cultural applicability. Furthermore, the BTI test has been shown to have acceptable levels of internal consistency across the five domains (Taylor & De Bruin, 2017).

This study used Cronbach's (1951) coefficient alpha (α) and McDonald's (1999) coefficient omega (ω) to examine the internal consistency of the BTI test. Table 15 shows that the internal consistency estimates for the BTI test are high across all the factors when compared to the standardisation studies (Taylor & De Bruin, 2017). All the factors had a coefficient alpha (α) higher than .90, which shows that the test is a reliable measure of personality. The distributions depicted in Figure 18 with the density plots show that Conscientiousness, Openness to experience and Neuroticism have multimodal distribution, but overall, the distribution appears normal. This is confirmed by the Shapiro-Wilk normality test results in Table 10.

The overall profile of the group can be gleaned from Table 5. The group is slightly more introverted with extraversion at a 46.86 winsorised mean, while also showing lower openness to experience with a winsorised mean of 46.23, both about 1 standard deviation below the mean. This means that they are more practical than abstract. The key question in this study, given that personality is an established predictor of work performance and is second only to cognitive intelligence, was whether EI remains a predictor of work performance after controlling for personality. Indeed, we now know that the reason mixed models of EI are better predictors is that they oversample personality factors (Joseph et al., 2015). Controlling for personality is therefore best practice for EI research, and the answer to the question above will be canvassed when the regressions are discussed.

5.1.3 Matrigma Descriptives

Cognitive intelligence, which belongs in the family of intelligences, is known to be the most robust predictor of work performance (Joseph et al., 2015; Libbrecht et al., 2014; Lievens & Chan, 2010; O'Boyle et al., 2011). As a result, any new individual difference predictor is generally benchmarked to cognitive intelligence and whether it can offer variance beyond what this predictor can do (Joseph et al., 2015; O'Boyle et al., 2011). This is an important standard both for adherents to cognitive intelligence and ability-EI researchers. Extant literature shows that ability-based EI is much more closely related to cognitive intelligence than it is to personality (Joseph & Newman, 2010; Schneider et al., 2016). Indeed, this would be because ability-based EI is itself regarded as belonging to a family of intelligences (Côté, 2014; Schmidt et al., 2016).

To measure cognitive intelligence, the respondents completed the Form A or B Matrigma test which was done via the JvR portal in the same way that the BTI test was done. Matrigma has five forms, from A to E. However, in this study, the participants were randomly assigned A or B which had 30 task items. It measures fluid intelligence and is a non-verbal test; it therefore reduces the risk of misunderstanding and bias due to the language factor (Mabon & Sjöberg, 2011). Most importantly, the test is a performance-based test; therefore, the test takers were given problem-solving tasks which made no reference to previously gained knowledge (Taylor et al., 2017). Detailed instructions were provided, and an explanation of the test was furnished together with the initial invitation to participate in the research.

The density plot in Figure 20 shows that the peaks were of similar densities and spread out. With the kurtosis at 1.76 in Table 7, it confirms that the distribution was flatter and widespread. Similarly, the results for the Shapiro-Wilk normality test in Table 12 indicate that the distribution deviated from normality. The absence of normality in the data invited the use of robust statistical techniques. The results in Table 7 point to a number of possible concerns. First, the full range of scores for the test was from 0 to 10 but in this study the range was from 0 to 6, and it was evident that a large number of participants got zero. To remove tests with zero scores would reduce the number of participants from 70 to about 55, making it difficult to do the regressions. The zero scores could point to the possibility that participants may either have struggled with the test, which is not abnormal with performance tests, or may have submitted it before completion, which could point to possible technical and/or procedural issues. Second, the winsorised mean for the group at 2.86 is lower than the SA norm at 5.5, which again creates concerns. Lastly, none of the participants scored in the high category.

In spite of the lower-than-expected test results, the Matrigma is a reliable test. Even though I did not have access to the item-level data scores to compute the internal consistency, the Cronbach's alpha was found to be at .98 both for Form A and B for Africa and South Africa (Mabon & Sjöberg, 2011; Taylor et al., 2017). Once again, the key question underpinning the study was: Does emotional intelligence remain a significant predictor after controlling for cognitive intelligence?

5.1.4 Credit Risk Assessment Descriptives

The introduction of the SME credit risk assessment as a moderator variable was in response to the call to context in EI research and practice (Côté, 2014). The call was to resolve the "ugly state of affairs'' (Joseph & Newman, 2010, p. 72) or the "researcher's dilemma" (Cherniss, 2010, p. 112) regarding the ability-based EI construct and its weakness in terms of incremental and predictive validity. As explicated in section 2.8, the basis for the call-to-context argument is that EI may have different effects on a criterion (e.g., work performance), depending on the situation in which the ability is utilised (Côté, 2014; Jordan et al., 2010; Joseph et al., 2015). I argued that an example of recognising context would be to consider an aspect of work or a job setting to approximate more closely the role that EI plays in the production of results (Ybarra et al., 2014). Studies that have directly referenced the context are sparse in number, as evidenced by the meta-analysis done in this area, and this remains one of the key gaps in the literature (Farh et al., 2012; Joseph & Newman, 2010; Joseph et al., 2015; Newman et al., 2010).

As discussed, at the heart of the call to context is the move away from bivariate associations between EI and the criterion (validity-generalisation model), which has produced weak results, towards the inclusion of contextual variables to ignite the relationship between EI and the criterion (moderator model or situation-specific model). The choice for this study was the situation-specific model which predicts that "EI explains unique variance in criteria when the organisation context or employee dispositions facilitate its deployment" (Côté, 2014, p. 472). To reflect context and test the relationship between ability-EI and work performance, I chose one of the big four banks in South Africa and focused on the SME credit risk assessment work environment, which had a few key features and would be relevant for testing emotional intelligence abilities. Lipshitz and Shulimovitz (2007) succinctly explain why this context is relevant, as follows:

> "Credit-granting decisions are uniquely suitable for studying decision making under risk or uncertainty: approving or rejecting a loan requires systematic assessment of risk; has

clear quantifiable outcomes that are frequently consequential; and is repeated enough under sufficiently similar circumstances to generate large samples and to permit the study of real-world expertise." (p. 215)

As I highlighted, bank lending and the assessment of credit risk are different for various customer segments (Agarwal & Ben-David, 2018; Campbell et al., 2019). The SME credit market, the focus of this study, is unique in that it is informationally opaque, thus exacerbating the information asymmetry between the loan officer and the borrower. Lipshitz and Shulimovitz (2007) acknowledge the role of emotions in the loan officer's credit-granting decisions. The use of the risk grade score variable to approximate the work context of loan officers is supported by extant literature (Campbell et al., 2019; Filomeni et al., 2016; Win, 2018). The failure to manage credit risk has implications not only for financial accounting loss but also for opportunity costs and transaction costs associated with a non-performing asset (Win, 2018). In as much as the risk grade score is derived from hard information relating to the borrower's previous financial behaviour in the SME context, it is an insufficient indicator for measuring the propensity to default. Hence the risk grade score is always negotiated away through the various stages until a favourable decision is found that balances the risk-and-return scale.

This study used the risk grade score for both the overdraft (OD) and term loan (TL) credit products. Both products are of central importance to SMEs in the management of their cash flow. The use of both scores was to remove reliance on a single indicator which could have had a spurious effect on the results. A score of 1 reflects the lowest-risk borrower and a score of 5 reflects the highest-risk borrower. Table 9 sets out the descriptives for the two risk grade scores. The winsorised means for risk grade OD and TL are nearly the same at 1.93 and 1.90, respectively. This means that on average the loan officers opted for lower-risk borrowers. However, an examination of the range reveals that there was a full range of scores, indicative of borrowers across the full risk spectrum.

A possible explanation for the similar winsorised mean could be that since this is a high-stakes operational environment, those who make it have been conditioned to work with largely lower-risk borrowers. The lack of variance in scores created a dilemma in predicting performance as it was difficult to measure individual difference – a critical principle in EI theory. The skewness and kurtosis fell within acceptable ranges, even though the risk grade TL was slightly more heavily tailed relative to a normal distribution. This is confirmed by the density plots in Figure 22 which show that both distributions were not normal, and the Shapiro-Wilk tests in Table 14.

5.1.5 Work Performance Descriptives

The focus on work performance as a variable of interest within EI research continues to grow (Côté & Miners, 2006; Farh et al., 2012; Grobelny et al., 2021; Joseph et al., 2015; Newman et al., 2010; O'Boyle et al., 2011). There are broadly three ways in which it has been operationalised in the various studies: by using supervisor, peer and self-report ratings (Grobelny et al., 2021; O'Boyle et al., 2011). Few studies have shown a preference for supervisor-rated work performance measures, despite their objectivity, as opposed to self-ratings because of lower predictive value (Grobelny et al., 2021).

The issue of EI predictor-criterion matching is the subject of much discussion in Libbrecht et al. (2014). The authors opine that "the inconsistent associations between EI and performance do not necessarily reveal weakness in the construct of EI. Rather they reveal potentially theoretically sensible patterns of association" (Libbrecht, et al., 2014, p. 70). Even the purportedly objective measures are not without challenges. Joseph et al. (2015, p. 304) point out that these also tend to be contaminated as they "reflect both employee performance behaviour and environmental factors that constitute a psychometric nuisance". Work performance in this study was conceptualised and operationalised as an objective measure, relating to what an employee does in job-related situations and as linked to the outcomes of the organisation (Grobelny et al., 2021). Despite its objectivity and close approximation to employee performance behaviour, the measure also suffers from environmental factors which possibly constituted a psychometric nuisance.

As highlighted, this study used post-issuance loan performance, as measured by charge off and delinquency, for work performance. To reiterate, charge off is when payment has been outstanding for 180 days (six months) and the matter has been transferred to the legal department for collection. In contrast, delinquency is when a borrower has fallen behind on their payment by a single day after the agreed payment date. In other words, it is any instance when a loan is one day past due date. By using post-issuance loan performance, this study followed in the footsteps of previous studies which showed that loan officer performance is related to loan performance. Post-issuance loan performance or loan quality is an adverse indicator of the outcome of the credit risk assessment conducted on the borrower at the time the loan is granted. Yet it is also not inconceivable that other exogenous factors may ultimately have a bearing on performance; such is the nature of retrospective performance measures. This study conceptualised this variable as an important, individual difference variable.

The decision to use two measures for work performance was to avoid a dependence on one measure, which could confound the outcome. In Table 8, the descriptives for charge off and delinquency show that the min–max and range variance between these two variables are not significant, meaning that there is not a lot of spread. The implication of this small variance is that it was difficult to predict a constant. Variability would have allowed for better prediction but that would also have meant that the bank had condoned lower performance. Therefore, similar to the credit risk assessment contextual variable, this shows that very few clients within this population were delinquent (24%) or were charged off (12%). Once again, this could be because of the bank's very strict credit policies or, among those who succeeded, it was because of their conservative approach to the management of risk.

Both charge off and delinquency skewness show that they are not symmetrical. However, it is the large estimates for kurtosis for delinquency that point much more clearly to a non-normal distribution. Indeed, the density plots in Figure 21 show that both charge off and delinquency are positively skewed and have long tails and delinquency has a much sharper peak. The Shapiro-Wilk test in Table 13 further confirms that the underlying distributions of both variables were non-normal.

5.2 CONCLUSION TO THE DESCRIPTIVES DISCUSSION

The main study variables and their results have been discussed. All the variables were extracted from extant literature and applied to the study by following the best practice for EI research (Côté, 2014; Joseph et al., 2015). The three tests used in the study are internationally recognised and have been found to be reliable. Although the results of the Matrigma cognitive intelligence test were not as expected, it is still a reliable test with good SA norms. It is worth noting, however, that the respondents would have completed about 364 task items from the various tests: 141 items for the MSCEIT, 193 items for the BTI and 30 items for the Matrigma. This would have been demanding on the respondents and could have had an unintended effect on the respondents' concentration, thus impacting the results.

By their nature, the two performance tests, and the MSCEIT in particular, require tighter administration and they are pricey (O'Boyle et al., 2011). It would seem that the inclusion of these tests may have had unintended negative consequences for the study. This has important implications for the discipline in that alternative tests may need to be identified. These points are canvassed further under the limitations of the study in Chapter 6.

The use of the contextual variable risk grade and dependent variable work performance, as conceptualised, means that this study is the first to do so. This is also the first study to do so within the South African context. Previous studies focusing on the banking sector used mixed-model EI and were mostly concerned with the role of EI in influencing service delivery to customers (Kaura, 2011; Nadeem et al., 2019; Roland & Olalekan, 2020). The data for both the risk grade and work performance variables were obtained from the bank's systems. The results, however, show that the data were non-normal and had low variability, and this precluded further and more detailed analysis. This limitation with the criterion measure could have impacted the results. This finding has implications for individual difference studies because they are predicated on variability of data. Variability in data should be explored earlier so as not to limit deeper analysis.

The next section discusses correlations and the regression models for the hypotheses.

5.3 DISCUSSION OF HYPOTHESES (CORRELATIONS AND REGRESSIONS)

This section discusses and interprets the results of the **hierarchical multiple regression** that underpinned the correlations and regressions statistical analysis in the context of the extant literature, the research question and the objectives of the study, while highlighting the implications for research. To facilitate the results discussion in relevant sections, both the mediation and moderation analysis hypotheses are discussed jointly.

5.3.1 Hypothesis 1

H1*: Emotion Perception correlates with Emotion Facilitation which correlates with Emotion Understanding which, in turn, correlates with Emotion Regulation.*

One of the most foundational elements of the **emotional intelligence construct** is the parsimony it offers across definition, construct, model and measurement dimensions. Without a doubt, this is one of the most defining contributions to theory and literature by the founding scholars. As outlined in section 2.3 in the literature review, Mayer and Salovey (1997) suggest that "emotional intelligence involves the ability to perceive accurately, appraise and express emotion, the ability to access and/or generate feelings when they facilitate thoughts, the ability to understand emotion and emotional knowledge; and the ability to regulate emotions to promote emotional and intellectual growth" (p. 10).

The basis of **hypothesis 1**, therefore, was to first test for this parsimony. Hypothesis 1 hypothesised that Emotion Perception correlates with Emotion Facilitation, which correlates with Emotion Understanding, which in turn correlates with Emotion Regulation. The results in Table 18 show that the main hypothesis can be accepted, meaning that the null hypothesis is rejected. The two tests of association show that while the association between the branches was not perfect, it was significant ($p \leq .001$). Furthermore, all relationships were moderate and positive. The corresponding scatterplots in Figure 23 also confirm the association. Therefore, the findings support the hypothesis and confirm the combined integrative function of the branches.

The support for hypothesis 1 is significant and constitutes the first step in the integrative function of the MSCEIT. Without support for hypothesis 1, it would not have been possible to confirm the coherence of the branches into a single factor (convergent validity) of EI (Legree et al., 2014; MacCann et al., 2014). In this case, it would not have been possible to use and rely on the MSCEIT total score. Furthermore, many of the previous studies have confirmed that EI is a hierarchical model that consists of four branches, from the simplest task to the most complex task, with each representing one of the four abilities (Barrett & Gross, 2001; Joseph & Newman, 2010; MacCann et al., 2014; Mayer et al., 2001; Mayer et al., 2004; Rivers et al., 2012). It is a causal model with no particular dimension privileged over the other, even though:

> "the lower two branches (perception and facilitation) collectively form the **'Experiential EI'** area, representing the direct processing of information in one's immediate environment, unmediated by higher-level strategic planning. Similarly, the two higher branches (understanding and management) collectively form the **'Strategic EI'** area, representing the strategic judgments and higher-level deliberate processing of emotional information." (MacCann et al., 2014, p358)

In as much as other scholars have offered further suggestions for a compensatory model (Côté & Miners, 2006) and a cascading model (Joseph & Newman, 2010), this integrative model remains the soundest. In line with the current research question and objectives, the next phase of the mediational analysis (hypotheses 2 to 6) tested whether, given that the EI constructs are related and this confirms the value of the MSEIT, it can predict important life outcomes. The next section addresses both the mediation analysis for hypotheses 2 to 6 and the moderation analysis for hypotheses 6a to 6d combined.

5.3.2 Hypotheses 2 and 6a

H2: *Emotion Perception does not predict work performance.*

H6a: *Credit risk assessment (risk grade) does not moderate the relationship between Emotion Perception and work performance (delinquency and charge off).*

The focus of **hypothesis 2** was to test whether the **Emotion Perception** branch individually predicts the work performance variables of delinquency and charge off. Emotion Perception is the most basic of the EI abilities in the hierarchy. As previously discussed, the branch concerns the ability to garner important information about others' attitudes, goals and intentions (Côté, 2014; Mayer & Salovey, 1997; Mayer et al., 2008; Mayer et al., 2016). Farh et al. (2012) is one of a few studies that isolated the Emotion Perception branch so that it could be specifically addressed. The authors argued that in as much as they were interested in all EI abilities, they believed that Emotion Perception was the driving component of the EI-teamwork relationship.

As discussed, in the SME environment, loan officers – in performing their jobs and in an effort to avoid Type II errors where they grant a loan to an undeserving borrower – have to screen a borrower's hard and soft information to make accurate inferences (Campbell et al., 2019; Filomeni et al., 2016). With the bank's decentralised model, in the early stages of the credit application process (refer to Figure 9) the loan officer devotes a significant amount of time to gathering information on the borrower's goals and plans. In SMEs this assessment is largely about the borrower rather than the business. As highlighted in section 2.8.2, this is where impressions are formed and gaps identified. This part of the process is manual and requires the loan officer to be alert, even though Table 4 shows that the overwhelming majority (98%) of clients were repeat clients.

The <u>first step</u> in the hierarchical regression specified both delinquency and charge off as **independent variables.** The results of the correlation are presented in Table 19 and the scatter plots appear in Figure 24. In Table 19 the results of association for Emotion Perception and the dependent variables of delinquency and charge off at $\hat{\tau}$: .04, $\hat{Z}$: .47, p:*1.00* and $\hat{\tau}$: .06, $\hat{Z}$: .54, p:*1.00,* respectively confirm that there is no relationship. The scatter plots in Figure 24 show some outliers, while in a few instances participants obtained zero scores but this is consistent with the overall theme of no correlations found. This finding supports the assertion made by Côté (2014) that a simple linear or bivariate relationship between EI and a criterion is not sufficient to understand the role of EI in predicting a criterion.

The results of the regressions in Figure 25 and Figure 27 provide further substance to this finding. Substantively, the final results for the first step for both variables show that the model was statistically non-significant (Table 20 and Table 21). For both models, the R^2 was negative. Moreover, it was found that Emotion Perception accounted for 1% of the variance in charge off and 2% of the variance in delinquency; therefore, the models fit the data poorly.

The <u>second step</u> included the control variables as predictors to both the above models. The diagnostic plots presented in Figure 26 and Figure 27 show heteroskedasticity and an absence of normality in the data. As highlighted, the results in Table 20 and Table 21 show the results for both models to be non-significant. The ultimate results for this step show that the R^2 value for charge off was negative, whereas for delinquency it was positive. The model shows that even after including the control variables, Emotion Perception can explain 5% of the variation in charge off and 1% in delinquency. This means that the Emotion Perception ability of loan officers does not have any bearing on the delinquency and charge off of the loans they underwrite. Therefore, hypothesis 3 is not supported.

The <u>final step</u> in the hierarchical regression included the **contextual variable**, risk grade, to test whether the relationship between the predictor variable, Emotion Perception, and the criterion, work performance, would be varied. **Hypothesis 6a** therefore hypothesised that the risk grade variables, overdraft and term loan, moderate the relationship between the predictor Emotion Perception and work performance variables of delinquency and charge off.

The results for the moderating role of risk grade between Emotion Perception and work performance were statistically non-significant. This means that the mediating process between Emotion Perception and the work performance variables of delinquency and charge off was not moderated by the contextual variable, risk grade. More specifically, the loan officer's ability to perceive emotions in borrowers has no bearing on the outcomes of their work performance, irrespective of cognitive ability, personality, gender and age. This outcome was in direct contrast to the specific-situation model principles. Even after accounting for the role of context, this relationship did not change (Côté, 2014; Campbell et al., 2019). This outcome means that the hypothesis (H6a) is rejected and the null hypothesis (H6a$_0$) is accepted.

5.3.3 Hypotheses 3 and 6b

H3: *Emotion Facilitation does not predict work performance.*

H6b: *Credit risk assessment (risk grade) does not moderate the relationship between Emotion Facilitation and work performance (delinquency and charge off).*

Hypothesis 3 stated that the **Emotion Facilitation** branch individually predicts the work performance variables of delinquency and charge off. As discussed, Emotion Facilitation is one of the most challenged branches in the hierarchy of branches (Fan et al., 2010; Farh et al., 2012; Palmer et al., 2005; Rossen et al., 2008). In contrast, there is also evidence of this factor and branch in the hierarchy and therefore it is used frequently in EI research (Joseph et al., 2015; Libbrecht et al., 2014; O'Boyle et al., 2011). This branch represents the direct processing of information in one's immediate environment (MacCann et al., 2014). More specifically, it is about "how well individuals capitalize on the systematic effects of emotions on cognitive activities such as creativity and risk taking" (Côté, 2014, p. 466). As opined, in the SME environment, the process of collection and the use of soft information are the basis for risk taking because of the limitations posed by hard information. Its facilitation, it was argued, makes a significant difference.

In the first step in the hierarchical regression, where both delinquency and charge off were specified as **independent variables**, the results were similar. Once again, in this case, the results were expected, given the outcome of the correlations in Table 19 and Figure 24. The correlation test between the input variable, Emotion Facilitation, and the outcome variables, delinquency and charge off, were found to be non-significant. The result of a non-significant, simple linear association was in line with extant literature (Côté, 2014). Hence, it was expected that this outcome would have implications for the regression models. The results for the regression diagnostics in Figure 29 and Figure 31 provide the first indication. More importantly, the final results for the first step for both variables show that the model was not statistically significant (and Table 23). In both instances, the negative R^2 value associated with the model shows that Emotion Facilitation accounted for only 1% variation in delinquency and charge off; therefore, the model fits the data poorly. In other words, 99% of the variation in delinquency and charge off could not be explained by Emotion Facilitation alone.

The second step in the hierarchical model entailed the inclusion of the **control variables** as predictors to both the above models. The control variables were added to remove the variance and to allow for a more precise explanation. The diagnostic plots are presented in Figure 34 and Figure 36 and with both, heteroskedasticity and non-normality can be observed. The results, as presented in Table 22 and Table 23, show both models to be non-significant. Interestingly, the R^2 for delinquency suggests that 6% of the variation in delinquency is explained by Emotion Facilitation, whereas for charge off, 5% of the variation is explained by Emotion Facilitation. This is the second highest set of R^2 values obtained in all the models, but they were all statistically non-significant. In summary, this means that the ability to facilitate emotions does not predict work performance, even when controlling for the control variables of cognitive ability, personality, age and race. Therefore, hypothesis 3 is not supported.

The final step in the hierarchical regression was the more significant one of adding the **contextual variable**, risk grade, to understand if it would change the relationship between the predictor and the criterion. **Hypothesis 6b** posited that the risk grade variables, OD and TL, moderated the relationship between Emotion Facilitation and work performance (delinquency and charge off). The results of the regression model were statistically non-significant for both delinquency and charge off. This means that the mediating process between Emotion Facilitation and the work performance variables of delinquency and charge off was not moderated by the contextual variable, risk grade (overdraft and term loan). More specifically, the loan officer's ability to facilitate emotions has no bearing on the outcomes of their work performance, irrespective of cognitive ability, personality, gender and age. This result is in direct contrast to the specific-situation model principles because even after accounting for the role of context, this relationship did not change (Côté, 2014; Campbell et al., 2019). This outcome means that the hypothesis (H6b) is rejected and the null hypothesis ($H6b_0$) is accepted.

5.3.4 Hypotheses 4 and 6c

H4: *Emotion Understanding does not predict work performance.*

H6c: *Credit risk assessment (risk grade) does not moderate the relationship between Emotion Understanding and work performance (delinquency and charge off).*

Hypothesis 4 stated that the **Emotion Understanding** branch individually predicts the work performance variables, delinquency and charge off. Emotion Understanding, as highlighted in section 2.7.1, is part of the strategic judgements and deliberate processing of emotional information (MacCann et al., 2014). This ability is the most closely aligned to cognitive processing and abstract reasoning (Mayer et al., 2001; Mayer et al., 2008; Miners et al., 2018; Newman et al., 2010). Hence, previous studies have confirmed that EI has correlational and discriminant validity with other markers of intelligence (Legree et al., 2014; MacCann et al., 2014). A distinguishing feature of this branch is that it entails the ability to evaluate and plan action based on the information provided. Furthermore, it enables labelling, interpretation and dealing with complex, contradictory emotions.

Together with Emotion Regulation, this is one of the branches where a specific ability-based EI test has been developed. The Situational Test of Emotional Understanding (STEU) and the Situational Test of Emotion Management (STEM) are regarded as reliable tools to measure these two branches (MacCann, 2010; MacCann & Roberts, 2008). In Libbrecht et al. (2014), these two instruments were used with a group of medical students with varying outcomes for each of the branches. In the SME environment, this ability would assist with the strategic processing of emotions. It would be the precursor to the more complex processes achievable through Emotion Regulation. As explicated in section 2.8.2, when loan officers motivate the application through the stages of integrated assessment, modified assessment and final assessment, they continuously have to evaluate and exercise their judgement and discretion with the borrower and other parties involved in the process (Filomeni et al., 2016).

The <u>first step</u> in the hierarchical regression specified both delinquency and charge off as **independent variables**. Like the previous branch, the correlation results are presented in Table 19 and Figure 24. However, the results produced no surprises, given the outcomes of the correlations which were found to be non-significant. In stark contrast to these results, in one of the few studies that tested the linear relationship using individual branches of an ability-based test of EI, the results came out positive (Libbrecht et al., 2014). However, the authors used a student sample as opposed to a worker sample, with Grobelny et al. (2021) motivating the use of worker samples in these types of studies.

Given the results of the correlations, it was expected that they would influence the outcome of the regression models. To start with, the outcome of the regression diagnostics in Figure 35 and Figure 37 revealed the problems with the regression model. The summary of the final results for the first step for both dependent variables showed that the model was not statistically significant (Table 24 and Table 25). The R^2 for the charge off model showed that Emotion Understanding accounts for 1% of the variation in charge off, meaning that 99% of the change in charge off cannot be explained by Emotion Understanding alone.

The <u>second step</u> involved the inclusion of the **control variables** as predictors to both models above. Once again, the diagnostic plots presented in Figure 36 and Figure 38 show heteroskedasticity and non-normality. In Libbrecht et al. (2014), with the addition of the control variables of cognitive ability and conscientiousness of the personality test only, the model showed incremental validity for predicting the outcome variable over and above the control variables. This was a significant result for the quoted study. In this study, the results in Table 24 and Table 25 show both models to be non-significant. The R^2 for both delinquency and charge off show that a mere 1% of the variation in both variables can be explained by Emotion Understanding. This means that the Emotion Understanding ability of loan officers does not have any bearing on the delinquency and charge off of the loans they underwrite. Therefore hypothesis 4 is not supported.

With the <u>final step</u> in the hierarchical regression, the **moderator**, risk grade, was included in the model to test the relationship between Emotion Understanding and work performance. **Hypothesis 6c** hypothesised that the risk grade variables, OD and TL, moderated the relationship between Emotion Understanding and work performance (delinquency and charge off). In Libbrecht et al. (2014), a similar test was done for the individual branch of Emotion Understanding, and it was found not to be significant at $p = .23$. The authors explained that it was possible that Emotion Understanding was a distal predictor of EI. The findings from this study, which were consistent with Libbrecht et al. (2014), mean that the loan officer's ability to understand emotions has no bearing on the outcomes of their work performance, even when controlling for the control variables. More importantly, the addition of the moderator made no difference. Thus, the hypothesis (H6c) is rejected and the null hypothesis ($H6c_0$) is accepted.

5.3.5 Hypotheses 5 and 6d

H5: *Emotion Regulation does not predict work performance.*

H6d: *Credit risk assessment (risk grade) does not moderate the relationship between Emotion Regulation and work performance (delinquency and charge off).*

Hypothesis 5 stated that the **Emotion Regulation** branch individually predicts the work performance variables, delinquency and charge off. Emotion Regulation is the second of the strategic EI dimensions, together with Emotion Understanding. In a hierarchy of abilities, it is the apex of emotional management abilities (Côté, 2014). Section 2.7.5 highlighted that Emotion Regulation is the last step before work performance in that it turns the complex use of emotions into discernible results. It is about setting goals and strategies in relation to the intelligent use of emotions. Given its role in the hierarchy, extant literature has focused on this branch (Joseph & Newman, 2010; Libbrecht et al., 2014; Newman et al., 2010).

Starting with Joseph and Newman (2010), they found in their meta-analysis that through a cascading model, Emotion Regulation in jobs with high emotional labour demands predicted job performance. Similarly, in their study, Newman et al. (2010) isolated the impact of the Emotion Regulation facet and came to the same conclusion. Lastly, Libbrecht et al. (2014), using the STEM and STEU tests of emotional intelligence, arrived at more definitive findings. Unlike the Emotion Understanding branch, the Emotion Regulation branch was found to explain a unique variance in the criterion of interpersonal performance. The model was found to be significant at $p < .001$. Crucially, the authors found that Emotion Regulation showed incremental validity above personality and cognitive ability. It is important to highlight that the respondents in that study were medical students in an educational setting. SME bank lending extant literature makes it clear that the role of the loan officer is central in the systematic assessment of risk and the management of the process (Campbell et al., 2019; Filomeni et al., 2016). Throughout the various stages and at the highest level of decision-making involving executive management, the loan officer impacts decision-making and performance.

The <u>first step</u> in the hierarchical regression specified both delinquency and charge off as **independent variables.** The initial results of the correlation are presented in Table 19 and Table 27. The test results produced no correlation, and the tests were non-significant. These results are inconsistent with findings associated with this branch when isolated from the other branches (Joseph & Newman, 2010; Libbrecht et al., 2014; Newman et al., 2010). As a result, it was expected that the results of the regression model would also be non-significant. The diagnostics in Figure 37 and Figure 39 show the absence of non-normality, pointing to possible further outcomes. Crucially, the final results for the first step for both delinquency and charge off in Table

24 and Table 25 show that R^2 is negative and that Emotion Regulation accounts for 2% of the variation in both variables. In other words, 98% of the variation in delinquency and charge off could not be explained by Emotion Regulation alone.

The second step in the hierarchical model included the **control variables** as predictors to both models above. The diagnostics plots in Figure 38 and Figure 40 show a violation of the homogeneity of variance assumptions. The NVC test in both diagnostics was found to be significant. Consequently, the models for both charge off and delinquency were statistically non-significant and the R^2 value showed that Emotion Regulation accounts for 2% variation in charge off and 3% variation in delinquency. This means that the ability to regulate emotions does not predict the work performance of loan officers, even after controlling for cognitive ability, personality, age and race. This means that the Emotion Regulation ability of loan officers does not have any bearing on the delinquency and charge off of the loans they underwrite. Therefore, hypothesis 5 is not supported.

In the final step in the hierarchical regression, the **moderator**, risk grade, was added to the model to test the relationship between Emotion Regulation and work performance. **Hypothesis 6d** hypothesised that the risk grade variables, OD and TL, moderated the relationship between Emotion Regulation and work performance (delinquency and charge off). Farh et al. (2012) applied job context as a moderator in their study. They found that the high managerial work demand (MWD) job context strengthened the relationship between EI and work performance. This study's key differences were that a trait activation theory framework was used, job performance was measured using a survey and the proxy for cognitive intelligence was the GMAT test instead of a suitable cognitive test (Kong, 2014). The authors' reasoning was that high-MWD jobs contain "salient emotion-related cues" that facilitate deployment (Farh et al., 2012, p. 897). The non-significant outcome means that the hypothesis (H6d) is rejected and the null hypothesis ($H6d_0$) is accepted.

5.3.6 Hypothesis 7

H7: *Emotional intelligence abilities (together) moderated by credit risk assessment (risk grade) do not predict work performance outcomes (delinquency and charge off).*

The **final hypothesis (H7)** stated that all the **emotional Intelligence abilities** together moderated by credit risk assessment (risk grade) predict work performance outcomes (delinquency and charge off). **Hypotheses 2 to 5**, which were part of the mediation analysis, tested and provided results on when each of the branches occurred in the information-processing stages. The mediation results produced non-significant linear relationship models. Even with the addition of the contextual variable in **hypotheses 6a to 6d**, which was the moderation analysis, the results of the regression models were non-significant. On the basis of this outcome, the results for hypothesis 7 were not a surprise.

As discussed in section 2.4, EI is in effect one global factor underpinned by the four branches or dimensions (Fiori et al., 2014). It is an integrative model, where the branches operate individually and together to predict outcomes (Mayer et al., 2008; Mayer et al., 2016). The abilities are interrelated, part of one unit, yet at the same time are separated by when and where they occur in the information-processing stages (Schneider et al., 2016). At the heart of it all, the model depicts how well individuals perform tasks and solve problems related to emotions (Côté, 2014). This last hypothesis presented an opportunity to test the moderation model relationships.

As highlighted in previous studies, the SME lending environment is narrative based (Chen et al., 2015; Lipshitz & Shulimovitz, 2007). The loan officer motivates the application through the various stages (integrated, modified and final assessment) to a final outcome, which could have serious consequences for the bank's credit book and the SME industry as it may add to or skew the market – hence the importance of EI abilities. It follows, therefore, that the environment requires higher cognitive processing.

The <u>first step</u> in the model entered all **four branches as independent variables** and charge off and delinquency individually as dependent variables. In other words, there were two tests here for each of the dependent variables. The correlations in Table 28 and Table 29 were non-significant and this was consistent with the previous tests of linear association. Furthermore, the results of the diagnostic plots in Figure 41 and Figure 43 respectively show that the assumption of homogeneity of variances and the assumption of normality were violated, pointing to the possible outcome. The overall result of this step showed that R^2 is negative for both models (charge off and delinquency) and that the EI branches combined account for 2% variation in charge off and 3% variation in delinquency.

The second step in the moderation model included the **control variables** as predictors to both the above models. The diagnostic plots in Figure 42 and Figure 44 show a violation of the assumption of homogeneity of variances, linearity and normality. The NVC test in both diagnostics was found to be significant. As a result, the models for both charge off and delinquency were statistically non-significant and the associated R^2 value showed that EI abilities together account for 2% variation in charge off and less than .01% variation in delinquency. This means that the emotional intelligence integrative model does not predict the work performance of loan officers, even after controlling for cognitive ability, personality, age and race.

In the final step of the hierarchical regression, the **moderator**, risk grade, was added to the model to test whether it would ignite the relationship between EI abilities and work performance. In Farh et al. (2012), the addition of high managerial work demand (MWD) context seems to have produced differentiated results which strengthened the relationship between EI and the predictor, thus giving credence to this theoretical approach. In the present study, however, the results of the regressions were statistically non-significant for both charge off and delinquency. It is observed that the models improved, and this was the best model of them all in that 13% of the variation in charge off and 10% of the variation in delinquency could be explained by the EI abilities together, but the regressions were non-significant. Thus, the hypothesis (H7) is rejected and the null hypothesis ($H7_0$) is accepted.

5.3.7 Group Differences Discussion

As a direct consequence of the non-linear relationships, no correlations and non-significant regressions, I probed further by doing a subsidiary analysis to understand better whether any insights could be gained from partitioning the participants according to high and low EI scores. This was especially important as EI is the predictor and, more crucially, the test scores offered variance among the participants. In line with the structure of the MSCEIT test and using the South African norms, it was decided to split the group by using 85 as the mean cut-off (Gallant, 2005). Depending on the outcome, the regression analyses would be re-estimated.

The results in Table 28 for work performance and Table 29 for risk grade both came out as non-significant at $p > .05$. This means that there were no statistical differences in participants' charge off and delinquency (Table 28) when grouped according to their EI scores. Similarly, with risk grade overdraft and risk grade term loan (Table 29), the same conclusion was reached. The main explanation for this is what was already canvassed in section 5.1 – that there was a very small variation among the participants using their credit risk assessment and work performance variable. This reality meant that the individual differences could not be observed, thus violating a key principle of the EI theory. On this basis, there was no need to re-estimate the regressions.

5.4 CONCLUSION TO THE DISCUSSION

This chapter provided an interpretation of the results of the statistical analyses reported in Chapter 4 in relation to the extant literature. With the exception of H1, where the hypothesis was accepted, all the other hypotheses (H2 to H5, H6a to H6d and H7) were rejected. The current study used the best practice guide developed by Côté (2014) to anchor the research project, but the outcomes still diverged from the theory.

The resulting discussion highlighted the following: The independent variable used the internationally acclaimed, performance-based MSCEIT V2.0 test. The control variables for the well-known predictors of cognitive ability and personality also used the highly respected Matrigma and BTI tests. The former is a performance test and the latter is a personality test. All three tests showed very good reliability and therefore measured the underlying constructs consistently thus confirming the utility of these tests.

First, the distribution from the Matrigma test results was non-normal. In addition, the results did not come out exactly as expected in that, while it was a valid score, the number of respondents with a score of zero was high and the participants scored on average 2.82, which was lower than the South African norm of 5.5. This outcome could have been caused by the fact that the test content was challenging, which is in line with maximal performance tests. Second, the mean for the MSCEIT total score was 80.56, which was significantly lower than the US mean of 115. However, it was in line with the South African norm. Lastly, the results from the BTI indicated that the sample appeared to be slightly more introverted than most other South Africans and that loan officers tend to be more practical than imaginative, which is to be expected given the nature of the work to be done.

From a methodology and measurement perspective, therefore, the study applied the ‘gold standard’ in EI research and hence the results could be relied upon for analytical purposes.

However, with regard to the two other key variables, the moderating variable (credit risk assessment) and the dependent variable (work performance), the discussion highlighted the following: This is the first study to use the SME credit risk assessment context or setting in EI research and to apply the ability-based EI construct (by using the MSCEIT test) as a predictor of the work performance criterion in this context.

First, the SME credit risk assessment context was chosen in response to the call to context plea (Côté, 2014; Joseph et al., 2015; Ybarra et al., 2014). More specifically, these credit markets are informationally opaque and the elevated role that the loan officer plays allows for the deployment of emotional abilities. These markets are characterised by "information asymmetry between the borrower and the loan officer, clear quantifiable outcomes, large samples of data and the opportunity to study real-life phenomena" (Lipshitz & Shulimovitz, 2007, p. 215), thus introducing uncertainty and therefore emotions.

The specification of the credit risk assessment moderator variable (risk grade overdraft and term loan) was based on extant literature (Campbell et al., 2019). The study chose two variables to increase the possibilities for moderation. The algorithmic risk grade scores for each of the variables (overdraft and term loan) ranged from 1 (low risk) to 5 (high risk) with winsorised means at 1.90 and 1.93 respectively. The availability of this score triggered the first opportunity for the loan officer to interpret the propensity for default and to apply subjective information on the borrower to motivate for the granting of credit (Filomeni et al., 2016). With 98.36% of borrowers being existing borrowers, it would have been less costly to obtain the soft and qualitative information. However, a challenge presented itself with the lack of variation in the scores of the respondents. The lack of variation significantly limited the opportunity to look for individual differences and for further analysis. The reason for this could be that the bank has strict credit scoring and credit granting policies, with loan officers in these credit markets naturally only taking up applications within a certain range of risk grade scores. In spite of the conservative approach to credit, it is unlikely that the cognitive and emotional processes necessary to motivate a successful application would have been less demanding on the loan officer.

Second, the dependent variable of work performance was also specified from extant literature (Campbell, et al., 2019, Filomeni et al., 2016). In this case as well, the study opted for two variables, delinquency and charge off, to increase the chances of prediction. The findings showed that there was a low magnitude of charged off or delinquent loans (12% and 24% respectively) and also a low variability in the winsorised means of the two variables (charge off was .02 and delinquency was .03), which presented analytical challenges. This outcome is attributable to the conservative bank lending policies. Extant literature presents a number of possibilities relating to work performance measures, with conflicting views as to the best measure and practice (Grobelny et al., 2021). This study built on the emerging literature that tilts towards the use of objective measures of work performance. However, it is evident from this research that the use of objective measures is not without challenges. The basic predictor–criterion issues do not disappear as a result of the use of an objective measure of work performance (Grobelny et al., 2021; Libbrecht et al., 2014).

The specification of a criterion that EI responds to is still one of the more elusive elements of EI research, with some scholars arguing that there is nothing wrong with the ability-based EI construct's predictive ability but rather the specification of the criterion (Grobelny et al., 2021). Unfortunately, it is difficult to establish this for sure until we find a criterion that ability-based EI responds to. This study specified an objective measure which was based on task performance and related to the organisation's goals. Post-issuance loan performance was chosen because it is an adverse indicator of performance, which is directly related to the work and resulting interpretive judgements of the loan officer. However, we learn that the "psychological nuisance" with objective measures, according to Joseph et al. (2015, p. 303), is that they tend to be "contaminated by factors external to the individual meaning that they could be reflective of both individual performance and environmental factors". Libbrecht et al. (2014) undertook one of the few studies in which ability-based EI was incrementally predictive over and above cognitive ability and personality, outside the meta-analytic studies by O'Boyle et al. (2011) and Joseph et al. (2015). Yet these scholars relied on subjective measures of performance and it was also with a student sample. Given the challenges noted above, it is possible that with this study some of the highlighted problems with objective measures may have manifested, thus affecting the results.

The results of the correlations and regressions are significant for this study and for the field. The acceptance of hypothesis 1 confirmed the integrative functions of the branches. However, the rejection of hypotheses H2, H3, H4 and H5 was noticeable because it meant the individual branches do not predict work performance (charge off and delinquency). The absence of a relationship between the input and output variables in the mediational analysis was not ideal and implied problems for the regression analysis. Hence, the rejection of hypotheses H6a, H6b, H6c and H6d was expected. The absence of a moderating role of context (risk grade overdraft and term loan) on the work performance outcomes leaves the question about the role of a contextual variable wide open. This gap in knowledge is a critical factor as it is the essence of the research question.

Lastly, the rejection of hypothesis H7 means that the promise of the ability-based EI construct and its utility in predicting work performance outcomes for organisation members when context is considered remains unknown. As a result, the “ugly state of affairs” or “researcher’s dilemma” of having to choose between theory and data continues (Cherniss, 2010, p. 112; Joseph & Newman, 2010, p. 72). Given this situation, the key question is: are we at the end of the road with this construct or do the results of this study point to the need for further work to deliver on the promise?

As has been canvassed in the previous chapters, the promise of ability-based EI for business management scholars and practitioners alike was that it could predict important life outcomes, including in the workplace; and that it could do so in a way that complemented the explanatory power of general intelligence but exceeded the power of personality and other competing constructs. Thus far, the results for the construct that meets the standards of intelligence the most have been underwhelming – even after the introduction of a contextual variable aimed at igniting the relationship between EI and work performance outcomes (Côté, 2014).

The reality is that, a quarter of a century since attention started being paid to ability-based EI’s predictive power on work performance outcomes and more than three decades since the introduction of the construct, there is much we still do not know. The weight of the evidence, based on meta-analytic studies, suggests that self-report ability EI and self-report trait EI are superior predictors to ability-based EI (Grobelny et al., 2021; O’Boyle et al., 2011). However, the weakness with both self-report ability EI and self-report trait EI is well documented in Joseph et al. (2015). In this regard, the former is based on typical performance and may suffer from faking, while the latter is a predictor only because of heterogeneous domain sampling – in other words, it taps into a mix of other constructs. This situation perpetuates the ‘puzzle’ of EI research and hence it is expected that the construct will continue to live a ‘double life’ where it is lauded in practice but criticised in academic journals (Antonakis, 2015).

Despite the significant implications for theory and scholarship, EI remains a distinguishing feature of human social exchange (Krueger et al., 2009). That individual differences in outcomes like work performance and leadership can exclusively be explained using the established predictors of general intelligence and personality is untenable. Thus, instead of this being the end of the road, the results of this study point to a fork in the road. In other words, it is time to decide on the most suitable way forward. There are two options. The one is to continue the work of scholars in clarifying the ability-based EI construct's predictive power by refining its key components in line with the recommendations of the current study and studies like that of Grobelny et al. (2021) who argue for further empirical research within a well-defined context using their own guidelines. This option is based on the firm belief that it is still possible to develop additional knowledge in this field. The other option involves accepting that self-report ability EI, notwithstanding its limitations, offers the best prospect of predictive validity. The advantage of the self-report ability EI is that it has the same theoretical basis as ability-based EI, but their respective measurement strategies are different.

This study focused on the ability EI predictive power in relation to work performance outcomes by exploring context, using the situation-specific model within a unique setting and the disciplined application of the 'gold standard' of EI research. Despite this effort, we are still unclear about the significant meaning of EI in the workplace when context is considered. The findings and learnings from this study and the insights from other scholars are indicative of the direction and further refinements needed to make progress. This is all the more important, given the paucity of primary studies, compared to meta-analytic studies, on this construct. Hence, the most appropriate response is to continue to learn more about the role of context in EI research instead of settling on the most predictive EI measurement strategy of self-report ability EI because of its obvious weaknesses.

The next chapter discusses the recommendations for this field of research and also concludes the study.

6 CHAPTER 6 – RECOMMENDATIONS AND CONCLUSION

The previous chapters provided the background to and the context of the study, the literature applicable to the main concepts and variables, the methods used to collect and analyse the data, the results of the analysis and the interpretation of the results. This chapter begins with a brief summary of the findings and the key conclusions from the findings. It then discusses the contributions and limitations of the study, followed by recommendations for future research. The chapter brings the thesis to a close with a final conclusion to the study.

6.1 SUMMARY OF THE FINDINGS

As noted in Chapter 1, the primary aim of this study was to examine the relationship between emotional intelligence (EI) and work performance, and, in turn, to determine whether this relationship is moderated by context. The research question was: What is the role of emotional intelligence in terms of work performance in the SME credit risk assessment environment? The research objectives were:

a) To examine the relationship between emotional intelligence and work performance using the specific-situation model.

b) To understand the influence of context on the relationship between emotional intelligence and work performance.

The next section summarises the key findings from the study based on the results presented in Chapter 4 and the interpretation thereof in Chapter 5. The study used a quantitative research design to test an objective theory (EI) by examining relationships among variables. Extant literature, through both meta-analytic and primary studies, showed that ability EI was least predictive of the EI models, despite all its good properties, i.e., a well-reasoned construct, a valid measurement model and reliable tool. To examine the relationships and to advance theory, the study used the situation-specific conceptual model which motivates the exploration of context to ignite the relationship between EI and outcomes (Côté, 2014). EI is a latent variable and therefore not directly observable (Mayer, 2015). The results were obtained using a hierarchical, multiple-regression statistical analysis technique which allowed for the testing of multiple relationships.

The study addressed the research aims and objectives and the research question, as set out below.

First, the unit of analysis for this study was the 70 loan officers working in the SME lending area at one of the big four banks in South Africa who had complete records of all the variables outlined in the study's conceptual model (Figure 12): three psychometric test results (EI and control variables), risk grade data for the overdraft and term loan measures (credit risk assessment), and work performance variables data for the delinquency and charge-off measures (post-loan issuance work performance).

Second, the unit of observation was the 3 700 loans for the SME segment which had been manually approved (i.e., not approved via the automated scorecard) after going through the various approval stages and being taken up by the borrowers. These loans were linked to the 70 loan officers and were underwritten during the period 2018–2019. It was observed that a significant number (98.3%) were loans from existing borrowers known to the loan officers and the bank.

Third, the psychometric tests used were found to be reliable in that they measured the underlying constructs consistently. The results from the MSCEIT test (with the mean score range being 83.12–89.93) and personality test (with the mean score range being 46.23–51.96) came out as expected and were largely in line with similar South African studies. However, the results from the cognitive test showed that the highest score was 6 out of a range of 0–10 and the *winsorised mean* was 2.86. The results did not come out as expected; they were non-normal. A noticeable number of participants scored zero in certain sections and none of them achieved a high score.

Fourth, both the risk-grade contextual variable and work performance variable results were found to have limited variability, thus limiting the possibility of determining a variance based on EI abilities – a key requirement for EI research.

Finally, the results relating to the research question showed that only H1 was supported and the rest of the hypotheses were not supported, meaning that EI did not predict work performance – even when context was considered. A summary of the results from the statistical analysis discussed in detail in Chapter 5 is presented in Table 33 below for the mediation analysis (H1–H5), the moderation analysis (H6a–H6d) and the moderation model analysis (H7).

Table 33. Summary of findings for the tested hypotheses (Source: Author).

Hypothesis	Outcome	Summary Findings
Hypothesis 1: Emotion Perception correlates with Emotion Facilitation which correlates with Emotion Understanding which in turn correlates with Emotion Regulation	Supported	• Tests of association were significant ($p \leq .001$) and all relationships were moderate and positive
Hypothesis 2: Emotion Perception predicts work performance	Not supported	• Non-significant; correlations weak • Delinquency - $\hat{\tau}$: .04, $\hat{Z}$: .47, p:*1.00* • Charge off - $\hat{\tau}$: .06, $\hat{Z}$: .54, p:*1.00* • With control variables, including Emotion Perception, could not explain 98% variation in delinquency and 99% in charge off
Hypothesis 3: Emotion Facilitation predicts work performance	Not supported	• Non-significant; correlations weak • Delinquency - $\hat{\tau}$: .11, $\hat{Z}$: 1.18, p:*1.00* • Charge off - $\hat{\tau}$: .05, $\hat{Z}$: .57, p:*1.00* • With control variables, including Emotion Facilitation, could not explain 94% variation in delinquency and 95% in charge off
Hypothesis 4: Emotion Understanding predicts work performance	Not supported	• Non-significant; correlations weak • Delinquency - $\hat{\tau}$: -.01, $\hat{Z}$: -.13, p:*1.00* • Charge off - $\hat{\tau}$: -.07, $\hat{Z}$: -.80, p:*1.00* • With control variables, including Emotion Understanding, could not explain 98% variation in delinquency and 99% in charge off
Hypothesis 5: Emotion Regulation predicts work performance	Not supported	• Non-significant, correlations weak • Delinquency - $\hat{\tau}$: .06, $\hat{Z}$: .62, p:*1.00* • Charge off - $\hat{\tau}$: -.01, $\hat{Z}$: -.12, p:*1.00* • With control variables, including Emotion Regulation, could not explain 97% variation in delinquency and 98% in charge off
Hypothesis 6a: Risk Grade moderates the relationship between Emotion		• The regression model was non-significant • Delinquency ($R^2 = .85,\ F(13{,}47) =, p = 61$)

Hypothesis	Outcome	Summary Findings
Perception and Work Performance	Not supported	• Charge off - $R^2 = .07, F(13{,}47)1.33, p = .23)$ • The mediating process between Emotion Perception and work performance was not moderated by risk grade
Hypothesis 6b: Risk Grade moderates the relationship between Emotion Facilitation and Work Performance	Not supported	• The regression model was non-significant • Delinquency - $(R^2 = .09, F(13{,}47) = 1.45, p = .17)$ • Charge off - $(R^2 = -.05, F(13{,}47) = .80, p = .66)$ • The mediating process between Emotion Facilitation and work performance was not moderated by risk grade
Hypothesis 6c: Risk Grade moderates the relationship between Emotion Understanding and Work Performance	Not supported	• The regression model was non-significant • Delinquency - $(R^2 = -.01, F(13{,}47) = .96, p = .51)$ • Charge off - $(R^2 = -.05, F(13{,}47) = .79, p = .67)$ • The mediating process between Emotion Understanding and work performance was not moderated by risk grade
Hypothesis 6d: Risk Grade moderates the relationship between Emotion Regulation and Work Performance	Not supported	• The regression model was non-significant • Delinquency - $(R^2 = .10,\ F(22, 38) = 1.32, p = .22)$ • Charge off - $(R^2 = .13,\ F(22{,}38) = 1.40, p = .18)$ • The mediating process between Emotion Regulation and work performance was not moderated by risk grade
Hypothesis 7: All Emotional Intelligence abilities together moderated by Risk Grade predict Work Performance	Not supported	• The mediation analysis produced non-significant linear relationships (H2–H5) • EI abilities could not explain 97% and 98% variations in delinquency and charge off • The moderation analysis regression models were non-significant (H6a–H6d) • With control variables, including EI, could not explain 99% variation in delinquency and 98% in charge off • The moderation regression models were non-significant (H7) • EI abilities could not explain 90% variation in delinquency and 87% in charge off

The summary findings further illuminate the challenges with this field of research, despite its promise for business scholars and practitioners alike. The next section arrives at final conclusions about the findings and is followed by the sections covering the study's contributions and limitations as well as recommendations for future research.

6.2 CONCLUSION REGARDING THE FINDINGS

As explicated in Chapter 2 (specifically section 2.9), the foundational basis for EI research is summarised by Cherniss (2010) as follows: "The ability-based theory of emotional intelligence is based on three premises: (a) Individuals differ in their ability to perceive, understand, use and manage emotions; (b) Emotions play an important role in life; (c) These differences affect life outcomes differently, including the workplace" (p. 111). The results of research conducted by scholars have been mixed, causing Joseph and Newman (2010, p. 72) to talk about the "ugly state of affairs" and Cherniss (2010, p. 112) to refer to the "researcher's dilemma".

In the problem statement for this study, I highlighted that, given the unremarkable results, a call has been made in the extant literature for a more precise understanding of how EI predicts different criteria when context is considered (Côté, 2014; Ybarra et al., 2014). Thus, this study built on previous work but moved away from the simple bivariate approach by considering other research models, such as those examining mediator and moderator relationships. This was for the purpose of arriving at better, more informed insights regarding the relationship between a predictor and a criterion, which in turn would enhance our understanding of EI abilities (Côté, 2014; Côté & Miners, 2006; Farh et al., 2012; Ybarra et al., 2014; Yip & Côté, 2013).

Despite this study having followed best practice methods for research of this nature, as outlined in Côté (2014) and Miners et al. (2018), the findings show that the consideration of context as a moderator does not necessarily lead to better predictor–criterion outcomes. Nevertheless, there are important lessons and conclusions to be drawn from the study. The lessons outlined below will add to the research by offering more precise insights into the relationship between EI abilities and work performance outcomes when context is considered. Having conducted this study, we now know the following:

a) The ability-based EI construct is the most helpful and relevant for measuring abilities associated with emotions because of its underlying concepts (cognition and emotion), its integrative model of problem-solving abilities and its measurement of abilities using maximal performance tests.

b) The data collection methods for the psychometric tests – even though recommended in the extant literature – are costly and present a heavy administrative burden to researchers and participants.

c) The conceptualisation and operationalisation of the contextual variable (moderator) is a critical component of the approach and design of such studies and their outcomes. In particular, the underlying data must vary so as to test for variance in the context variable and the deployment of abilities.

d) The conceptualisation and operationalisation of the criterion variable is equally important, and the underlying data must also vary so as to test for variance in EI abilities.

e) Soft information in the SME credit risk assessment context is important for the loan underwriting process (both the application and approval stages) because of the inherent lack of hard information and asymmetry between the borrower and loan officer.

Even though this study was conducted in line with the 'gold standard' of ability-based EI research, a few questions remain. In other words, this is what we still do not know:

a) Principally, we still do not have any definitive finding on the role of context in the relationship between EI abilities and work performance.

b) We have not acquired any insight into the usefulness of the specific-situation model, as put forward by Côté (2014), or the call to context to assist researchers in determining the relationship between EI and outcomes.

c) Owing to the above, we are not in a position to confirm the utility of the ability-based EI construct in predicting outcomes of organisation members or even general life outcomes. The incremental and predictive validity questions remain open.

The next section discusses the contributions of the study.

6.3 CONTRIBUTIONS OF THE STUDY

This section discusses the contributions of the study at the theoretical, methodological and practical levels.

Much of the research conducted on ability-based EI takes for granted the fact that EI is an intelligence, but questions remain as to whether or not it contributes meaningfully to the prediction of work performance outcomes. The research in this area has been ongoing for at least a quarter of a century, with no definitive answer to the main question surrounding the predictive validity of ability EI. However, with each study, we have gained new knowledge, allowing scholars to refine their approach towards greater clarification of the construct. More importantly, primary study research remains nascent. This study, therefore, argues that the results hold significance for scholarship in that there is still room for further refinement as we have not stopped learning. The construct remains strong, but it is practically weak. The contributions of the study are presented in that context.

6.3.1 Theoretical Contribution

First, as indicated in the problem statement, this study heeded the call to context made by various scholars to close the gap in the incremental and predictive validity of EI (Antonakis, 2015; Antonakis et al., 2009; Ashkanasy & Dasborough, 2015; Cherniss, 2010; Côté, 2014; Côté & Miners, 2006; Daus & Ashkanasy, 2005; Jordan et al., 2010; O'Boyle et al., 2011; Ybarra et al., 2014). The call to context constitutes an attempt to advance theory by placing the respondents in the environment which approximates the production of results, thereby generating emotions.

This study contributes to theory by referencing a specific contextual variable within the unique SME credit risk assessment work environment. It conceptualised and operationalised the risk grade (overdraft and term loan) contextual variable as a critical step in the loan approval process, which prompted the deployment of emotional processes (Campbell et al., 2019). Even though the risk grade score is initially the outcome of an algorithm that identifies the propensity of the borrower to default, it is inevitably integrated with soft information to motivate the loan approval. The findings showed that the relationship between the input and output variables was not moderated, possibly due to other reasons. However, that should not detract from the fact that this is the first study to use the situation-specific model of Côté (2014) to explore the relationship between EI and criteria at the various levels of the contextual moderator. Hence, even though the results of the moderation analysis hypotheses were not supported, they reveal a need for further investigations into the role that EI and context play in predicting the work performance outcomes of organisation members in high-stake jobs, as a means to develop theory.

Second, this is the first study to integrate the ability-based EI construct and the SME credit risk assessment literature. Previous studies conducted on the issue of SME credit risk assessment have explored several possible influences on loan officers and on SME lending decisions and outcomes. For instance, previous research has focused on phenomena like sports, weather, gender, proximity to head office, intuition and other mixed EI models (Bacha & Azouzi, 2019; Campbell et al., 2019; Lipshitz & Shulimovitz, 2007; Roland & Olalekan, 2020). This study makes an important contribution to research by focusing on the quality of the loan officers' decision-making, elucidating the credit-granting process and using ability-based EI to reveal the determinants of success. This opens the door to further inquiry pertaining to ability EI as opposed to the prevalent use of mixed or trait EI, with its known limitations. Moreover, the lessons learnt should help guide researchers in being more pointed and precise in the application of the theory.

Third, given the quickening pace of technology uptake and digitalisation, it was expected that developments in the credit risk assessment environment and in SME lending practices could potentially close the gap in information asymmetry between loan officers and borrowers (Filomeni et al., 2016; Filomeni et al., 2021). This is the first study in the South African SME lending space to go into a significant amount of detail in mapping out the SME loan application and lending processes. The study suggests that, despite technological advances, the use of soft information – where discretion has to be applied – remains embedded in the process and can benefit the outcome (Agarwal & Ben-David, 2018).

This elucidation is important for theory development and strongly points to the need for more studies to further illuminate this area, which could lead to better contextual variable conceptualisation and operationalisation. Such research could also help with the selection and/or design of training interventions for SME loan officers aimed at enhancing their ability to work with soft information to positively influence post-loan issuance performance.

6.3.2 Methodological Contribution

A key methodological contribution of this study is its disciplined application of the 'gold standard' of EI research to promote better understanding of the construct and its influence on work performance outcomes (Côté, 2014; Miners et al., 2018). As a result, we have learnt a great deal about the things that contribute to the practical weakness of the construct. The study pioneered the application of the ‘gold standard’, as put forward by Côté (2014) in his seminal paper, by meticulously applying the steps below:

a) Providing a clear, concise definition of the chosen EI construct;
b) Selecting a performance-based measurement tool to test the construct;
c) Controlling for other, well-established explanatory variables such as cognitive intelligence and personality (Big Five) to ensure that there were no spurious outcomes;
d) Specifying a contextual variable or moderator that closely resembles reality in terms of the way that work is done in that particular area;
e) Moving away from bivariate models and employing the moderation model to test the relationship between EI and the given criterion.

This study builds on the work by Campbell et al. (2019) to operationalise the contextual or moderator variable (risk grade) and dependent variable (work performance) but does so in a different environment. The contextual variable (risk grade), which is unique to the environment, is an algorithmic output based on the borrower’s past financial behaviour. As revealed in the literature, this measure is relevant to the processing of soft information by the loan officers and the interpretive judgements which act as justifications for successful credit applications.

The capturing of a contextual variable using a metric measure was a crucial part of the methodology. It allowed for the simplification of the analysis by referencing a real-world work situation without diluting how work is done. In other studies where this measure has been applied, it has not been used as a contextual variable, even though authors have argued that there is a direct link between it and the adverse indicators of delinquency and charge off (Campbell et al., 2019). In this way, the study has contributed to this variable becoming relevant for the production of results and how work is performed, even though the outcome of the hypotheses could not answer the question as to whether the variable is related to work performance outcomes. Furthermore, this approach/application helps with the refinement of both the contextual variable measures (moderator) and the post-issuance loan performance measures (work performance) within an SME credit risk assessment environment, in particular, and possibly other environments as well.

Finally, the hierarchical, multiple-regression model used to test the hypotheses was extensive. This is one of a few studies in ability-based EI research to have examined multiple mediator and moderator relationships and interaction effects in one model. In this regard, it specified a mediation analysis, a moderation analysis and a moderation model analysis. The independent variable measure used four individual scores and an overall score; the moderator variable and the dependent variable each had two measures. The inclusion of the contextual variable and use of two moderator and dependent variable measures is what differentiates this study from previous studies. Previous studies have not specified such extensive relationships and variable measures (Farh et al., 2012; Yip & Côté, 2013). Furthermore, the model controlled for demographic factors, such as age, gender, tenure and race, and non-demographic factors, such as cognitive intelligence, personality and repeat lending. The use of the R statistical software facilitated the multi-pronged and complex analysis, while the inclusion of tenure and repeat lending specifically introduced a new dimension and richness. In the light of this study, researchers will be able to explore further permutations using the same model.

6.3.3 Practical Contribution

This study adds to the extant literature by searching for the incremental and predictive validity of the ability-based EI construct within organisational management contexts (Grobelny et al., 2021). The study lends weight to the quest by organisational management scholars to understand the heuristic value of EI. Even though the results of the study were not supported, they provide useful insights into the conceptualisation of the moderator (contextual) variable and dependent variables (work performance) in such models. The situation-specific model espoused by Côté (2014) can be further refined, based on the outputs from this study.

A further practical contribution of the study emanates from its application of the MSCEIT, the Matrigma (cognitive test) and the BTI (personality test) in a high-expectations work environment, such as the SME credit risk assessment context. The number of test instruments, even though prescribed in the guidelines for EI research, could, though, act as an obstacle because of the demands placed on the participants (Côté, 2014; Miners et al., 2018). In this study, participants responded to 364 task items across the three tests. Further work is needed to simplify the application of psychological instruments. However, the value of maximal performance tests as opposed to typical performance tests in the measurement of abilities was confirmed.

Finally, this study illuminates the loan application and approval processes in SME lending (Agarwal & Ben-David, 2018). The depiction of these processes in Figure 9 and Figure 10 respectively could prove useful for researchers, managers and employers who wish to optimise the work of loan officers and the processes they use to motivate loan approvals.

6.4 LIMITATIONS OF THE STUDY

The limitations of the study mainly relate to the research design and methodology. As explicated in section 3.4.1, the study used a single organisation sample frame, which means it focused on only one of the big four major banks in South Africa. While this was a pragmatic move, occasioned by the difficulty of accessing employee (loan officer) data and borrower data due to the prescripts of the Protection of Personal Information Act 4 of 2013 (POPIA), it meant that the study would have limited scope for generalisation to the banking industry and South Africa. The limitations of a single organisation sample frame also affected other aspects of the study, such as sample size, due to the concentration of risk associated with one organisation.

In section 3.4.2, the study set out the sampling procedure. From the population of 300 loan officers who work in the SME sector in the bank, 106 responses were received and after data cleaning there were 70 usable records. The final statistical analysis was performed on the 70 usable records, which represented 3 700 loans. The study motivated the reasons for the sample size and why it was sufficient to perform the statistical analysis (Morton et al., 2012; Siddiqui, 2013). Therefore, the quality of data was confirmed and sufficiently motivated. However, the sample size of 70 limited the types of statistical tests that could be performed and their predictive power.

The three psychometric tests used meant that the respondents had to answer all 364 task items in one go. While the respondents were given the latitude to complete one test per sitting, it is clear that the tests were demanding on respondents' time and mental faculties. The decrease from 106 responses to 70 usable records was mostly due to incomplete psychometric data. A good example of this was the Matrigma cognitive test outcomes which showed an unusually high number of respondents with zero scores. Furthermore, the item-level data for this test could not be extracted, which precluded meaningful validity analyses. In high-stakes environments where there is significant pressure on performance, the implementation of the full suite of tests, as recommended in EI research, could be limiting.

An important building block in EI research is variability in respondents' results (Cherniss, 2010). As EI is a latent variable and not directly observable without variability in results, it is difficult to conclude that the difference in performance is attributable to EI abilities (Grobelny et al., 2021). This study found that there was very low variability in the respondents' work performance variables and the risk-grade scores of the borrowers whom they motivated for loan approvals. The low variability in these scores was a significant limiting factor in the analysis as no effect size could be calculated.

Lastly, the operationalisation of the work performance variables of delinquency and charge off could have affected the study. Both delinquency and charge off are established, adverse indicator measures of post-issuance loan performance and are therefore thought to be closely associated with the performance of loan officers (Campbell et al., 2019). The use of objective criterion measures is common in EI research, but it could be limiting because it carries with it a 'psychological nuisance' where it is difficult to separate individual performance from environmental factors (Grobelny et al., 2021; Libbrecht et al., 2014).

6.5 RECOMMENDATIONS FOR FUTURE RESEARCH

Owing to the fragmentation in EI research caused by construct and definitional ambiguity, research on ability-based EI using the 'gold standard' has been sparse (Joseph et al., 2015; Miners et al., 2018). This weakness in extant literature manifests in the lack of coherence between the literature on the measurement of EI and its predictive value (Joseph et al., 2015). Much of the significance of the construct has been established using meta-analytic studies as opposed to primary studies (Grobelny et al., 2021; Van Rooy & Viswesvaran, 2004). Hence, one of the key recommendations is for the research on the heuristic value of ability EI in organisational management settings to continue so as to close the gap between general intuition and the reality of the construct. Through this primary study we have learnt the importance and role of context in approximating how work is done and how that may relate to EI as a predictor, but the learning was incomplete because of the results. It is recommended that more work be done on theories that describe the relationship between EI measures and moderators and their effect on the chosen criterion. In a recent meta-analytical study, Grobelny et al. (2021) suggest, based on their findings, the use of moderators like job status (manager or staff), job type (occupation) and industry.

Secondly, future research on ability-based EI should pay attention to several research design and methodology imperatives in order to build on what we now know, alleviate the constraints and deliver more precise outcomes:

a) The application of the full battery of EI, cognitive and personality tests should be reconsidered. With this study, it is clear that the full application of all the batteries of tests may have been too demanding for a population that is not used to psychometric tests. A trade-off is required, and the implementation of simpler, cheaper and shorter instruments should be considered. This may have the effect of increasing the sample size and predictive power as more records would be available for statistical analysis.

b) A critical component of EI research is variability in results, which was a significant limitation in this study. It is recommended that future studies focus on areas that naturally produce variability in the respondents' moderator (contextual variable) and criterion measure (work performance variable). Once again, the choice of job status (manager or staff), job type (occupation) and industry may be crtical. This aspect should be checked and confirmed at the design and data collection stages.

c) The operationalisation of the criterion measure (work performance) requires further work. Most studies that have found positive results in the predictive value of EI have been outside the organisational management setting, i.e., education settings, and have referenced an interpersonal measure. This study used an objective measure only, which may have inadvertently affected the outcome due to 'psychological nuisance' (Libbrecht et al., 2014). A key consideration going forward is the inclusion in the testing of criteria that are non-technical and much more related to interpersonal performance – for instance, subjective measures, like leadership. It is recommended that a combination of objective and subjective measures be utilised because a focus on both results and behaviours is much more representative of the multi-dimensional nature of work performance (Grobelny et al., 2021).

Lastly, this study's conceptual model was extensive and specified a number of relationships and variables unique to the setting, signalling a move away from bivariate models, with the advantage being that the possibility of prediction increased (Côté, 2014). However, introducing too much complexity could also detract from prediction. The recommendation for researchers is to keep a good balance in the number of variables in the model and not to add complexity and thereby detract from the end result.

6.6 CONCLUSION

This study explored whether or not ability-based EI problem-solving areas (branches), individually or together and moderated by context, predicted the work performance of loan officers at the different levels of the moderator. To test the relationship, the contextual variable (moderator) was operationalised to approximate the SME credit risk assessment environment. The criterion measures were operationalised to reflect the work performance outcomes of loan officers within this informationally opaque environment.

Business management scholars and practitioners alike have been drawn to this particular area of individual-differences research because of the prospect of EI relating to the performance of organisation members in a way that complements the explanatory power of general intelligence, while exceeding the power of personality and other competing constructs (Côté, 2014; Mayer et al., 2008). Extant literature shows that, despite a well-theorised construct, a parsimonious model and reliable measurement tool, the results have been weak – a situation variously described as the “researcher’s dilemma” and an “ugly state of affairs” (Cherniss, 2010, p. 112; Joseph & Newman, 2010, p. 72).

In an effort to address the problem of weak results and to advance knowledge, this study used the specific-situation model which motivates for the inclusion of a contextual variable (moderator) in what was largely a bivariate relationship (Côté, 2014). Except for the first hypothesis relating to the relationship between the EI branches, the results of this study showed that none of the other hypotheses was supported, as the models were insignificant. In other words, the loan officer’s EI abilities had no bearing on their work performance outcomes, irrespective of cognitive ability, personality, race, gender and age.

Notwithstanding the findings, the study charted new territory, advanced our knowledge and contributed to our understanding of the role of EI abilities in predicting outcomes in organisational settings when context is considered. The limitations of the study together with the recommendations for future research present a clear opportunity for the further development of this area of research.

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APPENDIX A – ABBREVIATIONS AND ACRONYMS

Abbreviation	Meaning
BTI	Basic Traits Inventory
CFA	Confirmatory Factor Analysis
EFA	Explanatory Factor Analysis
EI	Emotional Intelligence
FFM	Five-Factor Model
GIBS	Gordon Institute of Business Science
GMA	General Mental Ability
HMR	Hierarchical Multiple Regression
MEIS	Multifactor Emotional Intelligence Scale
MHS	Multi-Health System
MI	Management Information
MSCEIT	Mayer-Salovey-Caruso Emotional Intelligence Test
NDA	Non-Disclosure Agreement
OD	Overdraft (bank product)
PMA	Primary Mental Ability
POPIA	Protection of Personal Information Act 3 of 2014
SME	Small and Medium Enterprise
STEM	Situational Test of Emotion Management
STEU	Situational Test of Emotion Understanding
TL	Term Loan (bank product)

APPENDIX B – OUTLINE OF THE MSCEIT V2.0 QUESTIONNAIRE

Task 1 – Faces (Emotion Perception).

For each of four photographs of a face, participants rate the extent to which the facial expression shows each of five different emotions. The rating scale ranges from 1 (No emotion) to 5 (Extreme emotion).

Task 2 – Pictures (Emotion Perception).

Participants are shown six pictures which show either a landscape or an abstract design. Participants rate the extent to which five emotions are present in each picture. Ratings are made on a 1 to 5 scale, where scale points are each anchored by an emoticon cartoon face indicating various levels of the emotion.

Task 3 (Emotion Facilitation).

Sensations - Participants are asked to describe the direction and degree of their emotions in relation to other tactile and sensory stimuli using a continuum.

Task 4 (Emotion Facilitation).

Facilitation – Participants are asked to identify the emotions that would best facilitate a type of thinking.

Task 5 – Changes (Emotion Understanding).

The test consists of 20 five-option, multiple-choice questions for which test takers must identify how an emotion would change according to changes in a situation or time course.

Task 6 – Blends (Emotion Understanding).

Participants complete 12 five-option, multiple-choice questions for which they must identify how different emotions interact to form new emotions.

Task 7 – Emotion management (Emotion Management).

For each of six vignettes describing an emotional situation, test takers rate four possible responses for their effectiveness in managing the emotions involved. Ratings are made on the following 5-point scale: (a) Very ineffective, (b) Somewhat ineffective, (c) Neutral, (d) Somewhat effective, (e) Very effective.

Task 8 – Emotional relationships (Emotion Management).

For each of three vignettes describing an emotional situation, test takers rate the effectiveness of three possible responses for maintaining or building the social relationships of the vignettes' protagonists. Ratings are made on the following 5-point scale: (a) Very ineffective, (b) Somewhat ineffective, (c) Neutral, (d) Somewhat effective, (e) Very effective.

APPENDIX C – ADMINISTRATION OF THE TESTS

INVITATION TO PARTICIPATE IN THE DOCTORAL RESEARCH

Dear Absa Colleague,

I, Bongani Mageba, am **doing research towards a PhD degree** at the University of Pretoria's Gordon Institute of Business Science (GIBS). I am inviting you to participate in a **study entitled,** *"Emotional Intelligence as a predictor of work performance – An investigation using the Situation-Specific Model".*

Aim of the study:

The aim of the study is to **understand the impact of Emotional Intelligence on work performance** in the **credit risk assessment environment among small and medium enterprises (SMEs).** In addition, the study aims to develop a framework that employers can use to grow and enhance the skills of loan officers for better credit decisions and post-loan issuance performance.

The study, which is voluntary and confidential, is supervised by:

- Dr. Morris Mthombeni (Interim Dean of GIBS)

- Dr. Nicola Taylor (Director: Data Enablement – JVR Psychometrics)

Participating in the study is voluntary and of no cost to Absa or the individuals who agree to participate. Even though participation is voluntary, it would be ideal – for the validity of the study – to have as many of you participate as possible.

The assessments will be **handled with utmost confidentiality** under the supervision of Dr. Nicola Taylor, a registered psychometrist with the Health Professions Council of South Africa (HPCSA) (registration number PMT0073679). I, Bongani Mageba, will only have access to statistical correlations and group level outputs; not individual data.

Next steps – process:

A follow-up letter with a hyperlink will be sent to you within two days of your receiving this letter requesting that you **complete <u>three</u> online psychometric assessments** which will take between 50 and 70 minutes to complete. It is preferable that when you take the tests you do so in one sitting. However, they can also be taken individually, one at a time. All three tests <u>must be completed</u> for the study to be valid.

Contact details of the Researcher:

If you require any further information about this study, you may contact me on: 079 695 4012 OR send an email to: Bongani.mageba@absa.africa or magebabongani@yahoo.com.

Thank you in advance for your co-operation and support.

Yours sincerely,

Bongani Mageba
(PhD candidate)

<u>10.2 Frequently Asked Questions:</u>

Question 1: Who is Bongani Mageba?

Bongani Mageba is employed by Absa as Managing Executive: Non-Banking Financial Services within Relationship Banking. He is enrolled at the Gordon Institute of Business Science (GIBS) for a doctoral degree and has a passion for research and creation of new knowledge. He has obtained the necessary approvals to conduct this research within Absa.

Question 2: Is participation voluntary?

Even though the study is sensitive to the number of participants, in that as many participants as possible are required for the study's validity, it is entirely voluntary. Thus, nobody should feel forced to participate.

Question 3: Who are JvR Psychometrics?

JvR Psychometrics is a psychological test provider, with over 25 years of experience in the research, development and distribution of psychological tests in South Africa and Sub-*Saharan Africa.* Read more about them here:

https://jvrafricagroup.co.za/psychometrics/about

Question 4: Who is Dr Nicola Taylor?

Dr. Nicola Taylor is the supervisor for the current phase of the PhD research. She specialises in research using psychological tests. Dr. Taylor is also a senior research associate of the Centre for Work Performance at the University of Johannesburg.

Question 5: Why use psychometric tests instead of an interview?

The research process requires all participants to complete assessments using well-established and validated tools. This is a far more accurate and reliable method than interviews and provides objective results that can be compared to local and international benchmarks.

Question 6: How will the hyperlink work?

The next email will contain two hyperlinks: one for the MSCEIT, which is a measure of emotional intelligence ability, and one for both the BTI (a measure of personality) and Matrigma (a measure of general mental ability). You will be asked to provide some biographical details when you register to complete the assessments through the link.

Question 7: How long do I have to complete the tests?

You will have 7 days to complete the 3 tests. It is ideal that you complete all of them at once even though you can also choose to do them in three different settings. A single test must be done in one full sitting. It is crucial that you complete all three tests.

Question 8: Who will have access to the results?

Only JvR Psychometrics will have access to individual participants' results. All results will be treated with the utmost confidentiality and anonymised as soon they have been combined into a single dataset. Mr Bongani Mageba will be given anonymised and aggregate results.

Question 9: How will the results be computed?

For research purposes the psychometric results scores will be aggregated into team scores which, together with the fund results, will be used for interpretation. Participants will not be individually identifiable in the data analysis phase.

Question 10: Will the participants be entitled to the results of the assessments?

Absolutely; all participants will – upon request and at their own cost – be entitled to feedback on their individual assessment results. Should they be interested in the results of the study, a link to the final published PhD thesis will be provided.

Regards,

Bongani Mageba
PhD Candidate

SECOND LETTER TO POPULATION WITH HYPERLINK

Dear Colleague,

Thank you very much for considering participating in Bongani Mageba's research study titled: *"Emotional Intelligence as a predictor of work performance – An investigation using the Situation-Specific Model"*. **This is a follow-on email to the one you received a few days ago highlighting the purpose of the research.** Please note the following:

- Your participation in this research study is voluntary and no costs or reimbursements will occur; nor will there be any incentives or compensation for your participation.
- You may withdraw from the research at any time, with no negative consequences.
- Your answers will be kept confidential and you will be anonymous to the researcher. The data will be safely stored, password-protected, and kept for a minimum period of seven years in accordance with relevant legislation.
- The data will be used for Bongani Mageba's research study and may be used in future studies that evaluate the function of the questionnaires used. In addition, the results of the study may be used for journal publications and/or conference presentations. You will never be individually identified.
- You will not receive any reports on the results of the questions you complete unless you specifically request feedback, which you will have to pay for yourself.
- You may contact Bongani Mageba or Dr. Nicola Taylor if you have any questions regarding the research at:
- magebabongani@yahoo.com or nicola@jvrafrica.co.za.

By completing the assessments via the links below, you consent both to participate in the research study and to your responses from the questions below being used for the research study, final dissertation and future research studies.

Please find two links below to complete three assessments:

- Each assessment will take between 15 and 45 minutes to complete.
- Please set aside a time during which you will not be interrupted.

- You may complete each of the three tests at different times, but you must complete an entire test in one sitting or the system will not save your answers and you will need to start from the beginning.
- Instructions on how to complete each test will appear once you have accessed the assessment (you will have to register yourself on both systems).
- Please complete these on your own.

In order to access the **MSCEIT**, click:

http://s.mhs.com/Wp3x4X.

In order to access the **BTI** and **Matrigma**, click:

https://jvrresearch.jvronline.net/questionaire?assessment=3F6AEE39-8528-49E1-812A-FA044D523A46

See below for an explanation of what each of the psychometric tests is about:

MSCEIT: Is a measure of emotional intelligence. This gives an indication of how well you are able to identify your and others' emotions, understand what caused them, use emotions to make decisions, and manage the expression of your emotions. It involves answering different types of questions (from identifying emotions from pictures of faces, to what you would do in this situation, and how you usually approach things).

BTI: Is a measure of personality. It describes how you tend to behave in terms of five major aspects of personality, namely: extraversion, emotional stability, openness to experience, conscientiousness and agreeableness. All questions involve responding to statements using a 5-point rating scale in terms of how you would normally act, think or behave.

Matrigma: Is a measure of general cognitive ability. It looks at how you tend to approach problem solving, especially when faced with unfamiliar problems. The questions involve being presented with a series or matrix of images and having to select the next one or the missing image from a range of options. This test has a 40-minute time limit.

Should you have any questions or experience any technical difficulties, please contact Client Services at JvR Psychometrics (clientservices@jvrafrica.co.za) or call 011-781-3705 for help.
I would like to thank you in advance for your assistance and support for this piece of work, which will lead to much better credit risk assessment outcomes for individuals and businesses alike in the SME sector.

Best regards,

DR NICOLA TAYLOR
Director | Data Enablement
Fernridge Office Park | 15 Hunter Street | Ferndale | Randburg. T: +27 11 781 05/6/7 | C: +27 76 381 7804

THIRD LETTER TO MIDDLE MANAGEMENT OF THE POPULATION

Good evening, Colleagues

I hope you are all well.

Thank you very much for attending the session this past Monday wherein I covered the full scope of my doctoral research project. I promised that I would share with you the list of colleagues in your teams who have been sent the invitation to participate in the research process by completing the three psychometric assessments (see attached with two tabs). The invitation was sent to about 85 colleagues in this province. Once again, I would like your assistance and support as follows:

- Explaining to colleagues in your space what the research is about
- Encouraging as many colleagues as possible to participate
- Monitoring the levels of participation and take-up within your teams

I would like to have a minimum of **100 colleagues** countrywide participate so that I can meet the objectives of the study. I have a very tight deadline and would like to work to a two-week programme to monitor the returns:

- Friday, 17 September
- Friday, 24 September

I will therefore check in with you by sending you the names of people in your province who have completed all the tests both on the **17th Sept and 24th Sept** so that you can have the necessary information to encourage colleagues and monitor participation.

Lastly, I will try and set up a follow-up meeting with those of you who could not attend the session this past Monday. Please feel free to contact me or write to me if you have any questions.
Once again, thank you in advance for all your support and help.

Regards,

Bongani Mageba

PhD Candidate

FOURTH LETTER TO EXECUTIVE MANAGEMENT OF POPULATION

Hi KK,

Thank you very much for the discussion yesterday morning. It was really reassuring given my situation. KK, I'm very close but yet so far. I really need your involvement and support. See below the steps that I have followed thus far:

- Initial Introduction email about the study to all the Bankers in the KZN-MP Province – 17 July 2021 (see attached).
- **Email to all Bankers in the KZN-MP Province with the link for the test – 19 August 2021 (see attached email and list). This is the email that you can forward under your name to get the required responses.**
- Communication to Area Coverage Managers – 7 September 2021 (see attached email).
- Meeting with Area Coverage Managers nationally – 7 September 2021 (I covered about 60% of them nationally).
- Current returns from the KZN-MP Province – sitting at 1 based on my reconciliation.
- **The KZN-MP Province population is about 64 as per attached list – we should aim for the participation of about 30 colleagues.**

Keketso, as per the above, <u>I need about 30 responses</u> and, given the size of the population, it should not be below 25 responses for me to run the model. This will ensure that I get to the required level of analysis. There are two options for the implementation by the end of this week, but I'm happy for you to implement the best way to see fit:

- Set aside 1 h 30 mins on a particular day this week for colleagues to complete the three psychometric tests and allocate them to committed slots.
- Set aside about 30–40 minutes for three days until Friday or early next week for colleagues to complete the three psychometric tests

I'm very comfortable with whatever approach you come up with, as long as it can give me the requisite number of completions. The Credit team have more or less followed the approach above and we got a 76% return. **The colleagues who have participated have found it easy, fun and**

interesting. I would like to get all the responses by Friday 8 October as I've run out of time. Thanks in advance, KK, and let me know if you have further questions.

Regards,

Bongani Mageba
PhD Candidate

APPENDIX D – EXAMPLE OF NON-DISCLOSURE AGREEMENT

CONFIDENTIALITY AND NON-DISCLOSURE AGREEMENT

Entered into by and between:

Absa Bank Limited

(Registration no 1986/004794/06)

of 15 Troye Street

Absa Towers West

Johannesburg 2001

("**Absa**")

And

Bongani Mageba

("**the Employee**")

And

JVR Psychometrics

("**the Company**")

(hereinafter referred to individually as a "**Party**" and collectively as the "**Parties**").

The Parties have agreed that Absa will be disclosing certain agreed information to the Employee in connection with the Absa and or Absa Group Limited, including their affiliates and subsidiaries (‘Group’) business and its employees for the purposes of the Employee conducting Doctoral level research at the Gordon Institute of Business Science. The disclosure made by Absa to the Employee relates to certain proprietary, secret, sensitive or confidential information pertaining to clients, Absa or the Group’s business and processes and other employees which is required by the Employee in order for him to conduct the necessary research referred to above and as set out in the summary of the topic in clause 2.1 below.

It is also necessary that the Company agree to treat the information as confidential and to not make it public.

1. DEFINITIONS

1.1. The word “**Information**” shall mean all information, including but not limited to proprietary information, secret information or confidential information (and in particular sensitive business processes and/or policy and/or employee and/or client information) and all knowledge, data, specifications, business processes or operations, prototypes, drawings, know-how and Client and Policy and Human Resources information which is owned by Absa or controlled by a Party.

1.2. The term “**Intellectual Property**” shall include but shall not be limited to inventions, whether patentable or not, patents, trademarks, copyrights, know-how, business methods and trade secrets.

1.3. The words “**Material Form**” shall include but shall not be limited to printed form, computer readable form, coded form, or the like from which the Information or part thereof can be reproduced or derived.

2. INTRODUCTION

2.1. The Employee is currently employed as a Managing Executive in Absa.

As part of the requirements for him to qualify towards a PhD qualification, the Employee is required to gather data for his registered topic. The research topic for which data will be gathered is “Emotional Intelligence as a predictor of work performance – a focus on the Small Medium Enterprise credit risk assessment context”.

2.2. In order to conduct this research, the Employee will be exposed to sensitive and confidential Absa, Group, employee and client information and data.

2.3. Due to the sensitivity and confidentiality of the Information to which the Employee will be exposed, it is necessary for Absa to obtain an additional undertaking from the Employee over and above the confidentiality provisions as contained in the Employee's employment contract / letter of appointment.

2.4. To the extent that the confidentiality provisions in the Employee's employment contract / letter of appointment conflict with the confidentiality provisions set out in this agreement, the confidentiality provisions that provide the most protection to Absa will prevail as determined by Absa.

2.5. This Agreement is an addendum to the Employee's employment contract / letter of appointment and the remainder of the current terms and conditions of employment as contained in the Agreement remain of full force and effect.

2.6. Absa and the Employee acknowledge and agree that this Agreement constitutes a material term and condition of employment and will at all times be read together with the Employee's contract of employment / letter of appointment.

2.7. By the Employee's signature to this Agreement the Employee records that he has carefully read and reviewed the contents of this Agreement and acknowledges that he fully understands all of its terms and conditions, and has entered into this Agreement freely and voluntarily.

2.8. Due to the sensitivity and confidentiality of the Information to which the Company will be exposed, it is necessary for Absa to obtain an undertaking from the Company.

3. DISCLOSURE OF INFORMATION

3.1. The Parties acknowledge that the Information is sensitive, confidential, and proprietary, and is a valuable, special, and/or a unique asset belonging to Absa and the Group.

3.2. The Employee shall not, during or after the termination of his employment with Absa, and the Company shall not at any stage, disclose the Information or any part thereof to any person or entity which is not a Party to this agreement for any reason or purpose whatsoever, without the prior written consent of Absa. This restriction includes any other employee of Absa or the Group who is not entitled to the Information as a result of the position they hold within Absa. Where such written consent is given, the Employee and/or Company shall enter into a confidentiality and non-disclosure agreement with such third party in terms at least as extensive and binding upon them, as those set out herein, and provide Absa with a signed copy of such agreement within seven (7) days from the Employee and/or University disclosing the Information or part thereof to such third party.

3.3. The Employee and Company shall not, either directly or indirectly, utilise, employ, exploit or in any other manner whatsoever use the Information, or part thereof other than as set out herein, unless authorised, in writing, by an authorised official of Absa.

3.4. If it is uncertain whether any Information is to be treated as confidential, the Employee and Company shall treat such Information as confidential until written clearance is obtained from Absa.

3.5. The Parties agree that all Intellectual Property, which subsists in the Information, including rights to improvements and developments, shall belong to Absa and/or the Group and are its exclusive property.

4. TITLE

All the Information disclosed by Absa is acknowledged by the Employee and the University to be the exclusive property of Absa and the Group and the disclosure of the Information shall not be deemed to confer any rights in and to the Information on the Employee or University. Absa shall retain all rights, title and interest in and to its Information.

5. STANDARD OF CARE

5.1. The Employee and Company shall protect Absa and the Group's Information using not less than the same standard of care that the Employee and Company applies to its own proprietary, secret, sensitive or confidential information and that the Information shall be handled in such a way as to prevent unauthorised disclosure or access. In no event shall the Employee and Company exercise less than reasonable care.

5.2. If the Employee or Company becomes aware of any unlawful disclosure of Information, they must confirm the same with full details in writing to Absa without delay, failing which appropriate action may be taken against either the Employee, the Company or both.

6. RETURN OF INFORMATION

6.1. The Employee and Company agree that they are not entitled to retain in their possession or under their control, either directly or indirectly, part of the Information or copies thereof, which has been reduced to Material Form except insofar as it relates to the dissertation and the finalisation thereof.

6.2. Should the Employee or Company be in breach of their obligations in terms of clause 6.1 above and without prejudice of any other rights which Absa may have in terms of this agreement, Absa may request, in writing, at any time that Absa' and the Group's Information or any part thereof, which has been reduced to Material Form by the Employee and any copies thereof, be returned to Absa, with written confirmation to the effect that upon such return he has not knowingly retained in his possession or under his/its control, either directly or indirectly, part of the Information or copies thereof. The Employee and/or Company shall comply with any such request within 14 (fourteen) days of receipt of such request.

6.3. As an alternative to the return of the Information, as envisaged in paragraph 6.2, and at the request of Absa, the Employee and/or Company shall destroy the Information or part thereof and copies, which have been reduced to Material Form, and supply a written confirmation to the effect that all Absa and the Group's Information or parts and copies thereof have been destroyed within 14 (fourteen) days of receipt of such request.

7. EXCLUDED INFORMATION

7.1. The obligations pursuant to this agreement shall not apply to Absa and/or the Group's Information if:

7.1.1 the Information is or becomes publicly known, otherwise than as a consequence of a breach of this agreement or of any action of the Employee or Company; or

7.1.2 it can be proved that Absa or the Group's Information has been rightfully received by the Employee or Company from a third party without a breach of a duty or obligation of confidentiality; or

7.1.3 the Employee and/or Company can show that Absa and/or The Group's Information is disclosed or used with the prior written approval of Absa.

7.2. Notwithstanding the aforesaid in clause 7.1, the Employee and/or Company may disclose Absa or the Group's Information to satisfy a legal demand by a competent court of law or governmental body; provided however that in such circumstances, the Employee and/or Company shall advise Absa prior to such disclosure, as far as it is reasonably possible, so that Absa has an opportunity to defend, limit or protect itself against such production or disclosure. The Employee and/or Company shall disclose only that portion of Absa or the Group's Information which is legally required to be disclosed and the Employee and/or Company shall exercise reasonable efforts to obtain a protective order or other reliable assurance that confidential treatment will be accorded to any part of Absa and the Group's Information required to be disclosed.

7.3. In any dispute in terms of clauses 7.1 or 7.2, the onus of proof shall be on the Employee and/or Company.

8. TERM

Notwithstanding the duration of the Employee's employment with Absa or the finalisation of the research, the obligations set out herein will endure indefinitely.

9. ADDITIONAL ACTION

The Parties to this agreement shall execute and deliver such other documents and do such other acts and things as may be necessary or desirable to carry out the terms, provisions and purposes of this agreement.

10. ENTIRE AGREEMENT AND AMENDMENTS

10.1. Subject to clause 2.4 and 2.8 above, this agreement supersedes all prior agreements whether oral or in writing and constitutes the entire agreement between the Parties, with respect to the subject matter of this agreement.

10.2. No warranty, waiver, term or condition not contained herein shall bind the Parties, and this agreement shall not be amended, cancelled or novated, otherwise than in writing and signed by the Parties.

11. ENFORCEMENT

The failure to enforce or to require the performance at any time of any of the provisions of this agreement shall not be construed to be a waiver of such provision, and shall not affect either the validity of this agreement or any part hereof or the right of either Party thereafter to enforce each and every provision in accordance with the terms of this agreement.

12. HEADINGS

The headings of paragraphs are used for convenience only and shall not affect the meaning or construction of the contents of this agreement.

13. GOVERNING LAW

The law governing this agreement shall be the law of the Republic of South Africa and this agreement shall be construed and interpreted in accordance with the substantive law of the Republic of South Africa, and the agreement will be subject to the jurisdiction of the South African Courts.

14. NOTICES

All notices, demands, legal process or other communications under this agreement shall be given or made in writing, and shall be delivered personally, or sent by certified or registered mail with return receipt requested, addressed to the Party to whom they are directed at the address set out at the head of this agreement or at such other physical address in the Republic of South Africa as may be designated by notice from such Party, with a copy sent by facsimile at such number as the Parties hereto shall designate from time to time. Any notice, demand or other communication given or made by mail in the manner prescribed in this paragraph shall be deemed to have been received seven (7) days after the date of mailing.

15. SEVERABILITY

In the event any one or more of the provisions contained in this agreement shall for any reason be held to be invalid, illegal or unenforceable in any respect, such invalidity, illegality or unenforceability shall not affect any other provision of this agreement, but this agreement shall be construed as if such invalid, illegal or unenforceable provision had never been set herein, and this agreement shall be carried out as nearly as possible according to its original terms and intent.

16. EFFECTIVE DATE

Notwithstanding the date of signature hereof, the Effective Date of this agreement shall be ________________________2021.

17. ASSIGNMENT

This agreement is personal in nature between the Parties and is entered only for the benefit of the Parties. The rights and obligations of any Party may not be ceded, assigned or delegated without the prior written consent of the other Parties.

18. LIMITATION OF LIABILITY AND INDEMNITY

18.1. The Employee and/or Company shall be liable for all proven and awarded loss or damages Absa may suffer, including attorney and client costs, resulting from any unauthorised disclosure to any third party of any of the information as described herein by the Employee, the Company, its employees, agents and/or consultants.

18.2. The Employee and the Company shall ensure that this agreement or the exercise of this agreement does not infringe any third party's intellectual property rights and each Party indemnifies the other in respect of claims from third parties for such infringement.

19. BREACH

During the continuance of this agreement, if either Party (the "**Defaulting Party**") breaches any provision of this agreement, then the other Party (the "**Aggrieved Party**") shall be entitled at its election, to apply to a court of competent jurisdiction to restrain further disclosure of Absa's Information and to obtain any type of relief as may be appropriate. The aforegoing is without prejudice to such other rights as the Aggrieved Party may have at law.

20. NEUTRAL CONSTRUCTION, EXCLUSION OF THE CONTRA PROFERENTUM

The provisions of the Contract shall not be construed against a Party on the grounds that such Party drafted or was responsible for drafting any or the majority of the provisions.

For and on behalf of Absa duly authorised thereto:

SIGNED at ________________________ on _________________________ 20 _____

<u>AS WITNESSES:</u>

1. ___________________________ ___________________________

2. ____________________________ ___________________________

The Employee:

SIGNED at ________________________ on _________________________ 20 _____

AS WITNESSES:

1. ___________________________ ___________________________

2. ____________________________ ___________________________

The Company:

SIGNED at ________________________ on _________________________ 20 _____

AS WITNESSES:

1. ___________________________ ___________________________

2. ____________________________ ___________________________