Maturity Indicators for Organizations Addressing Low Probability High Impact Events:

The Collective Intelligence Maturity Assessment Model

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A thesis submitted to the University of Nicosia in fulfilment of the requirements for the degree of Doctor of Philosophy

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January 2020

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Abstract

This Thesis examines Collective Intelligence as a systemic dimension that can provide organizations addressing Low Probability High Impact Events (LoPHIEs), with an assessment of their maturity levels. Three main themes - Decision Making, Collective Intelligence (CI), and Maturity Assessment Models - were examined, for the first time jointly, to compose a Collective Intelligence Maturity (CIMA) Model.

Indicators and factors, which are of critical importance for the evolution and maturation of Collective Intelligence in teams and Collective Performance in relation to the management of LoPHIEs, are investigated at both a theoretical and empirical level. Three interconnected experiments were conducted, and primary data were collected. Following that, the analysis of the primary data led to a new model for maturity assessment. This model has resulted following a design science research methodology, with two iterations of the development cycle. During the first development cycle, an initial design of the CIMA Model has been proposed. In addition, an initial analysis of the primary data collected was performed and resulted into the identification of additional factors, which in turn advised the second iteration of the development cycle, where an improved design of the CIMA Model has been presented and a complete analysis of the primary data has been conducted. In the last phase of the second development cycle, the results of the data analysis were taken into consideration, and a final design of the CIMA Model has been presented. The final design integrates in full the maturity of the phenomenon under study. Consequently, the present study aims to enlarge the existing body of knowledge in the subject area and offer strategic decision-making support for the successful and sustainable management of LoPHIEs.

Acknowledgments

I would like to express my thanks and sincere gratitude to my supervisors for their academic guidance, motivation, and inspirational dedication to work. This research would not have been possible without their support and encouragement.

Gratitude is also expressed to those that have participated in the experiments conducted for the purposes of this research, and to the panel of experts that have been involved in this work, for their time and effort in providing validated feedback.

Finally, I would like to thank my family for their patience and understanding throughout this research.

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Chapter 1 Introduction and Background

1.1 Introduction

Humanity finds itself faced with several systemic problems, such as natural catastrophes, human-made disasters, crises, and others that have a devastating impact on the environment, communities, societies, as well as organizations worldwide (Klein, 2007). These events have very low probability of occurring, yet they cause a significant impact. Thus, they will be referred to in this Thesis as Low Probability High Impact Events (LoPHIEs). The nature of such situations can extend far beyond a local area, having significant implications upon the operations of involved and affected organizations (Hergert, 2004). The wildfires in Troodos Mountains in Cyprus in 2016, the 7.8 magnitude earthquake that struck Nepal in 2015, as well as the sequence of disasters resulting from the earthquake in Japan in 2011, are some examples of LoPHIEs. The aforementioned natural catastrophes that led to economic and technological disruptions, and life losses, highlight the complexity of handling effectively global risks (The Global Risks Report, 2014).

Hazards shift, and with them, various vulnerability patterns evolve (Engelbach et al., 2015). Within such contexts, consequences are disproportionate and difficult to contain or predict, with numerous challenges associated to volume, relevance, and quality of information relevant to decision making (Mendoza, Poblete and Castillo, 2010) together with the complexities of coordinating the activities of those affected or involved in the management of such events (Starbird and Palen, 2011). Unable to predict the next occurrence and its effects, governments, and enterprises all around the world are engaged in the design and implementation of various methods for disaster management with the primary objective to decrease possible impacts (Marjanovic and Hallikainen, 2013; Turoff et al., 2004a, 2004b). Appropriate preparations for such events may make the difference between a major disruption of operations in the affected organizations or their resilience and survival (Coombs and Holladay, 2010; Halder, 2017). Section 1.2 discusses the philosophical context of LoPHIEs. Section 1.3 identifies the research gap in relation to the defined problem. Section 1.4 states the research aim and objectives of this research. Finally, Section 1.5 provides an overview of the Thesis.

1.2 The Philosophical Context of LoPHIEs

The term “Black Swan” has been proposed by Nassim Nicholas Taleb as a visual metaphor for Low Probability High Impact Events (LoPHIEs). This metaphor relates to the fact that before the discovery of the black swan species (Cygnus atratus), there seemed to be a conclusive belief, confirmed by empirical evidence that all swans were white (Melamed, 2009; Taleb, 2008). The term “Black Swan” was first used by the Roman satirist Juvenal in AD 82 as a fictional irony based on a creature that did not exist, while Aristotle used metaphors of black and white swans to distinguish the improbable from reality. The ‘‘black swan’’ survived for 1,500 years, as a metaphor for something that did not exist. With the sighting of the first black swan, however, the myth was disproved, manifesting the existence of the improbable (Melamed, 2009). The situation exemplifies the severe limitations of learning from observations or experience and the fragility of our knowledge. The metaphor of the “Black Swan,” no longer hypothetical, is historically accredited to the difficulty in inductive logic, known as Hume’s Problem of Induction (Taleb 2007, 2008). The Problem of Induction is concerned with the inherent complications in formulating rules from observed facts and from those facts only. Going beyond what is often referred to as ‘‘Hume’s Black Swan’’, the Black Swan theory developed by Nassim Nicholas Taleb, offers a different perspective. The theory holds that the ‘‘Black Swan’’ is not merely a problem in logic, but as Taleb (2008, p. 2) notes, “[is] an empirical matter concerning the occurrence of unusual events: an ‘outlier’ or an exception that has the property of carrying a large impact.” The theory, therefore, is concerned with the occurrence of the improbable and the power of rare events of unknown magnitude and duration. A distinct characteristic of such events is the cruel surprise effect generated after the occurrence of the event and which, in some sense, is what makes its consequences worse. The impact of this branch of rare events takes place not only at a physical level; but also at an ideological level. The erratic nature of LoPHIEs affects the way in which risk and uncertainty are perceived and contributes to the creation of the "new normal" (Taleb and Pilpel, 2007); a notion that expresses the world as a newly and inherently insecure place (Burkeman, 2007; Cooper and Miller, 2002; Hooker and Aliis, 2009; Jones, 2009).

Due to the silent underlying causes that usually seem to shape LoPHIEs and consequently suggest in some cases even the slight possibility for their occurrence, the concept has been subject to heavy criticism (e.g., Easterbrook, 2007; Melamed, 2009; Savage, 2009). Emphasis, however, is mistakenly given to whether an event could be predicted or not (Taleb, 2008). LoPHIEs have a small but incalculable probability, meaning that while the occurrence of an event may be predicted, its magnitude, the total destruction of lives, wealth, or other losses that it might cause, cannot be estimated. Consequently, taking into consideration that the rarer the event, the more vicious the consequences are likely to be, the estimation of its impact is going to be enormously incorrect (Taleb, 2008; Taleb and Pilpel, 2007). In view of this, the problem examined and thoroughly described in the following Section is of high importance.

1.3 Problem Statement and Research Gap

The conceptual definition of LoPHIEs has three dimensions: 1) Threat 2) Decision time 3) Awareness (surprise). LoPHIES, appear as an unexpected surprise situation of serious threat to the decision-maker, allowing only a short time for decision before the situation significantly escalates. The combination of threat, short time for decision making and surprise, compose a basic definition of LoPHIEs. The evaluation and magnitude of the event depends on the decision maker's perception of the situation. Critical consideration on the matter, should not merely take into account the prominence of risk and uncertainty, but also the specific ways in which these notions are conceptualized (Tedeschi and Calhoun, 2004).

Following the three dimensions of the conceptual definition of LoPHIEs, organizations' preparedness to these events is distinguished into three phases, including methods that prepare the organization *before* the event; methods that are initiated *during* the event to limit damage and methods that examine the aftermaths (Bernstein, 2011; Coombs and Holladay, 2010; Coombs, 2007). Throughout these phases, the management of LoPHIEs involves the coordination of many different types of multi-faceted processes, ranging from highly structured and predefined processes guided by protocols and emergency operating procedures; to highly ad-hoc and emergent processes that are designed and managed as they evolve (Labadie, 2008; Lettieri, Masella and Radaelli, 2009; Lin Moe and Pathranarakul, 2006). Decision making under time pressure and uncertainty is the prime challenge in managing LoPHIEs (Vivacqua et al., 2016). A large number of studies on strategic decision-making, presented in detail in Chapter 2, reveal cognitive limitations in decision-making processes and demonstrate that high uncertainty reduces rationality. The findings of these studies strongly emphasize the irrationality of organizations in regards to decision making, in times of uncertainty (e.g., Cosier and Schwenk, 1990; Dean and Sharfman, 1993; Eisenhardt and Zbaracki, 1992; Kersten, 2005; Papadakis, Lioukas, and Chamber, 1998; Pinfield, 1986; Pinker, 1997; Tetlock, 2017). Upon the occurrence of LoPHIEs, uncertainty escalates. Therefore an organization in response to such events is more likely to base its strategic decision-making on bounded rationality (e.g., Dean and Sharfman, 1993; Fredrickson, 1985; Janis, 1983, 1989; Kahneman and Tversky, 1972; Kahneman, Slovic and Tversky, 1982; Makridakis and Taleb, 2009; Nutt, 1989a, 1989b; Pollack, 2003; Simon, 1987a, 1987b; Tversky and Kahneman, 1973).

A comparative assessment of existing approaches and methods used for the anticipation and management of LoPHIEs conducted by Diakou and Kokkinaki (2013), reveals several fundamental limitations (see Appendix I), (including Abramowicz and Henderson, 2007; Adams, 2006; Allen, McAleer and da Veiga, 2005; Andersen et al., 2005; Archak and Ipeirotis, 2008; Armstrong, 2010, 2008a and 2008b; Asai, McAleer and Medeiros, 2009; Bajo-Rubio, 2002; Bell, 2006, 2009; Bhattacharya and Thomakos, 2010; Christoffersen, Jacobs and Chang, 2012) out of which judgment or decision making biases are the most frequently cited, with a considerable impact on the quantification of probability, uncertainty and risk (e.g., Armstrong, 2006; Berg, Neumann, and Rietz, 2008; Donihue, 1993; Fildes et al., 2009; Goodwin and Wright, 2010; Jakoubi, Tjoa, and Quirchmayr, 2007; Onkal and Gonul, 2005; Pennock et al., 2001).

The effects of these biases can be lessened or eliminated through the use of Collective Intelligence (CI) (Bonabeau, 2009). The use of CI provides diversity of viewpoints and input that can deter pattern obsession, self-serving bias, belief perseverance, and negative framing effects (Bonabeau, 2009). According to studies conducted by Hong and Page in relation to the components of collective intelligence (Hong and Page, 2001 and 2004; Page, 2008), the most critical aspect affecting the quality of collective problem-solving is "cognitive diversity." Cognitive diversity is the difference in the way people approach a question or a problem. More specifically, it signifies diversity of perspectives (the way of representing situations and problems), diversity of interpretations (the way of categorizing or partitioning perspectives), diversity of heuristics (the way of generating solutions to problems), and diversity of predictive models (the way of inferring cause and effect) (Page 2008, p. 7). Based on the four specific conditions of cognitive diversity, defined above, "a randomly selected collection of problem solvers outperforms a collection of the best individual problem solvers" (Page 2008, p. 163). CI, therefore, through the outreach of many subjective views (which may carry biases individually), results into a diversity of assumptions, solutions, and beliefs, that collectively are found to mitigate human biases and lead to more objective decision outcomes (Bonabeau, 2009; Klein, 2007; Lyons, 2008; Malone, Laubacher, and Dellarocas, 2010; Nickerson and Sakamoto, 2010; Prpić, Jackson and Nguyen, 2014; Prpić, Taeihagh and Melton, 2015).

The level of any organization's resilience and readiness in dealing with LoPHIEs can be assessed with the use of a maturity assessment model (Ahern, Clouse, and Turner, 2004; Fisher, 2004; Fraser, Moultrie, and Gregory, 2002; Hakes, 1997; Spanyi, 2004). The integrative concept of resilience and preparedness for LoPHIEs embraces two main ideas: (1) the reaction to stressful events and (2) the sustainability of systems in handling such events (Reich, Zautra, and Hall, 2010). Throughout an extensive and systematic literature review conducted, it is concluded that CI has not been previously considered as a systemic dimension that can provide organizations with a methodological assessment of their maturity levels in dealing with or being affected by LoPHIEs.

1.4 Aim and Scope of the Thesis

Building on the theoretical foundations of maturity assessment models (Ahern, Clouse and Turner, 2004; Fisher, 2004; Fraser, Moultrie and Gregory, 2002; Hakes, 1997; Spanyi, 2004), the Thesis intents to design and develop a CI maturity model for the assessment of organizations' preparedness and resilience towards LoPHIEs. The development of such a model is important as it can offer decision support to teams assigned to LoPHIEs management, or even guide the strategic decision making required for successful and sustainable management. Within this research orientation, one main Research Question emerges:

What are the significant factors that need to be included in a CI maturity assessment model examining the preparedness of organizations for managing LoPHIEs?

In addressing the main Research Question of the current study, the following Research Objectives are proposed:

R.O. 1 Identify indicators related to the management of LoPHIEs.

R.O. 2 Explore indicators related to the management of LoPHIEs in the presence of CI-supported decision making.

R.O. 3 Design and develop a CI maturity assessment model.

R.O. 4 Validate how the proposed CI maturity assessment model can be applied to assess teams' maturity levels in dealing with LoPHIEs.

In consideration of the above-defined research objectives, Table 1 (see page 7) summarises the research directions to be explored in this Thesis.

Table 1: *Research Outline*

MAIN RESEARCH QUESTION	RESEARCH OBJECTIVES	INDICATORS TO BE EXAMINED FOR THEIR RELEVANCE TO THE RESEARCH OBJECTIVES
What are the significant factors that need to be included in a CI maturity assessment model examining the preparedness of organizations for managing LoPHIEs?	R.O. 1 - Identify indicators related to the management of LoPHIEs.	➢ Perceived threat of LoPHIEs ➢ Response time frame for Decisions related to LoPHIEs ➢ LoPHIEs awareness (surprise effect) ➢ Personality Traits ➢ Cognitive Abilities ➢ Demographics
	R.O. 2 - Explore indicators related to the management of LoPHIEs in the presence of CI-supported decision making.	➢ Diversity in Personality Traits ➢ Diversity in Cognitive Abilities ➢ Diversity in Demographic profile within teams ➢ Team Interaction ➢ Other indicators resulting from the literature review
	R.O. 3 - Design and develop a CI maturity assessment model.	➢ Indicators from other maturity assessment models ➢ Indicators from R.O. 2
	R.O. 4 - Validate how the proposed CI maturity assessment model can be applied to assess teams’ maturity levels in dealing with LoPHIEs.	➢ Indicators from R.O. 3 that have been validated through experiments

The researcher will adopt a design science research methodology for the development of the proposed Collective Intelligence Maturity Assessment (CIMA) Model. A systematic literature review will be conducted to examine the indicators included in Table 1 (see page 7) for their relevance to the research objectives and the development of the CIMA Model. Expert opinion will also be acquired for the design of the proposed model. The design of the proposed maturity model will be verified and validated. This will be achieved by conducting three interlinked experiments (Chapter 3, explains in detail the design of these experiments).

1.4.1 Significance of the Problem

As communication, financial, and other world systems become progressively complicated and interconnected, incremental change gives ground to cascading disruptions and the rise of systemic risks (Collins, 2019). Identification of direct causality between risks becomes increasingly problematic demanding for the development and implementation of mature processes and mechanisms for handling LoPHIEs, as well as new approaches designed to fit the uncertain qualities of the modern world, which complement to the traditional notions of risk and uncertainty (Collins, 2019; Kleindorfer, 2008; Marjanovic and Hallikainen, 2013). Technology and environmental risks have a notable role in shaping the global risks landscape for individuals, governments, and businesses. In addition, the rising geopolitical and geo-economic tensions among the world's major powers, portray at present, a deepening risk, resulting in ineffective trade and investment relations. Psychological stress related to a feeling of lack of control in the face of uncertainty, also affects the broader global risks landscape, primarily through impacts on social cohesion and politics (Collins, 2019).

Natural catastrophes and human-made disasters persistently highlight the complexity of handling effectively global risks, resulting in economic and technological disruptions and life losses (The Global Risks Report, 2014). Since 2012, the cost of supply chain and operational disruptions due to natural and human-made disaster events and the deepening of interconnected global risks, which cause the overall worldwide resilience to weaken, are gaining increased awareness (Resilinc, 2018; Slubowski, 2017).

The number of disaster events recorded in 2017 amount to 301, of which 118 were human-made disasters and 183 natural disasters (Bevere, Schwartz Pourrabbani and Sharan, 2018). These disasters, together, were responsible for the death of more than 11,000 people worldwide. The number of natural disaster events alone, recorded in 2018, according to Munich Re NatCatSERVICE, amount to 850 (Löw, 2019). Indeed, 2018 was the fourth costliest year since 1980, in terms of overall losses (Bevere, 2019). More information on natural hazard exposure risks and natural catastrophe events, categorized based on the overall losses and number of victims, are provided by the Munich Re NatCatSERVICE and the Swiss Re CatNet. Facts and statistics for 2018, from various sources, on global catastrophes, are provided in a report prepared by the *Insurance Information Institute*. A comprehensive overview of natural catastrophes that occurred in 2018 is presented in Appendix II.

1.5 Overview of the Thesis

The Thesis is divided into five chapters:

Chapter One defined the research area and the statement of the problem being explored by the current Thesis. It offered a discussion on the central idea and background of the research problem and proceeded to present the conceptual definition of the problem being investigated. It explained the research gap and provided an overview of the aim and scope of the Thesis. In addition, it introduced the main research question and objectives. Furthermore, the Chapter drew attention to the significance of the research problem and outlines the structure of the Thesis.

Chapter Two of the Thesis is focused on providing a detailed review of influential literature. First, the concept of heuristics and cognitive biases, and second, the treatment of choice under uncertainty, are examined. Furthermore, the concept of intelligence at the individual level – the ''g'' factor and at collective level, the 'c'' factor – Collective Intelligence (CI), is explored. *Maturity Assessment Models* are thoroughly reviewed. The focus next shifts to investigate different design methodologies for the development of a maturity model and to present limitations and criticism on the concept of maturity assessment overall. Furthermore, influential maturity assessment models and their potential application in LoPHIEs settings are reviewed.

Chapter Three of the Thesis provides the methodological foundation of the research, the specific analytical techniques applied, and the sources of data are discussed and justified. The Chapter begins by defining the nature of the study and its purpose. It then moves on to discuss in detail the philosophical positioning most closely related to the current study. The research choice, which is one of the fundamental elements of the research design, is examined. Several research strategies for the development of the proposed model are presented. A full cycle for the development of maturity models consists of four phases, namely: define scope; design model; evaluate design; reflect evolution. The completion of two iterations of the development cycle is intended. Experimental Research Strategy justifies the methodological foundation based on which the design of the proposed maturity model was applied. The experimental research strategy, as the main source of primary data collection in this Thesis, with the conduction of multiple experiments, is discussed. Criticism on the methodology selected for the evaluation of the maturity model design is also presented and addressed. The design of the multiple experiments that will be implemented is also discussed. The internal and external validity of the experiments is also addressed. Information on how the analysis of the primary data will be conducted together with the selection criteria for the statistical analysis software are explained.

Chapter Four details the complete process followed for the development of the Collective Intelligence Maturity Assessment (CIMA) Model and constitutes an analysis of the data gathered through the experimentation process (the three interlinked experiments that have taken place during the ‘evaluate design’ phase of the first development cycle), in order to assess the design of the proposed maturity model. In addition, the Chapter examines whether the specific research questions of the Thesis are answered. The Chapter is initially concerned with the first development cycle in which an initial design of the CIMA Model is proposed. In addition, during the first development cycle, an initial analysis of the primary data collected through the three interlinked experiments is performed. The initial analysis of the data has led to the identification of additional factors that play a significant role in the maturation of CI in teams and has created the need for further literature review for the interpretation of the research findings. This, in turn, advised the initiation of the second iteration of the development cycle and eventually led to the development of the final design of the CIMA Model. Therefore, after the completion of the first development cycle, the Chapter proceeds to examine the second development cycle in which an improved design of the CIMA Model is presented. Furthermore, during the second development cycle, a complete analysis of the primary data is conducted. In the last phase of the second development cycle, the results of the data analysis are taken into consideration, and a final design of the CIMA Model is presented. The final design of the CIMA Model integrates in full the maturity of the phenomenon under study.

Chapter Five brings together the main conclusions of the Thesis and draws out the key findings and their significance. In addition, it examines the extent to which the research objectives have been achieved and discusses the main contributions of this study and its limitations. Finally, it considers issues for future research and presents a broad research agenda in an attempt to facilitate a greater understanding of the specified research topic.

Chapter 2 Literature Review

2.1. Introduction

Chapter One provided background information on the field in which the gap in theory exists. This Chapter examines the gap in theory identified within the context of LoPHIEs (the field in which the gap in theory exists). Managing LoPHIEs involves very complex situational decision-making, that necessitates addressing challenging matters, such as what needs to be done, how, when, by whom, and with which resources (Labadie 2008). Human knowledge, creativity, and experience are key elements of these processes. As seen in Chapter One, managing LoPHIEs requires a very different approach to management - more mindful and accommodating to impossible-to-predict needs (Marjanovic and Hallikainen, 2013).

This Chapter studies initially the concept of decision making, which is an important function in management. It investigates the theoretical background of the heuristics and biases program as well as the treatment of choice under uncertainty. The Chapter then moves on to examine in detail the concept of *Collective Intelligence (CI)*. Its application in the specified field of study comprises the proposal of this Thesis for covering the research gap identified. CI is a potentially powerful concept through which to understand the collaboration, competition, and decision-making processes of complex, adaptive social systems (Woolley and Fuchs, 2011). The definition, the theoretical origins, and the implications of intelligence at the individual level (general intelligence or ''g'' factor) are provided. In addition, the predictive validity of general intelligence is examined. In a similar manner, the intelligence that develops in teams (Collective Intelligence or the ''c'' factor) is also studied. In a separate sub-section, the concept of Transactive Memory Systems (TMS), is also examined. Transactive memory is a collective mechanism for encoding, storing, and retrieving data (Wegner, 1986; Wegner, Giuliano, and Hertel, 1985), and just as collective intelligence, it emerges naturally when people work together. Furthermore, the concept of crowdsourcing is addressed. The evolution, forms, methods, and different domain applications of crowdsourcing are examined. Crowdsourcing is a special form of CI that takes advantage of the wisdom of crowds. The potential of crowdsourcing in the management of adverse events is also investigated.

As previously discussed in Chapter One, the Thesis aims to develop a Collective Intelligence Maturity Assessment (CIMA) model. Accordingly, the Chapter examines, at last, the origins, nature, and use of maturity assessment models. It reviews different design methodologies for the development of a generic maturity assessment model and addresses criticism on the concept of maturity assessment. Influential maturity models and their potential application in LoPHIEs settings are also examined.

2.2 Decision Making

2.2.1 Heuristics and Cognitive Biases

Theoretical Background

Research in the 1950s by Herbert Simon, pioneer of artificial intelligence, discovers that the human brain has limited capacity in processing information (Taleb, 2008). The concept, upon which the research on "bounded rationality" is based, claims that humans cannot hold everything in mind while formulating choices. There is a need, therefore, to use shortcuts when doing so (Simon, 1987a). These shortcuts (heuristics) reduce the total amount of thinking humans have to do in order to come to quick and efficient decisions (Simon, 1987b). Expanding on this, Pinker (1997, p. 1), supporter of the computational theory of mind, notes that "[humans] depend on a huge library of heuristic shortcuts that include our beliefs". As Daniel Kahneman, Amos Tversky, and Dan Ariely have discovered, the challenge with these shortcuts is that they are not purely a simplification of rational models but are often rather irrational (Taleb, 2008). The biases, being the side effects of heuristic shortcuts (Taleb, 2009), started an empirical tradition called "heuristics and biases."

A study conducted by Kahneman, Slovic, and Tversky (1982), specialists in uncovering areas where humans are not gifted with rational probabilistic thinking and optimal behavior under uncertainty, illustrates that humans do not simply make mistakes in probability, but that these errors are systematic. Since Kahneman's, Slovic's and Tversky's discoveries, a whole discipline called "behavioral finance and economics" has been developed (Simon, 1987b; Taleb, 2007); and research advancements in the field have inspired academics of various domains, over the past two decades. Heuristics and biases in strategic decisions have been successfully studied, providing answers to some questions while raising many more (Garbuio, Lovallo and Elif, 2013; Gilovich, Griffin and Kahneman, 2013; Kahneman and Tversky, 2017; Kahneman, 2011; Powell, Lovallo and Fox, 2011). Scholars have identified numerous ways in which the basic human nature can mislead an actor when making important decisions. For example, when generating solutions, there is a tendency to look for information that validates current assumptions (self-serving bias) and to sustain those assumptions even in the presence of contrary evidence (belief perseverance). Also, when evaluating solutions, there is a tendency to see patterns where none exist (patterns obsession) and to be excessively influenced by the way a solution is presented (framing) (e.g., Bernhardt, Krasa and Polborn, 2008; Besley and Prat, 2006; Gal-or, Geylani and Yildirim, 2012; Gentzkow and Shapiro 2006, 2010; Groseclose and Milyo, 2005; Larcinese, Puglisi and Snyder, 2008; Mullainathan and Shleifer, 2005; Price, 2003; Reuter and Zitzewitz, 2006; Yildirim, Gal-Or and Geylani, 2013).

Two Cognitive Systems: The Dual Process Model

Cognitive psychology research assumes a 'dual-process model' of brain functions (e.g., Chaiken and Trope, 1999; Sloman, 2002). The Concept of the 'two cognitive systems,' holds that when humans make decisions, two 'systems' work simultaneously; and makes the distinction between cognitive operations that are associative and quick from others that are rule-governed and slow (Kahneman and Frederick, 2002). The way the two systems are characterized by researchers, differs to some extent (e.g., Kahneman and Frederick, 2002; Stanovich and West, 2002; Thaler and Sunstein, 2008); however, as Evans (2008) highlights, there seems to be a consensus on a distinction between processes that are automatic, rapid and unconscious and those that are thoughtful, slow and conscious.

Kahneman and Frederick suggest the terms Intuitive system and Reflective system for Systems 1 and 2 respectively (2002, p. 51) and explain that "System 1 quickly proposes intuitive answers to judgment problems as they arise, and System 2 monitors the quality of those proposals, which it may endorse, correct, or override. The judgments that are eventually expressed are called intuitive if they retain the hypothesized initial proposal without much modification." Thaler and Sunstein (2008, p. 23) characterize heuristics and biases as "emerg[ing] from the interplay between the Automatic System and the Reflective System" and hold the view that heuristics and biases arise when the Reflective System (2) fails to sufficiently adjust or rectify incorrect intuitive judgments developed by the Automatic System (1). Kahneman and Frederick (2002, p. 59) offer a different view on the matter, suggesting that specific heuristics are intentionally used by System 2, for example, when unsure about a decision but needing to make one (perhaps quickly) and lacking prior knowledge or reasoning.

Heuristics and Cognitive Biases seen as Adaptive Responses to Situations

The research in the decision-making domain often focuses on what rational choices are assumed to be and whether these are framed as shortcomings in human reasoning or as adaptive strategies. Considering the debate on cognitive biases and heuristics, one may argue that contemplating an alternative perspective on rationality and behavior is essential. The behavioral economics viewpoint formulated by Tversky and Kahneman (1974), Thaler and Sunstein (2008), and others, is frequently considered as presenting humans as essentially flawed, less-than-rational creatures whose cognitive biases lead into sub-optimal behavior and therefore need to be 'fixed.' From this point of view, the fact that humans are 'boundedly rational' (e.g., Simon, 1955) is a defect that often leads to bad decision making (March, 1978).

However, a gradually increasing number of scholars (e.g., Gigerenzer, 2006; Gigerenzer and Selten, 2001; Gigerenzer, 2008; Todd and Gigerenzer, 2012), drawing more closely on Simon's original descriptions of bounded rationality, put forward the view that our cognitive biases and the heuristics employed (Simon, 1956, 1969/1981), are in many cases adaptive; they are not sub-optimal, but in fact, very well optimized considering the time and processing constraints humans face in everyday life contexts. As Slee (2006, p.

27) explains, ''choices are often our "best response" to the world and the actions of those around us''. This view equates Lockton's (2012) argument that much of human behavior can be seen as decision-making; and that many heuristics possibly leading to biases are, in fact, part of humans' adaptive responses to situations.

Most Prominent Heuristics and Cognitive Biases Affecting Judgement

Availability and Representativeness Heuristics

The availability heuristic urges people to judge the importance and the relative probability of a given event as a function of the ease with which it comes to mind (Tversky and Kahneman, 1973, 1974). It is concerned, therefore, with how people are influenced by how easily characteristics or examples come to mind (how 'available' they are). This implies that humans rely on their mental sampling, which is, in fact, affected by the ease of retrieval. The main factors that determine the assigned probability of a given event, as Taleb (2009) explains are: salience (the ability of the media to get our attention), recency (how long ago the event took place) and imaginability (how easy the event is to visualize). Recency effects, as Lockton (2012) notes are more generally associated with information still being held in people's short-term working memory. The representativeness heuristic is closely related to the availability heuristic, since it corresponds "to humans' tendency to judge the probability of an event belonging to a category, based on how representative it is to that category and not how likely it actually is" (Taleb, 2008, p. 6).

Biases inherent in the availability and representativeness heuristics are reported to affect estimates of risk. A pioneering study conducted by Lichtenstein et al. (1978) examined absolute and relative probability judgments of risk. The study illustrates that while people are capable of recognizing in general terms which risks may carry enormous harm and which insignificant one when asked to quantify risks more precisely, they severely overestimate the frequency of rare causes of harm and underestimate badly, the frequency of common causes of harm. It seems that people do not make inferences from experienced small hazards to a possibility of significant risks; instead, the past experience of small hazards sets a perceived upper bound on risks (Yudkowsky, 2008).

The literature suggests that both the availability heuristic and the representativeness heuristic carry primary responsibility for the failure to guard against adverse events. This is due to the fact these closely related heuristics influence humans' tendency to ignore the probabilities of rare events and cause the decision-maker to overestimate the likelihood of their occurrence (Taleb, 2008; Tversky and Kahneman, 1974). In addition, limited sampling of rare events (Hertwig et al., 2004), prompts the decision-maker to underestimate that same likelihood (Payzan-LeNestour, 2015). Barberis (2013) provides a relevant review. Similarly, conjunction fallacy urges people to overestimate conjunctive probabilities and underestimate disjunctive probabilities (Tversky and Kahneman, 1974; Yudkowsky, 2008). Sides et al. (2002) provide a comprehensive summary of experimental tests conducted to justify the conjunction fallacy.

Cognitive Dissonance and Hindsight Bias

Cognitive dissonance theory was developed by Festinger in 1955 and is now an introductory concept in modern psychology. In his theory, Festinger (2008) argues that if our cognitions (thoughts, perceptions, and memories) clash, and we become aware of this contradiction, then they are dissonant. However, due to the fact we cannot be comfortable in the presence of cognitive dissonance, the phenomenon of hindsight bias, as Festinger (2008) notes, takes place to resolve the problem and enable us to understand the world around us. Hindsight bias has been characterized as the I-knew-it-all-along effect due to the fact after the occurrence of an event and the disclosure of the eventual outcome, people are reported to give a much higher estimate for the predictability of that outcome, than those who predicted the outcome without advance knowledge. Hindsight bias, therefore, makes events explainable, as if they could have been predicted (Gardner, 2013; Taleb, 2009, 2008).

In a relevant experiment conducted by Fischhoff and Beyth (1975), subjects were presented with historical accounts of unfamiliar incidents. Providing the accounts as background knowledge, the subjects were divided into five groups and were asked to predict the probability of four outcomes for a given historical account (for example a conflict between the British and the Gurkhas in 1814: (1) British victory, (2) Gurkha victory, (3) stalemate with a peace settlement or (4) stalemate with no peace settlement). When sometime after, the groups were unexpectedly asked to remember their own predictions, four groups working under an experimental mode, were respectively told that the four outcomes were the actual historical outcome; while the fifth group, working under a control mode, was not presented with any historical outcome. The findings of the experiment showed that in every case, each of the four experimental groups remembered/reconstructed assigning considerably higher probabilities than the assigned initially historical outcomes believed to have occurred, and lower for those believed to have not, than did any other group or the control group. This illustrates that in an attempt to understand past events, humans essentially test hypotheses or rules employed both to interpret and to anticipate the world. If in hindsight, the surprises that the past held and holds are systematically underestimated, those hypotheses or rules are subjected to extremely weak tests (Fischhoff, 1982); and therefore, humans find themselves being surprised by catastrophes lying outside of their anticipation and beyond their historical probability distributions. Concerning this, Taleb (2008) suggests that the availability heuristic causes hindsight bias.

2.2.2 Treatment of Choice under Uncertainty

Beliefs

The focused study on understanding heuristics and biases within the decision-making domain arose mainly from investigating people's judgment under conditions of uncertainty (Lockton, 2012). Daniel Ellsberg (1961) was the first to demonstrate the fact that decision-makers act differently under conditions of unknown states (the "u" world) than under Knightian risk. An experimental analysis and a review of Ellsberg's research findings are provided by Halevy (2007). Klibanoff, Marinacci, and Mukerji (2005), and Nau (2006) have examined the differences in beliefs and preferences in situations that involve both ambiguous and non-ambiguous probabilities and provide a review of theoretical advances on the matter. The term 'ambiguity' is used in the decision science literature to refer to a decision situation between Knightian risk and uncertainty, in which some information in regards to the probabilities of unknown states or parameters, affecting the decision context, might be known, but perhaps not with the complete accuracy associated with Knightian risk. Kleindorfer (2008) has also independently examined the treatment of choice under ambiguity or uncertainty and reveals that a comprehensive understanding of the important elements of ambiguity and uncertainty in the KuU metaphor, in contrast to the treatment of choice under risk, requires extending the traditional frame of decision science to embrace the precise process of belief formation.

In strategic decision making, beliefs are used to explain how people form future expectations using available information (Garbuio, Lovallo, and Elif, 2013). A relevant series of experiments have been conducted by Heath and Tversky (1991). The experiments examined the conditions under which decision-makers are more willing to bet on their vague beliefs or on clear chance events (differences in choice between risks that are based on 'objective probabilities' and those that are based on subjective events). The findings revealed that decision makers' familiarity with the situation at hand might affect their preferences. Decision-makers are more willing to bet on chance when they do not feel competent or knowledgeable but prefer to bet on their vague beliefs in cases where they feel exceptionally competent and knowledgeable. A similar behavior has been described in the finance literature in regards to investors' preferences for international versus domestic equities and national versus local ones (French and Poterba, 1991). One explanation for this phenomenon is that those who think of themselves as "competent and knowledgeable" believe that they can justify their choices better, both when the outcomes of their choices are positive as well as negative. The point of this experiment and others is that the nature of anticipated legitimation, even in experimental settings, can have significant effects on the outcomes of choice under uncertainty (Kleindorfer, 2008).

Overconfidence

The literature on psychological and behavioral decision making, in regards to choices under ambiguity and uncertainty, takes into consideration several crucial issues, discussed in detail in Kleindorfer et al. (1993) and Schoemaker (2002). Among these issues, overconfidence is one of the most evident psychological underpinnings of belief formation (Hayward and Hambrick, 1997; Reed and DeFilippi, 1990; Zajac and

Bazerman, 1991). Individuals' tendency to be in general overconfident (in most cases in regards to their abilities) and myopic is heavily discussed in the literature, and, as the study conducted by Heath and Tversky (1991) suggests, the condition is worsened when expertise and judgment are required. In addition, when dealing with the unknown, a mix of rational and irrational behavior is observed. Moore and Healey (2008) identify three different ways overconfidence usually takes place. First, people overestimate their actual abilities, performances, levels of control, or chances for success. Second, people over-place their own performance relative to other people's performances, such as ranking themselves above the median, also known as the above-average effect. Finally, overconfidence has been studied as excessive precision in one's own beliefs (e.g., Alpert and Raiffa, 1982; Soll and Klayman, 2004).

Overconfidence results in decisions being made based on people's explicit and indirect predictions. Relevant studies conducted by Tetlock (2017) and Ahuja and Mahmoud (2006), respectively, prove that overconfidence and the tendency to believe that the future can be accurately predicted become more profound when individuals possess expert knowledge. For instance, in LoPHIEs settings, members of a crisis team, who possess "expert" knowledge, driven by their belief that they can accurately predict how a crisis event might evolve, can easily influence other team members. Therefore, paradoxically, if not managed appropriately, experience and knowledge can become impediments when handling LoPHIEs.

Very relevant to belief formation and overconfidence is the way in which uncertainty is perceived, and information search takes place. A significant body of research demonstrates that humans often underestimate the uncertainty associated with the outcomes of their decisions. Therefore, an important aspect of the knowledge gathering process is the assessment of the relevant uncertainties (Kahneman, Slovic, and Tversky, 1982). Excessive information search is often driven by high perceived uncertainty (Buhr and Dugas, 2002; Tallis, Eysenck and Mathews, 1991) with individuals engaging in data gathering beyond any reasonable level in an attempt to increase a sense of control. Studies on decision heuristics reveal that less information does not necessarily compromise the quality of a judgment or a decision and that in some situations, less information might actually be more (e.g., Gigerenzer and Goldstein, 1996;

Hogarth and Karelaia, 2007; Karelaia, 2006). Confirmation bias is also strongly associated with belief formation and overconfidence; since it plays a fundamental role in decision makers' tendency to overweigh evidence that supports a particular, pre-existing point of view, without objectively searching for evidence that might cause them to change their mind (Baron, 1994; Schulz-Hardt et al., 2000). Kunda (1990) explains that decision-makers are often motivated to reach specific conclusions by conceptualizing (in a biased fashion) a convincing case for their favored hypothesis.

Expert Prediction Fails

Evidence of forecasting has been recorded throughout ancient history. Being as much science and art, forecasting, in its contemporary form, touches every aspect of humans' lives. In every way that people and organizations act and plan, they make implicit speculations about the future (Ahuja and Mahmoud, 2006). Every day humans evaluate and employ a range of probabilities for almost every rational choice made. Instincts and experience enable humans to understand what is possible, what is likely, and what is typical (Haigh, 2000; Rosenthal, 2008). A study conducted by The Economist in 1984 proved that although short-term predictions may be accurate, despite their repeatedly good intuition, humans are incapable of making accurate predictions far enough into the future (Orkin, 2000). For the study, sixteen people, including economics students at Oxford University, chairpersons of multinational companies, former finance ministers, and London dustmen, were asked to make a ten-year economic prognostication. After reviewing the forecasts, a decade later, the study concluded that, on average, the predictions made were vastly inaccurate, regardless of the participants' expertise (Gardner, 2013). The results of the study echo Haigh's (2000) argument that even though a right judgment of the chances of different outcomes and an understanding of the concept of probability may lead to informed decision-making, expertise on probability does not guarantee good prognostication.

A long-term study led by the psychology researcher Philip Tetlock (2017), explained in detail in the book *Expert political judgment: how good is it? How can we know?* verifies Haigh's (2000) argument. Two hundred four experts were recruited for the study, including journalists, economists, and political scientists, and the results of 27,450 expert predictions on economic and political trends were examined in an effort to determine the accuracy of expert predictions. The study revealed that the experts, who made exceptionally incorrect predictions, were not comfortable accepting the world as complex and uncertain. On the other hand, experts who performed better than average were comfortable enough with the notion of complexity and uncertainty that even questioned the ability of anyone to forecast the future. A second fact revealed by Tetlock's study is that expertise, knowledge, and information, beyond a certain point, lead to more confidence but not more accuracy. This view is supported by many scholars (e.g., Gardner, 2013; Haigh, 2000; Orkin, 2000; Pollack, 2003; Rosenthal, 2008; Sinek, 2011; Taleb, 2009) who claim that no model or technique, no style of thinking and no amount of new research can eliminate uncertainty completely. Numerous studies in quantum mechanics and meteorology verify this view and explain the contribution of chance in human failure to forecast the future. Experiments by research meteorologists illustrate the effect of chaos and non-linearity, where chance becomes an obstacle to weather forecasting. Heisenberg's famous *Uncertainty Principle* in quantum mechanics confirms that in some form, chance is a fundamental part of the way reality is perceived and can never be eliminated (Orkin, 2000; Rosenthal, 2008).

There are numerous intellectual approaches to probability. Since the notion of "probability" is fundamentally entwined with the definition of risk, probability is also relevant to the observer (Kaplan and Garrick, 1981); and has slightly different meanings to people in different disciplines (Taleb, 2007). The concept of subjective probability, developed by Ramsey and Braithwaite (1932) and de Finetti (1937), as Taleb (2009, p. 5) explains, suggests probability "as a degree of belief, subjective to the observer, expressing it rationally as he wishes under constraints of consistency in decision making." Haigh (2000) notes that this view provides an additional explanation as to why expert predictions fail. The failure lies in the way in which specific information at hand is used; because the evaluation of the odds may differ greatly if different information is available. Expanding on this, Rosenthal (2008) argues that additional information generates an immediate re-evaluation of the probabilities, but these are not at all times appropriately re-evaluated. The tendency of humans to consider as distant or ignore the probabilities of highly unlikely events and their impact is, according to Haigh (2000), the main reason for the failure of specialist prognostication.

Distinction between Risk and Uncertainty

In everyday use, both risk and uncertainty entail a similar situation in which an aspect of the future cannot be predicted (Rose, 2001). Risk implies the likelihood of something terrible happening, while uncertainty does not necessarily indicate a value judgment of the possible outcomes (Rose, 2001). In his book *Risk, uncertainty, and profit*, Knight (1921) introduced the concept of uncertainty to economics and his investigation on profit and its origins, led to the establishment of the economic definition of the two terms, in which the distinction between them is more apparent (Howden, 2008; Rose, 2001). The essential distinction between risk and uncertainty, according to Knight (1921), is that risk arises when future events occur with measurable probability, and therefore it is characterized by known probability distributions. Given the fact that risk can be measured on the basis of empirical observations, outcomes can be examined, and risk can thus be contracted entirely on the market (for example in insurance contracts), and humans are able to take action to protect themselves against it (Kaplan and Garrick, 1981; Kleindorfer, 2008; Rose 2001). In contrast, uncertainty is characterized by a decision making context in which probability distributions on future event outcomes are not or cannot be estimated with assurance at the time of choice (Kleindorfer, 2008). As an unknowable entity, uncertainty is best presented in Shackle's (1949) analogy, which explains the impossibility of measuring uncertainty. Because the circumstances under which uncertainty occurs cannot be examined through empirical observation, uncertainty cannot be quantified; therefore, defensive actions (as Rose (2001) argues) cannot be taken against it. Keynes (1973) has also independently examined the distinction between risk and uncertainty.

Risk is usually defined in terms of the likelihood of threat, injury, loss, or other adverse outcomes and can be classified in numerous ways, for example, financial, operational, technological, and environmental. According to Aven, Renn, and Rosa (2011), risk definitions can be grouped into three categories. The categorization includes definitions describing risk as (1) a concept based on events, consequences and uncertainties, (2) a modeled, quantitative concept, and (3) risk measurements (reflecting risk characteristics). Approaches to risk, at their majority, share some idea of uncertainty in regards to what may happen in the future and how that can impact what humans value (Becker and Tehler, 2013; Renn, 1998). As Berdica (2002) notes, in several studies, the concept of risk is believed to involve two elements: (1) the probability (or likelihood) of the occurrence of an adverse event and (2) the impact of this adverse event. The first element is concerned with risk assessment, while the second is concerned with risk management (Piyatrapoomi et al., 2004). The assessment of the various influencing factors and the consequences of risk depend on the perception of the actors involved.

Measuring risk entails substantial uncertainty resulting from diverse degrees of subjectivity, something that makes it more complex to obtain an objective composition of the likelihood of a negative event and its impact (Berdica, 2002). In relation to this condition, risk can be described as both subjective and objective (Kaplan and Garrick, 1981). On the one hand, qualitatively, risk is relative to the observer, while on the other hand, as Jaynes and Bretthorst (2003) argue, any two rational observers, given precisely the same information, must judge the risk identically. Therefore quantitatively, risk depends on the information at hand, but beyond that, it is independent of the personality of the observer (Jaynes and Bretthorst, 2003; Kaplan and Garrick, 1981). Savage (2009) suggests that the basis of probability management, which is formed by a number of striking advances in data structures, software, and managerial outlook brings new transparency in understanding risk and uncertainty. In addition, Savage (2009) supports Keynes' (1973) argument that probabilities are an essential element of everyday life as well as for making a choice and that these cannot be isolated from the evidence underlying statements of likelihood, which involve mental models of causation and prediction and other cognitive activities that are by their very nature personal or subjective to the decision-maker.

The distinction between the two notions of risk and uncertainty, as Taleb (2008, p. 12) points out, ''is not trivial because it leads to a gap in knowledge between the uncertainty treated by the literature and our experience of operating in the real world". Since Knight's (1921) introduction and Mises' (1949) expansion upon the concept of uncertainty, there have been difficulties in developing an approach that correctly uses the concept. Mises (1949) agrees that a world without uncertainty would be a world without action.

Strategic Decision Making - Rationality vs. Bounded Rationality

In daily life, humans make estimates and manage diverse probabilities for nearly every rational decision made (Haigh, 2000; Rosenthal, 2008). As Sinek (2011, p. 15) notes, “Every instruction we give, every course of action we set, every result we desire, starts with the same thing: a decision.” The decision-making process is based on what perceived as known and on an understanding of the world that may not, in fact, be entirely accurate (Sinek, 2011; Taleb, 2009). “Logic dictates that more information and data are key.” (Sinek, 2011, p. 13). As repeatedly documented, however, no model or technique, no amount of data, and no style of thinking can accurately inform decision-making (e.g., Gardner, 2013; Haigh, 2000; Orkin, 2000; Pollack, 2003; Rosenthal, 2008; Taleb, 2009). Regardless of the amount of data available, not all decisions come about to be the right ones. The impact of incorrect decisions is, in some cases, minor, and in others, it can be catastrophic (Sinek, 2011). A clash between rational and irrational decision-making explains how we live our lives and even conduct business (Eisenhardt and Zbaracki, 1992; Sinek, 2011).

Decision-making is at the heart of every strategic process due to the fact that it contains critical decisions that draft the direction of an organization (Eisenhardt and Zbaracki, 1992); and it is indeed, among the most vigorously studied domains of management (Eisenhardt and Zbaracki, 1992; Papadakis, Lioukas, and Chamber, 1998). Many researchers that have studied the area acknowledge cognitive limitations in decision-making processes (e.g., Anderson, 1983; Carter, 1971; Cyert and March, 1962; Pinfield, 1986). A study conducted by Dean and Sharfman (1993) analyzed 57 strategic decisions in 24 organizations, in an effort to examine rationality. Among the main findings of their study is that a high degree of uncertainty reduces rationality. Concerning this, Eisenhardt and Zbaracki (1992, p. 21) note that Dean’s and Sharfman’s (1993) study indicates that “decision makers can move along the rationality vs. bounded rationality continuum.” The results of the study conducted by Dean and Sharfman (1993) are echoed by an extended list of studies completed by other researchers, revealing that decision-making procedures are repeatedly boundedly rational (e.g., Cosier and Schwenk, 1990; Cosier, 1981; Janis, 1983, 1989; Nutt, 1989a and 1989b; Schweiger, Sandberg, and Ragan, 1986; Schweiger, Sandberg and Rechner, 1989). As previously explained, the concept upon which "bounded rationality" is based suggests that humans use shortcuts (heuristics) while formulating choices (Simon, 1987a). These shortcuts are often found to be irrational rather than simplifications of rational models (Taleb, 2007), resulting in regular errors in the assessment of probabilities (Kahneman, Slovic and Tversky, 1982).

Numerous studies indicate that rationality is multidimensional (e.g., Eisenhardt and Zbaracki, 1992; Eisenhardt, 1989; Fredrickson, 1985; Isenberg, 1986). A study conducted by Fredrickson (1985) illustrates that business executives engage in aspects of rational decision-making only partially. While they are able to put together contingency plans (strategy based on rationality), they seem to act quickly on incomplete information (strategy based on bounded rationality). As Fredrickson (1985, p. 821) notes, "The executive's approaches were simultaneously rational and intuitive." Another study led by Eisenhardt (1989) shows that efficient decision-makers acquire information from multiple sources, but analyze only a few; and while they develop various alternatives of probabilistic outcomes, they only thinly evaluate them. In addition, another study conducted by Isenberg (1986) demonstrates that business strategies are developed based on both rationality and bounded rationality.

As illustrated in the above studies, decision-making is facing several cognitive limitations. Numerous studies imply that rationality is multidimensional, providing evidence that shows that decision-making approaches can be simultaneously rational and irrational, while others demonstrate that decision-making processes are repeatedly irrational. Dean's and Sharfman's (1993) study which reveals that high uncertainty levels reduce rationality as well as several experimental evidence that document anomalous behavior that highlights the mistakes humans are likely to make when uncertainty is ignored are fundamental drivers in this thesis. The experimental research suggests that people are not axiomatically rational in the presence of uncertainty (e.g., Camerer and Weber, 1992; Fox and Tversky, 1995; Heath and Tversky, 1991; Hogarth and Kunreuther, 1995; Kahneman and Tversky, 1984; Kunreuther et al., 1995). In crisis, disaster, and emergencies, uncertainty escalates. Placed under considerable uncertainty, those affected or involved in the management of an adverse event, are required to take strategic decisions. Considering the findings of the abovementioned studies, however, the strategic decision-making for the settlement of such events is more likely to be based on bounded rationality. Responsible for the increased uncertainty in such situations, as Cambridge Risk Solutions (n.d.) notes, is the enormous quantity of information that arises continuously. A great deal of information concerning the event is received on an irregular basis through multiple media. Much of it is delayed, out-dated, corrupted or gets lost, while in its majority, the information received is, in most cases, irrelevant. The danger of receiving invalid, contradictory, unclear, or inconsistent information is enormously high. Kersten (2005) examines literature that emphasizes how irrational organizations can be in crises. As Coombs and Holladay (2010, p. 255) state, "[Irrationality] goes a long way in explaining why an organization refuses to speak to any constituents or chooses to attack constituents rather than inform them." The way in which BP managed its Deepwater Horizon oil spill in 2010 is an excellent example demonstrating how an organization in crisis is more likely to engage in irrational decisions, leading to the unsuccessful management of the event.

2.3 Collective Intelligence (CI)

2.3.1 The g Factor

Definition, Theoretical Origins and Implications

Intelligence reflects humans' broad and deep capability for comprehending their surroundings and it may be defined as a general capacity that involves among other things, the ability to plan, solve problems, reason, think in abstract ways, learn fast, understand complex ideas and learn from experience (Gottfredson, 1997). Expanding on the above, it can be argued that intelligence is the result of the combination of two abilities: (1) the ability to 'figure things out on the spot' and (2) the ability to recall and repeat things that have been figured out in the past. Intelligence, according to Schlinger (2003), can be seen as a descriptive term for an instance of behavior in a specific context or for a group of related behaviors, for example, those called verbal, spatial, mathematical. Although many have contributed to the conception of intelligence as a qualitatively unique attribute, its origin may be traced to the British psychologist and statistician Charles Spearman and the movement of the intelligence testing (Schlinger, 2003).

Psychologists have repeatedly found that, when individuals perform a wide variety of different cognitive tasks, a single statistical factor predicts much of the variance in their performance (e.g., Deary, 2013; Spearman, 1904). This factor is often called general intelligence or ''g''. The statistical factor ''g'' for individual intelligence has been discovered by psychologists long before it was known what processes in the brain were actually linked with this factor. Spearman (1904), conceptualized ''g'' as a 'mental energy', displayed by the ability to handle above all, symbols and not just abstract ideas. Since its discovery in 1904, the general factor of intelligence ''g'' has generated considerable controversy. Even today, there is a limited understanding of how intelligence, as we recognize it, develops and of the neural processes that enable some individuals to be more intelligent than others (Gray, Chabris and Braver, 2003; Woolley, Aggarwal and Malone, 2015). Intelligence theorists and behavior geneticists have argued for years that the factor analysis of scores on standardized intelligence tests offers compelling evidence for the existence of intelligence as a mental or cognitive capacity. However, the use of factor analysis on standardized intelligence test scores has been seriously called into question by several academics (Schlinger, 2003). In relation to this, it is noteworthy that although Spearman argued that a general intelligence underlies all skills and emphasized ''g'' as the explanatory factor in intelligence, he also recognized that ''g'' may not account for all the variances in a matrix of scores; and hypothesized specific factors or ''s'' that influence specific skills or abilities (Kane and Brand, 2003; Schlinger, 2003).

Predictive Validity of General Intelligence

The Chinese were the first to use written mental tests in order to predict performance. They ended this practice, however, in 1905, the same year. Alfred Binet introduced the first standardized test intended to measure the construct most psychologists and educators long identified as intelligence. Thorndike and Lohman (1990), point to two historical influences in the development of measures for intelligence. The first influence began with intelligence testing becoming a means of ensuring that educational resources are allocated to the students who could most benefit in an era where universal education became a reality in the late nineteenth century. The second influence was the growing belief that individual differences in cognitive ability could be empirically quantified. The quantification of the mind established psychology as a science, with intelligence tests as the primary instrument for measuring cognitive ability (Kane and Brand, 2003). Many researchers have repeatedly demonstrated that general intelligence ''g'', emerges from the correlations among how well different individuals do a wide variety of different cognitive tasks (e.g., Deary, 2000; Spearman, 1904). This single factor can then be used to distinguish the personal performance levels of different individuals and to predict which are likely to perform well on other tasks in the future.

Crinella and Yu (1999, p. 299) explain that ''People who are proficient at solving a given problem tend to be proficient at solving others; those less capable of solving that problem tend to be less capable of solving others. The psychometric representation of this phenomenon is the general intelligence or g factor, obtained whenever scores on a battery of diverse problem solving tests are factor analysed.'' In relation to this Deary (2013) argues that there is a broad consensus that meaningful variance among individuals exists at three levels: third-level general cognitive ability (g), explains that individuals who perform well at one mental task tend to have also good performance at other types of mental tasks; second-level broad domains of cognitive functioning (group factors), explains that people who perform well within one domain (for example verbal ability) tend to perform also good at other tasks in that domain; and first-level test-specific variation explains the performance of people with strengths in specific and narrow mental skills.

2.3.2 The c Factor

Definition, Theoretical Background and Implications

Even though as previously examined, considerable progress has been made over the past century, in defining and systematically measuring intelligence in individuals (Deary, 2000; Woolley et al., 2010) and although the performance of groups in specific tasks (Hackman and Morris, 1983; McGrath, 1984) has been studied for decades by scholars in various domains, the initiative of measuring group intelligence in the same way individual intelligence is measured (by assessing how well a single group can perform a wide range of different tasks and using that information to predict how that same group will perform other tasks in the future), is relatively new. Studies that have employed the statistical approach developed to measure individual intelligence ‘‘g’’, in order to systematically measure group performance and the intelligence of groups, demonstrate that there is a single statistical factor for groups, precisely analogous to intelligence at the individual level (Woolley and Bell, 2011; Woolley et al., 2010). This factor, called Collective Intelligence (CI) or ‘‘c’’, predicts how well a group will perform on a wide range of different tasks (Engel et al., 2015). CI, therefore, can be defined as the general ability of a group to perform a wide variety of tasks (Woolley, Aggarwal and Malone, 2015 and Woolley et al., 2010) and it may be characterized, according to Castelluccio (2006) and Klein (2007), as a synergistic and joined channeling of the efforts of many minds towards selecting actions in response to a challenge. It is important to note here that synergy is described as the increase in performance by the collective group beyond what can be accomplished by individuals (Kerr and Hertel, 2011; Larson, 2010). A comprehensive review of relevant studies conducted in the field is provided by Woolley, Aggarwal, and Malone (2015) and Woolley et al. (2010).

The term “collective intelligence” holds many meanings, ranging from the behavior of a “complex adaptive system” (e.g., Bloom, 2001) to the distributed knowledge or capability in human systems in which the whole is greater than the sum of the parts (e.g., Atlee and Pór, 2000; Woolley et al., 2010). Such CI emerges from the collaboration of many individual entities. Research on CI began with studies of mass behavior and combined theories of parallel signal processing and group selection to produce a theory of how complex adaptive systems operate (Bloom, 2001). More recently, studies in the field are mainly focused on how networked information and communication technologies are enabling groups of individuals to advance their cumulative knowledge (Faraj, Jarvenpaa and Majchrzak, 2011; Johnson and Ambrose, 2006); on the potential advantages of leveraging collective knowledge for problem solving, such as through crowdsourcing (Gulley and Lakhani, 2010; Malone, Laubacher and Dellarocas, 2010); and on how collective problem solving may be able to achieve considerably faster and improved solutions that no individual can achieve alone (Gulley and Lakhani, 2010; Jeppesen and Lakhani, 2010).

As it has been discovered, CI depends not only on the characteristics of the individuals in the group but also on how they work together. In relation to this, Engel et al. (2015) notes that CI is a property of the group itself, not just the individuals in it. This view is in harmony with Woolley's, Aggarwal's and Malone's (2015) argument that a group's CI is greatly influenced by two facts: (1) Group Composition, such as the individual skills of team members, cognitive diversity and individual intelligence and (2) Group Interaction, such as structures, processes and norms. Further, they maintain that CI emerges from a combination of bottom-up and top-down processes within groups, strongly associated with group composition and interaction. Bottom-up processes involve the combination of group-member characteristics that contribute to and enhance group collaboration. On the other hand, top-down processes include group structures, norms, and routines that regulate collective behavior in ways that enhance the quality of coordination and collaboration. These bottom-up and top-down aspects of groups both interact and combine to produce CI. Studies examining bottom-up compositional features and how they enable CI, found that groups whose members have higher average individual intelligence are generally better able to adapt to changing environments and absorb new information (e.g., Devine and Philips, 2001; Ellis et al., 2003; LePine, 2005). In respect to this, it is noteworthy that CI predicts future performance and learning in a wide range of environments (Woolley, Aggarwal and Malone, 2015 and Woolley et al., 2010). Respectively, the same studies uncovered that the average and maximum intelligence of individual group members is only moderately associated with c. These findings suggest that having a number of intelligent people is not enough, alone, to make a smart group (the c factor in groups is not strongly correlated with the average intelligence of the team members or with having one super-smart person) (Woolley et al., 2010).

An aspect of group composition strongly related to CI is the level of diversity in the group. Cognitive diversity, including perspectives and styles of thinking (Kozhevnikov, Evans and Kosslyn, 2014), is of particular relevance to CI, since it is directly associated with group members' ability to communicate with each other. To investigate the effect of cognitive diversity in group performance, a study conducted by Aggarwal et al. (2015), examines CI (Woolley et al., 2010) and team learning (e.g., Argote, 2011 and Argote and Ingram, 2000). The findings of the study highlight that groups whose members are moderately diverse, do better than those that are very similar or very different in cognitive styles. In relation to this, an earlier study conducted by Aggarwal and Woolley (2013a) stresses the fact that groups, whose members are remarkably different, face communication difficulties and are unable to coordinate effectively. In the same manner, this implies that groups composed by members with strong similarities to each other lack the diversity of perspectives and skills needed to perform well on a variety of tasks that necessitate different ways of encoding and information processing (Ausburn and Ausburn, 1978; Kozhevnikov, Kosslyn and Shephard, 2005). Nevertheless, an intermediate level of cognitive diversity seems to be appropriate for enhancing CI (Aggarwal and Woolley, 2013b). An additional discovery made, reveals that there is a strong correlation between CI and team learning and that the first acts as a mediator between team learning and cognitive diversity. In addition, cognitive style diversity is found to indirectly influence team learning through CI. Collectively, the findings of the abovementioned studies highlight the importance of CI as a central construct for understanding the drivers of team performance (Aggarwal et al., 2015) and strongly suggest that the individual skills most critical for CI are those that improve the ability of group members to collaborate effectively or that enhance the collaboration by bringing a sufficient diversity of perspectives.

Research aiming to examine, jointly and independently group performance (Hackman and Morris, 1975; Kerr and Tindale, 2004; Kerr, 2010; Steiner, 1972; Volmer and Sonnentag, 2011) and synergy (Larson, 2010), has been carried out in numerous contextual settings. Mannix and Neale (2005) provide an extensive review of studies on diversity, covering fifty years of research in the field and illustrate the relationship between group members' differences (in terms of skills and knowledge) and increased group performance. Individuals in a group both engage and affect each other in ways that improve performance. Teams that can perform effectively in changing contexts and align their members' resources into processes that offer consistency in performance are likely to be more valuable than teams that fall the moment there is a change in the environment (Aggarwal et al., 2015). A team's effectiveness is the construct of inputs, processes, and outputs. This thread goes beyond task performance and also incorporates the attitudes and behavioral outcomes of the team members (Cohen and Bailey, 1997; Kozlowski and Ilgen, 2006). Performance effectiveness relates directly to the outcome and is determined by the quality or score for a particular task, and it is evaluated by an externally defined standard (Larson, 2010).

Factors Significantly Correlated with CI

Woolley et al. (2010) examined several group and individual factors considered to be good predictors of CI. The findings of their study, contrary to expectations, showed that motivation, group cohesion, and satisfaction, do not predict group performance. In addition, it is interesting to note that in contradiction to mainstream literature on team performance, it has been discovered that the c factor is not predicted by social cohesiveness (Stokes, 1983) and psychological safety (Edmondson, 1999), factors that previous research suggested might be predictive of well-functioning groups (Engel et al., 2014; Kim et al., 2015; Woolley et al., 2010). The findings of their study, further demonstrate that a teams's CI is positively affected by three factors: (1) the average social sensitivity of team members (Baron-Cohen et al., 2001a), (2) the proportion of females in the team and (3) the equal distribution of conversational turn-taking and participation in discussion. The three factors found to be significantly correlated with CI are analyzed below in detail.

The first factor is closely associated with an ability called 'Theory of mind' or 'ToM'. Theory of mind is viewed by a number of scholars as a subset of a broader group of skills and abilities linked with the more general concept of emotional intelligence, and it is among the small group of abilities within the broad category of emotional intelligence that can be most reliably measured (i.e., Yip and Cote', 2012). Theory of mind abilities are a significant determining factor of group CI even when the group has extremely limited communication channels (Engel et al., 2014). ToM is measured in experiments conducted in the field by the ''Reading the Mind in the Eyes'' RME test which involves basic aspects of emotion recognition and face perception and it is designed to be a ''pure'' theory of mind test since it measures people's ability to judge others' emotions and mental state from looking only at pictures of their eyes. The test measures a deeper, domain-independent aspect of social reasoning (Engel et al., 2014). The justification that the RME test is indeed measuring theory of mind as Baron-Cohen et al. (1997) explains, stems from the fact that the target words are mental state terms (describing cognitive mental states) and are not just emotion terms.

Engel et al. (2014) verify the findings of the study conducted by Woolley et al. (2010) and reveal that groups of adults with higher average ToM scores also have significantly higher collective intelligence. In addition, ToM measure is found to be equally predictive of CI in both face-to-face and online groups, even when the members of online groups collaborate only via text chat and never see each other's eyes or facial expressions. Indeed, a large and growing body of research has focused on the importance of individuals' ability to make inferences about others' mental states (e.g., Apperly, 2012; Baron-Cohen et al., 2001b; Flavell, 1999; Heyes and Frith, 2014; Premack and Woodruff, 1978; Saxe and Powell, 2006). Many studies highlight the importance of Emotional Intelligence (EI) and related abilities to team performance (Barsade and Gibson, 2007; Feyerherm and Rice, 2002; Jordan et al., 2002). Therefore, its connection with CI is in line with existing work, proving the importance of the abilities of team members in recognizing one another's nonverbal emotional expressions, leading to team group effectiveness (Elfenbein, Polzer, and Ambady, 2007; Elfenbein, 2006). The broader construct of EI does not only encompasses social awareness (an ability which is closely linked with theory of mind), but also self-awareness, self-management, and relationship management (Mayer, Caruso and Salovey, 2000; Mayer and Salovey, 1993).

It is evident from the above, that theory of mind abilities associated with RME scores facilitate group collaboration in ways beyond what is solely captured by the amount of verbal communication (Engel et al., 2014). Baron-Cohen (1997) found that females are significantly better on this test of theory of mind than males. This finding extends earlier work conducted by Hall (1978), and it is strongly associated with the second factor identified as significantly correlated with CI, which is concerned with the percentage of females in a group. Analogous to ToM measure, as verified by Engel et al. (2014), the proportion of females in groups is a strong predictor of CI across communication media (face-to-face vs. online). This specific significant predictor of CI is highly explainable statistically, considering that there are apparent gender differences in cognitive development, such as females being superior in tests like the RME and males being superior in tests utilizing spatial skills (Halpern, 2012; Kimura, 1992; Witelson, 1976). It may be argued, therefore, that what is needed for a group to be collectively intelligent, is a number of members who are high in social sensitivity. Consequently, if highly socially perceptive members form a team, then it may not be of great significance whether they are females or males.

The third factor significantly correlated with CI is concerned with the total amount of communication that takes place within groups. CI is found to be predicted by how equally work contribution and communication are distributed among group members (Engel et al., 2014; Kim et al., 2015; Woolley et al., 2010). It has been observed that groups, where the conversation is dominated only by a few members, are less collectively intelligent than those with an equal distribution of conversational turn-taking (Pentland, 2010). This specific factor is also found to be positively correlated with c factor in both online and face-to-face groups (total amounts of spoken communication in face-to-face groups and written communication in online groups) (Engel et al., 2014).

All three factors (group's average social sensitivity, percentage of females in the group and speaking turn variance), have equal predictive power for CI; though only the predictive power of social sensitivity is found to be statistically significant (Woolley et al., 2010). Considering this and drawing back to the top-down and bottom-up process, being involved in producing CI (analyzed in the previous sub-section), it is noteworthy that the c factor appears to depend both on the composition of the group (e.g., average member intelligence) and on factors that emerge from the way group members interact (e.g., their conversational turn-taking behavior) (Michaelsen, Watson and Black, 1989; Tindale and Larson, 1992).

Predictive Validity of CI

Fields such as organizational behavior, industrial, and social psychology have examined various factors that predict group performance (Hackman, 2002; Ilgen et al., 2005; Larson, 2010). However, the focus of these studies has been in almost all cases on a specific task, aiming to provide answers in regards to what leads most groups to perform well on that kind of task. The differences between groups were treated in these studies, as undesirable errors. Woolley et al. (2010) examine whether the CI of the group as a whole has predictive power above and beyond what can be explained by knowing the abilities of the individual group members. The findings of their study document team collective intelligence as a much stronger predictor of team performance than the ability of individual team members; and as illustrated in the previous sub-sections, collective intelligence includes a group's capability to collaborate and coordinate effectively, an aspect which is profoundly more important for group performance than individual ability alone (Woolley, Aggarwal and Malone, 2015).

Engel et al. (2015) explore the generality of a computer-based measure of CI to a variety of settings, in order to test the degree to which the c factor emerges not only across different tasks but also across communication media (face-to-face vs. online), group contexts (short-term ad hoc groups vs. long-term groups) and cultures (US, Germany, and Japan). Their study reveals that a general c factor emerges consistently in groups executing tasks collaboratively across communication media, group contexts, and cultures; and that it is even in such settings, a much stronger predictor of team performance, than the ability of individual team members. This supports the generality of the metric for studying groups across various modes of communication, group contexts, and cultural settings. Furthermore, the findings of the study strongly suggest that CI is correlated with performance on complex tasks (Engel et al., 2014; Woolley et al., 2010).

A research of tacit coordination in laboratory teams, conducted by Aggarwal et al. (2015), found that CI is a significant predictor of teams' ability to coordinate their choices in a behavioral economics game, despite the fact team members were unable to communicate verbally with each other. In relation to this, prior studies strongly suggest that CI in teams is not only associated with team members' abilities to exchange information effectively via verbal communication but also to abilities in understanding nonverbal signals (Engel et al., 2014; Woolley et al., 2010). Additionally, the literature on individual intelligence demonstrates that people with more cognitive resources learn faster, both explicitly and implicitly (Chabris, 2007). These findings suggest that even in activities that teams are not required to learn a new procedure or set of skills explicitly, CI enables both high performance at any given point in time and also improves performance over time. These results provide reliable evidence for the existence of a general collective intelligence factor that predicts the performance of a group on a wide range of tasks. In this respect, the use of intelligence tests provides an approach to predict individuals' performance on a range of tasks, but can also be used to predict group performance (Engel et al., 2014).

Diversity and its Impact on CI

Teams are becoming the work settlement of choice for succeeding a wide variety of organizational goals and can be found at every level of an organization, from production teams to top management teams. Most organizations, however, promote teamwork while being uncertain about how different types of diversity contribute to performance. The word ‘‘diversity’’ is used to describe numerous types of differences among individuals. Diversity, therefore, generally refers to any characteristic that may lead an individual to perceive others as different from self (Triandis, Kurowski, and Gelfand, 1994) and this concerns any aspect of differentiation. For example, differentiation in gender, race, age, marital status, values, attitudes, functional background, education, occupation, pay and performance (Milliken and Martins, 1996; Jehn, Northcraft, and Neale, 1999; Harrison and Klein, 2007; van Knippenberg and

Shippers, 2007). Harrison and Klein (2007, p. 1200) define diversity as “the distribution of differences among the members of a unit”.

Several studies provide substantial evidence that diversity in teams leads to enhanced overall performance outcomes (e.g., Ely and Thomas, 2001; Horwitz and Horwitz, 2007; Lu et al., 2015; Martins et al., 2012). More specifically, diverse teams are found to outperform homogeneous teams, especially when uncertainty is high (e.g., Gruenfeld et al., 1996; Hamilton, Nickerson and Owan, 2003; Jackson, 1992; Mello and Ruckes, 2006; Nemeth, 1995 and 1986; Nemeth and Goncalo, 2005; Nemeth and Kwan, 1987; and Richard, 2000). In addition, an increasing number of studies reveal that team diversity plays a critical role for successful group performance in relation to collective behavior (e.g., Analytis, Wu and Gelastopoulos, 2019; Perc and Szolnoki, 2008; Santos et al., 2012; Santos, Santos and Pacheco, 2008; Yang et al., 2009; Yun, Masuda and Kahng, 2011) and collective intelligence in a wide range of tasks, such as problem-solving (Hong and Page, 2004; Liker and Bokony, 2009; Page, 2014), prediction of preferences (Müller-Trede et al., 2017), game theory (Mann and Helbing, 2017) and decision-making (Conradt, List and Roper, 2013; Galton, 1907; Jönsson, Hahn and Olsson, 2015; Krause et al., 2011; Lorenz et al., 2011; Luan, Katsikopoulos and Reimer, 2012; Mavrodiev, Tessone and Schweitzer, 2013; Novaes Tump et al., 2018). On the other hand, however, a considerable number of studies document contradictory findings (e.g., Ancona and Caldwell, 1992; Homan, 2019; Lau and Murnighan, 2005; O’Reilly and Flatt, 1986; Phillips et al., 2004; Thatcher, Jehn, and Zanutto, 2003; Timmerman, 2000). As Hansen, Owan and Pan (2013) note, this is the case when diversity is defined in terms of variation in information or expertise (e.g., Gruenfeld et al., 1996; Stasser, Stewart and Wittenbaum, 1995; Wittenbaum and Stasser, 1996; Robinson and Dechant, 1997), something that results to two serious difficulties in examining diversity. First, in most contexts, it is very complicated to isolate the effect of salient demographic differences from differences possibly correlated with personal attributes such as personality, knowledge, and ability. Due to this, it is often not possible to identify the mechanism that mediates the effect of diversity. Second, aiming to identify the mediating mechanism, most studies focus on the investigation of a specific group process such as communication, commitment, and conflict. Due to this, many studies express failure to obtain clear implications for the overall impact on team performance.

Webber and Donahue (2001) maintain that the absence of a unified theoretical framework in the literature for understanding diversity in teams, as well as the lack of a universally accepted typology of diversity, are the main reasons for the extremely mixed empirical evidence. Harrison and Klein (2007) propose three distinctive types of diversity, in an attempt to address the issue and provide a useful theoretical framework with guidelines for research on diversity: 1. Separation, 2. Variety, and 3. Disparity. Separation type of diversity is concerned with differences among team members in beliefs, values, or attitudes in regards to team goals and processes. This type of diversity leads to conflict and eventually disturbed and reduced task performance (Byrne, 1971; Schneider, Goldstiein and Smith, 1995; Tajfel, 2010). Variety type of diversity is based on information process theory (Hinsz et al., 1997) and cognition theory (Campbell, 1960; Harrison and Klein, 2007), and it is concerned with qualitative differences in team members. Minimum variety occurs when a team is homogeneous while maximum variety occurs when all team members are from different pools of informational resources, for example, from different fields or distinct educational (functional) backgrounds. Heterogeneity in teams creates greater information richness, and consequently, the outcomes related to the variety type of diversity lead to superior innovation and creativity as well as higher decision quality and increased flexibility. Disparity, which is the last of the three types of diversity proposed by Harrison and Klein (2007), is based on theories of tournament compensation (Lazear, 2000; Lazear and Shaw, 2007) and deprivation (Deutsch, 1985; Harrison and Klein, 2007). Disparity type of diversity assumes that team members have different levels of attributes such as status, prestige, pay, and power. Minimum disparity indicates that all team members have the same position. Maximum disparity occurs when only one or two team members possess socially valued resources (Harrison and Klein, 2007). Disparity leads to more competition among team members, reduced cooperation, and fosters offending behavior or attitudes and may even suppress creativity.

Other scholars have also outlined different dimensions of diversity. Milliken and Martins (1996) distinguish two types of diversity: 1. observable diversity and 2. non-observable diversity. Indeed, organizational behavior researchers tend to mostly focus on characteristics of group composition that are salient such as age, race, and gender (See Bantel and Jackson, 1989; Cummings, 2004; Kanter, 1977; Konrad and Gutek, 1987; Pelled, 1996; Rothbart and John, 1993; Stangor et al., 1992; Tsui, Egan, and O'Reilly, 1992; Williams and O'Reilly, 1998 for theoretical frameworks and survey). When differences are salient, diversity is likely to provoke responses that are due to bias. Pelled (1996) classifies diversity in terms of the degree of job relatedness and visibility.

A well-articulated distinction of the different types of diversity, is offered by Jehn, Northcraft, and Neale. According to Jehn, Northcraft, and Neale (1999), there are three types of diversity: (1) social category diversity, (2) cognitive or informational diversity, and (3) value diversity. The first type, social category diversity, reflects differences in gender, sexual orientation, ethnicity, race, religion, age, and physical abilities. The second type, cognitive diversity, is concerned with differences in personality, motivation, experience, cultural background, training, expertise, education, and information (Mannix and Neale, 2005). Lastly, value diversity encompasses differences in the perception of the team's task, goal, or mission. Preferably, a team is best to have high cognitive diversity and low value diversity. High cognitive diversity ensures that the team has the necessary tools and information to solve problems effectively, while low value diversity means the team is unified in its purpose (Medin, Bennis and Chandler, 2010).

Williams and O'Reilly (1998) argue that the possible effects of diversity on team performance can be described on the bases of three main theories: 1. Social categorization, 2. Similarity/Attraction, and 3. Information and Decision-Making. The first two theories are concerned with the establishment of sub-groups within the team and can be defined by notable characteristics such as gender or age (social categories) or may consist of team members that identify themselves to be similar on dimensions such as attitudes or interests. Diversity in teams, based on these two theories, leads to reduced communication within a group and may consequently have a severe negative effect on team performance. The

Information and Decision-Making theory, on the contrary, adopts a resource-based view and argues that heterogeneous team members are part of different networks; and as a result of this, the information set available to the team is enhanced. Consequently, based on this theory, the effect of diversity on performance is assumed to be positive because the decision-making process of the team is based on a broader information set. It may be argued, therefore, that the impact of diversity on performance depends on the relative strength of the effects described by those theories.

Responses to diversity are significantly influenced by several beliefs in regards to diversity, in such a way that the more people believe in the value of diversity for team functioning, the more positively and favorably they react to team diversity (van Knippenberg, De Dreu and Homan, 2004; van Knippenberg and Haslam, 2003). Various studies present evidence that individuals vary in the extent to which they value diversity (e.g., Cox, 2003; Ely and Thomas, 2001; Kossek and Zonia, 1993; Mor Barak, Cherin, and Berkman, 1998). People also differ in their beliefs about and attitudes concerning diversity (e.g., Hostager and De Meuse, 2002; Strauss, Connerley, and Ammermann, 2003; van Knippenberg and Haslam, 2003).

Collective Decision Making

Several studies have documented that Collective Intelligence can lead to high-quality output (e.g., Giles, 2005; Lemos, 2004; Shankland, 2003; von Hippel, 2006), more accurate predictions and improved decision making (Greenstein and Zhu, 2012). For instance, Galton (1907), Franz and Larson (2002), and Surowiecki (2004) demonstrate that the average estimate of a group when making guesses can be more accurate than experts' estimates. Similarly, Cummings and Quimby (2018), investigate both the role of improved decision support and the potential added value of CI in the execution of various tasks. A team's potential has been traditionally conceptualized as the ''resources'' that are available to the group in the form of information, intelligence or other abilities of individual team members (Devine and Philips, 2001; Lepine et al., 1997) typically measured as the aggregate of individual members' g or general intelligence (Lepine, 2005; Neuman, Wagner and Christiansen, 1999; Tziner and Eden, 1985) or the particular expertise or task-specific cognitive abilities of team members (Neuman, Wagner, and Christiansen, 1999; Woolley et al., 2007; Woolley et al., 2008). Indeed, considerable evidence documents that cognitive abilities shape team performance. For example, the general intelligence of members has been shown to predict team learning (Ellis et al., 2003) as well as many team effectiveness criteria (LePine, 2005; Neuman, Wagner and Christiansen, 1999). The association between performance and cognitive ability is particularly strong for unfamiliar tasks (Devine, 1999). Aggarwal et al. (2015), extending earlier studies conducted by Joshi and Roh (2009) and van Knippenberg and Schippers (2007) (examining how group performance is affected by the diversity of group members), investigate the role of CI as a mechanism through which team diversity influences team learning. They maintain that when the appropriate cognitive diversity is achieved in a team, then the ideal condition for CI to emerge is accomplished; this, in turn, is likely to impact the rate at which a team can learn with experience, meaning that any effect of cognitive diversity on learning will be mediated via the mechanism of collective intelligence. Expanding on the above, it may be argued that the benefits of diversity extend beyond merely bringing together multiple points of view. In relation to this, Loyd et al. (2013) support the view that diverse groups of individuals tend to put more effort into tasks than homogeneous groups do. O'Brien and Owens (1969) demonstrate that the performance of teams working on a task that requires a high degree of cooperation and communication is most affected by the member with the lowest cognitive ability because that person tends to slow the rest of the group. On the contrary, for tasks that the ideal strategy is to select the best member (for example, running a race or answering a factual question), the cognitive ability of the highest-scoring member predicts performance (Devine and Philips, 2001; Volmer, 2006). Finally, more complex tasks that require each member of the team to perform a sub-task and then combine inputs into a team product are most affected by the average ability of team members. This is happening because the higher average cognitive ability is associated with a greater propensity to adapt to a changing environment, as well as to learn from new information discovered in the course of work (e.g., Ellis et al., 2003; LePine, 2005).

As seen in previous sub-sections, the existence of negative correlations between people's predictive models, which tends to lower the collective error and make the group smarter than the average individual within it, is a requisite for collective intelligence to emerge (Landemore, 2012). Negative correlations are themselves the result of cognitive diversity in the group (Hong and Page, 2009; Joshi and Roh, 2009; Landemore, 2012; van Knippenberg and Schippers, 2007). Hong and Page provide theoretical findings about the relative importance of cognitive diversity and individual ability for collective problem-solving and predictions (Hong and Page, 2009, 2004, 2001; Page, 2014). Page (2008) explains the value of cognitive diversity in teams through what he calls the “diversity prediction theorem” and the following equation: Collective error = average individual error – prediction diversity. Collective error captures the quality of the group’s decisions. Average individual error reflects how accurate the people are within the group. Prediction diversity captures the dispersion of views or how different the group members are. The collective error is always smaller than the average individual error. This is the reason why a group performs better than an individual.

Research on Collective Intelligence holds that central to collectively intelligent systems is the capability to engage in both convergent and divergent styles of thought, as well as to take advantage of the insights from reflection into course-correcting changes (Bloom, 2001; Woolley et al., 2010). Each of these different styles of collective thought requires particular social interaction processes to occur successfully in collectives (Larson, 2010; March, 1991; McGrath, 1984), whether those collectives are small groups (Woolley et al., 2010) or organizations. Woolley and Fuchs (2011) examine the diverse nature of collective intelligence within the field of organization science and identify five different types of collective activities: defining, bounding, opening, bridging, and grounding. They argue that these five collective activities represent divergence, convergence, and reflection activities. Convergent thought generally occurs in collectives during judgment and decision-making processes (Woolley and Fuchs, 2011). Relevant to this, Larson (2010) describes collective decision making as a cognitive activity in which it is often very difficult (in some cases even impossible) for members to demonstrate conclusively to one another that a proposed response is, in fact, correct. Divergence, on the other hand, consists of pushing an existing area of discourse to consider new paths and different perspectives (Woolley and Fuchs, 2011).

In relation to the above, it may be argued that perhaps the most essential role of a team is surfacing, pooling, and weighing information so as to arrive at an informed decision. A relevant well-documented example originates from the study of shared versus unshared information. Shared information is knowledge available to the entire group, whereas unshared information is unique to a particular individual within the group. The goal of a team is to consider all relevant and available information. However, the research consistently shows that teams fail to consider unshared information. A study conducted by psychologists Stasser and Titus (1985) examines the way in which effective teams incorporate unshared information into their decisions. The literature on strategy and collective decision making suggests that the higher the volume of information groups can use, the better their decisions will be (Woolley et al., 2013). Many of the documented deficiencies in collective decision making are attributed to a lack of information or biased processes that lead to an inability to use all of the available information (Kerr and Tindale, 2004; Stasser and Titus, 1985; Staw, Sandelands and Dutton, 1981). An increasing number of studies, suggests that more information is not always a good thing and that under some circumstances; groups are harmed in their effort to access too much information, since emphasis on information-seeking may in some cases lead teams to disregard vital knowledge and skills held by team members (Bresman, 2010; Haas and Hansen, 2005; Wong, 2004). Borgatti and Cross (2003) highlight that groups formed by members with on-going relations are subject to relational factors that lead to biases in regards to the exchange of information in such a way that members tend to seek information only from those they know and have access to. This, in turn, may result in inconsistencies in how the same group performs different tasks, minimizing the degree to which a CI factor would predict performance across domains. Thus, one may argue that CI emerges in a more consistent fashion in task-oriented short-term groups as they focus on a given task under time constraints, preventing existing relationships and prior assumptions about group members from affecting task-oriented interaction (Engel et al., 2015).

Woolley et al. (2013) investigate how team strategic orientation may affect information-seeking behaviors in teams and consequently influence the way in which decision-making takes place. Team strategic orientation refers to a team's approach in pursuing goals in relation to others, and it is believed to have a strong influence on how individual members and the group as a whole respond to subsequent problems and take decisions (Levine, Higgins and Choi, 2000; Woolley et al. 2013). This is achieved primarily by altering the way in which individual members perceive their environment. This, in turn, alters collective decisions and actions (Woolley et al. 2013). Orientation in teams is found to affect critical aspects of the problem-solving process, including which information is taken into account, how this information is weighted and integrated, and which members exercise influence. These aspects affect the group's final solution to the problem at hand (Levine, Higgins, and Choi, 2000; Woolley, 2011). Perceived problem scope, which is an element hugely vulnerable to perceptual bias, plays a fundamental role in team strategic orientation. Perceived problem scope refers to the extent to which team members believe they need to be broad versus selective in their approach to understanding and planning activities in a situation (Jonassen, 2000; Patel, Groen, and Arocha, 1990; Wood, Mento, and Locke, 1987; Wood, 1986).

The processes that team members undertake are what convert members' skills, expertise, and other inputs (operating in the environmental context of the team) into a group product or other form of output (Marks, Mathieu, and Zaccaro, 2001). Team process, therefore, refers to team members' behaviors and interactions occurring over time. Confidence plays a fundamental role in the way in which team processes are shaped and influences collective decision making. In line with past research, Schuldt et al. (2015), investigate how confidence expressed by decision-makers acting individually, may shape the confidence expressed by groups they comprise. The findings of their study show that the confidence expressed by groups is higher than the confidence expressed by individuals; significantly, however, this pattern is found to vary remarkably by the type of the group. Groups formed only by members with low-confidence (low-confidence groups) seem to demonstrate the most considerable increase; groups including an equal number of low-confidence and high-confidence members (mixed groups) show a moderate increase, while groups formed only with high-confidence members (high-confidence groups), show no increase. These results stress the conditions under which groups express greater confidence than individuals and offer insights for the composition of collaborative decision-making teams (Schuldt et al. 2015).

2.3.3 Transactive Memory Systems (TMS)

The study of Transactive Memory Systems (TMS) is of particular interest to this Thesis since the concept of transactive memory offers an effective way of understanding individual and group behavior through the examination of the style in which individuals and groups process and structure information. Transactive memory is a collective mechanism for encoding, storing, and retrieving data (Wegner, 1986; Wegner, Giuliano, and Hertel, 1985). Just as collective intelligence, transactive memory systems emerge naturally when people work together. Such systems develop on the basis of two functions that take place simultaneously, the operation of the individuals' memory systems and the processes of communication that take place within a team. Transactive memory is thus not traceable to any of the individuals alone, neither can it be found somewhere "between'' individuals. Instead, just as collective intelligence, it is a property of the group itself (Wegner, 1986).

Transactive memory systems have been studied extensively by practitioners and scholars in the knowledge management domain. It is well recognized that transactive memory systems lead to improved team performance by making available to team members, expertise in a more effective manner and by enhancing the productiveness of the entire collaboration process (Lewis, 2004). Wegner, Giuliano, and Hertel (1985) argue that in order to understand how such systems function, it is needed to take into account their components. A person's memory involves processes commonly understood to take place at three different stages. At first, information is encoded as entered into memory (encoding stage); the information then resides in memory (storage stage), and finally, it is recovered during the retrieval stage (Wegner, 1986). In this way, at a team level, transactive memory enables each member to benefit from the team's shared memory by taking responsibility for remembering items and then by attending to the categories of knowledge encoded by other team members, in order for those items within those categories to be retrieved from other members when needed through communication with each other. With such a structure in place, teams have a transactive memory that is greater than either of the individual memories of the team members (Wegner, Erber, and Raymond, 1991). In relation to this, Littlepage et al. (2008) note that transactive memory enables the development of patterns that complement specialized knowledge, and as a result, the total amount of knowledge available to the team is expanded.

Empirical and theoretical research on knowledge and thinking processes implies that specialization, credibility, and coordination are indicators of TMSs. Transactive memory is developed when an individual understands what another individual knows and uses that understanding to cultivate different but complementary knowledge (Moreland, 1999). In relation to this, Lewis (2003, p. 590) explains, ‘‘Members will only develop different knowledge if they can rely on others to remember other task-critical information. Absent this, members would likely develop overlapping or redundant knowledge instead of differentiated expertise. Specialization and credibility exist and are related because members have developed transactive memory and thus are true manifestations of TMSs.’’ Concerning the above, Hollingshead (2001) holds the view that central to every effective transactive memory system is cognitive interdependence among team members. In addition, further argues that such cognitive interdependence usually arises due to the structure of the group task and serves to stimulate and sustain the growth of transactive memory (Hollingshead, 2001). Indeed, numerous earlier studies that have investigated the effects of transactive memory imply that it is not team membership itself that prompts the development of transactive memory, but rather the interdependence with others (e.g., Hollingshead, 1998a, b; Levine and Moreland, 2014; Moreland, 1999; Wegner, Erber, and Raymond, 1991). Concerning this, Brandon and Hollingshead (2004, p. 634) note, ‘‘there is agreement that people are interdependent in the sense that each person’s actions have an impact on others’ outcomes and that individuals are more dependent to the extent that they cannot unilaterally guarantee themselves good outcomes (cf. Kelley and Thibaut 1978)’’. In this sense, each member’s performance is linked to the performance of the other team members, since they all rest on each other to accept responsibility for storing data (Brandon and Hollingshead, 2004; Hollingshead, 2001). Thus, each team member’s performance relies not only on their own knowledge but also on the knowledge of others in their team.

Brandon and Hollingshead (2004) maintain that transactive memory systems can vary in terms of the degree to which team members' perceptions about others' task-related expertise are accurate (accuracy), the degree to which members have a shared representation of the transactive memory system (sharedness), and the degree to which team members participate in the transactive memory system (validation). In a related manner, Wittenbaum, Hubbell, and Zuckerman (1999), Wittenbaum, Vaughan and Stasser (1998) and Wittenbaum, Stasser and Merry (1996) view transactive memory as one form of tacit coordination found in workgroups. Tacit coordination is based in part on group member task assessment and resource allocation, including group member perceptions of the group task, performance criteria, the cooperative or competitive nature of the task, procedures or strategies for accomplishing the task, individual judgments about existing resources, the utility of the individual's contributions toward accomplishing the group task, and an assessment of the costs and benefits of the individual's contributions to the task.

Seen as a management process of knowledge integration, a transactive memory system can assist in enhancing team performance. A positive relationship between team performance and TMS has been confirmed in previous studies (e.g., Kanawattanachai and Yoo, 2007; Lewis, 2004; Zhang et al., 2007). The findings of these studies indicate that transactive memory systems can lead to higher levels of team performance when team members solve problems together (Littlepage et al., 2008). Also, studies comparing team performance and best-member performance on the completion of several tasks shows that teams can exceed the performance of the best team member (e.g., Laughlin et al., 2003; Michaelsen, Watson and Black, 1989; Tindale and Larson, 1992). This, as Littlepage et al. (2008, p. 226) explains, ''suggests that within a general domain of knowledge, persons who are not the most expert member can still contribute specific knowledge that can facilitate group performance''. Furthermore, laboratory experiments conducted by several scholars (e.g., Liang, Moreland and Argote, 1995; Moreland and Myaskovsky, 2000; Moreland, 1999; Moreland, Argote and Krishnan, 1996) show that team members who are trained together on a task develop the differentiated and specialized knowledge characteristic of transactive memory and are able to collectively recall a larger volume of task-relevant information. On the other hand, team members who are individually trained on the same task are more likely to develop overlapping task knowledge and recall overall, less information. Moreover, the findings of these experiments demonstrate that teams who developed TMSs are capable of completing tasks more accurately than other teams, indicating that TMSs do indeed enhance group performance.

2.3.4 Crowdsourcing

Evolution, Forms, Methods and Different Domain Applications

A new and rapidly emerging model of socio-technical systems for collective intelligence, associated with advancements in ICT and its potential, can be found in the increasing use of IT-mediated crowds for knowledge purposes (Prpić and Shukla, 2013, Prpić, Jackson and Nguyen, 2014). In this domain, Crowdsourcing (Brabham, 2008, 2009, 2010) is being widely applied in a growing number of contexts and the knowledge generated from these phenomena is well-documented (e.g., Agerfalk and Fitzgerald, 2008; Brabham, 2008; Horton and Chilton, 2010; Huberman, Romero and Wu, 2009; Huberman, 2008; Wu, 2009). The concept of collective intelligence has indeed been popularized as the wisdom of crowds and related concepts such as crowdsourcing, prediction markets, and co-creation (Prahalad and Ramaswamy, 2004). However, it is of crucial importance to clarify that although crowdsourcing is a case of collective intelligence, not all cases of collective intelligence are crowdsourcing.

The term “crowdsourcing” was coined by Jeff Howe, editor at Wired Magazine, to describe the practice of acquiring ideas, information, or sources and services by inviting input from a large number of individuals. “Crowdsourcing”, as Howe (2009) argues, is a special form of Collective Intelligence that takes advantage of the wisdom of crowds and has changed the way groups of individuals produce knowledge, generate ideas, and make them active. Many similar concepts and definitions are being discussed, surrounding the concept of crowdsourcing, for example, peer production, radical decentralization, wikinomics, mass innovation and more (e.g., Benkler, 2008; Chesbrough, 2003; Leadbeater and Powell, 2009; Malone, 2007; Surowiecki, 2004; Tapscott and Williams, 2008). Liu (2014) reviews relevant literature and identifies three different categories of research focus in regards to the term. The first category includes scholars who tend to use the term in a broadway discussing only partial aspects of crowdsourcing. The second category offers broad characterizations of crowdsourcing applicable to multiple domains (e.g., Brabham, 2013, 2015; Grier, 2013; Halder, 2014; Hetmank, 2013; Howe, 2009); while the third category includes researchers focusing on characterizing crowdsourcing based on its relation to other concepts, such as outsourcing, collective intelligence, and human computation. The type of work produced by the crowd broadly varies from idea generation, data collection, image labeling to scientific problem solving (Cooper et al., 2010; Kittur and Kraut, 2008; Von Ahn and Dabbish, 2008, 2004). Brabham (2013) lists some of the numerous forms of crowdsourcing. A well-known example of a crowdsourcing outcome is the distributed encyclopedia „Wikipedia“(Surowiecki, 2004).

Crowdsourcing is used broadly by businesses based on a distributed problem solving and production model, in which a network of individuals of diverse knowledge, heterogeneity and number is asked to voluntarily undertake a task of variable complexity and modularity via a flexible open call (Brabham, 2008; Estelles Arolas and González-Ladrón-De-Guevara, 2012; Howe, 2009). Seen as a form of participative online activity, crowdsourcing may be characterized as the act of taking a job performed traditionally by a selected individual and outsourcing it to an undefined, generally large network of individuals, a ''crowd'' (Howe, 2009). In this respect, a Crowd is any population of individuals who provides knowledge through Crowd Capability. A Crowd can exist inside of an organization as well as externally, or it can be a combination of the two (Prpić and Shukla, 2013). For instance, many organizations use IS-tools such as “Wikis” (Wagner and Majchrzak, 2006) to access the knowledge of dispersed groups within the boundaries of the organization; or utilize IT-mediated crowds as partners for innovation (Boudreau and Lakhani, 2013). In a related manner, other organizations are generating collective intelligence by employing IT-applications known as Predication Markets, which serve to gather large sample-size forecasts from distributed populations, both internally and externally (Arrow et al., 2008; Hankins and Lee, 2011).

The success of the crowdsourcing model depends on the assumption that online communities have "collective intelligence" (Lévy, 1997) or "crowd wisdom" (Surowiecki, 2004). This assumption is supported by empirical research. Page (2008) found that problem-solving processes benefit from cognitively diverse communities, even communities of non-experts. In relation to this, Surowiecki (2005, p. XVII) notes that "If you put together a big enough and diverse enough group of people and ask them to 'make decisions affecting matters of general interest', that group's decision will, over time, be 'intellectually superior to the isolated individual', no matter how smart or how well-informed he is." Cranshaw and Kittur (2011), examine the Polymath Project (an experiment in large scale collaborative mathematics), in order to better understand its success and shortcomings as an online community and tool for open collaboration. Similarly, Gowers (2009), drawing from the Polymath Project, outlines three potential advantages of large-scale collaborations. The first is concerned with the role of chance in problem-solving. The higher the number of individuals involved in solving a problem, the higher the odds that one person will, by chance, discover a critical insight. Diversity and different areas of expertise is the second advantage of large-scale collaborations. A large number of contributors, working towards solving a problem, generates a collective expertise that cannot be achieved by small groups of contributors. Lastly, it is argued that since different people have different characteristics, each contributor will accordingly adopt different roles in the problem-solving process.

Crowdsourcing in the Field of Crisis and Disaster Management

The initiative of utilizing ICT-based crowdsourcing processes for crisis management is relatively new and aims towards a framework in which knowledge is being expanded interactively by multiple actors. The growing debate about the way knowledge is produced and shared in the contemporary world, as well as the emergence of new information and communication technologies, are bringing a different perspective to the existence of new forms of ''collaborative production of knowledge''. Crowdsourcing is, indeed, gaining recognition as an important source of information in crisis situations, and the different aspects of the utilization of crowdsourcing in crisis management are actively being explored by many researchers and practitioners (e.g., Brabham, 2013, 2015; Halder, 2017; Howe, 2009; Kokkinaki, 2013; Liu, 2014; Zobel, 2013). A comprehensive summary of relevant mobile and web-enabled applications utilizing CI and Crowdsourcing is included in Appendix III.

Taking the above context into account, crowdsourcing in crisis-mapping can be considered as a specific form of collaborative production of knowledge, having significant practical effects. An example of "collaborative production of knowledge" and crowdsourcing in crisis-mapping is the so-called "volunteered geographic information", in which the production of information, in all phases of a crisis, is carried out by both experts and citizens, through new technologies (Neubauer et al., 2013). Currently, several crowd-sourcing platforms support disaster management, enabling the gathering of information from citizens for the affected areas, as well as their analysis and visualization. The term crowdsourcing in such contexts refers to a way of organizing the work, which involves an information system to coordinate and monitor tasks performed by people. Moreover, the term can be understood as a production model where the intelligence and knowledge of volunteers are used to solve problems, create content, and develop new technologies in relation to crisis management. Neubauer et al. (2013) examine the applicability of crowdsourcing in the field of crisis and disaster management (CDM) and highlight the difference between the various types of crowds and crowdsourcing and provide a definition for crowd-tasking in the area of CDM.

The potential of crowdsourcing in the management of adverse events is evidently enormous since it has proven to be an effective tool for mobilizing the public. Past experiences, for example, the earthquake in Haiti and the downfall of governments in Libya and Egypt, illustrate that the information obtained through crowdsourcing can be thorough and as accurate as the information gathered through hardware sensors and official channels (Meier, 2012). Such events, as Neubauer et al. (2013) argue, imply the capacity of crowdsourcing in effectively managing crises as they occur or immediately afterward. Sutherlin (2013) provides a critical analysis of the best practices in crowdsourcing for the management of adverse events.

Similarly, a detailed overview of the challenges related to crowdsourcing in crisis situations is provided by Bott and Young (2012).

2.4 Maturity Assessment Models

2.4.1 A Generic Model for Maturity Assessment: Origins, Nature, and Use

A large number of maturity models developed across various domains by both academics and practitioners, have been studied extensively (de Bruin et al., 2005; Pöppelbuß and Röglinger, 2011; Weber, Curtis and Gardiner, 2008) and include maturity models that aim to verify and evaluate specific aspects of social and technical systems' 'maturity'. For example, models developed to measure the maturity of practices such as strategic alignment, strategic human capital management, innovation management, enterprise architecture and knowledge management, IT service capability, and program management (de Bruin et al., 2005). An extensive literature review on maturity assessment models is provided by Diakou and Kokkinaki (2015). With maturation being the primary subject matter of maturity models, it is essential to define central constructs related to maturity and maturation (Becker et al., 2010). The notion of maturity is frequently used to describe the advancement of both organizations and people. The underlying idea is that maturity is a linear process in which a person or an organization improves in relation to its qualitative or quantitative capabilities. Based on formulated guesses resulting from foreseeable patterns of evolution and change, maturity models provide theories about how capabilities advance gradually and include a sequence of levels that form an anticipated, desired, or logical maturation path (Becker, Knackstedt, and Pöppelbuß, 2009; Gottschalk, 2009). This is the reason why, according to Prananto, McKay, and Marshall (2003), maturity models are also called stage models, stage theories, or stages-of-growth models. Higher levels of maturity are indicative of an increased change in numerous dimensions including consistency, formality, competence as well as the ability to comprehend and show commitment in the context of a maturing element (Russell et al., 2010). With the advancement of these qualities and their integration into the improvement activities, decision-makers, with the support of maturity models, are able to determine whether possible benefits have been identified at the maximum. Moreover, the implementation of maturity models can support decision-makers in balancing opposing objectives in a more comprehensive manner (Mettler, 2011).

The term 'maturity', in the literature concerning maturity assessment models is in most cases reflected in a one-dimensional manner, focussing either on: Process maturity - in order to assess the extent to which a particular process is accurately defined, managed, measured, controlled and effective (Fraser and Vaishnavi, 1997; Paulk et al., 1993); Object maturity - to evaluate the degree to which a specific object such as a machine, a software product or similar, meets a level of sophistication (Gericke, Rohner and Winter, 2019); or on People capability - to measure the level in which knowledge creation can be supported by the workforce to advance expertise (Nonaka, 1994). Consequently, according to the above, the basis regularly used in social systems for assessing maturity are processes/structures, objects/technology, and people/culture (referred in most instances as maturity factors). These factors have a strong dependency and effect on maturity. In relation to this, Wang (2008) argues that the influence of these factors combined or individually, is not always specified and that other perspectives/factors may also have an impact on maturity. According to Mettler (2011), interesting conditions with respect to the understanding and development of maturity in social systems are contained in the theories of the emergence and diffusion of innovations. The work of Rogers (1962) and Utterback (1971) is very relevant in this respect and provides an additional approach to the concept of maturity being reflected in social systems. Soanes and Stevenson (2006) note that generally, 'maturity' can be defined as: "The state of being complete, perfect or ready." The notion of maturity, therefore, implies progress of evolution in the achievement of a target or the manifestation of a specific ability from a primary to a preferred or usually occurring end-stage. Maturity levels are vital elements of maturation paths (Pöppelbuß and Röglinger, 2011). Maturity models are arranged in a hierarchical order into numerous layers corresponding to different levels of maturation (de Bruin et al., 2005); while the logical relationship between successive levels, helps reveal the justification behind maturation (Kuznets, 1965).

A maturity level represents, therefore, the achievement of a new capability level and provides the foundations on which practices at subsequent maturity levels can be built on (Curtis, Hefley and Miller, 2009).

Many organizations implement maturity models in order to disclose existing maturity levels and define a future desired state, including identifying the essential corresponding actions and prioritizing measures for improvement as well as the evaluation of the organization's status in terms of the quality of a process or the implementation of a specific program; and the removal of imperfect capabilities (Dinter, 2012; Rohloff, 2009; Rummler and Brache, 2013). The tools implemented to achieve this, provide blueprints for guiding the organization and for designing and implementing a system of continuous improvement (Rosemann and De Bruin, 2005; Rummler and Brache, 2013). The main objective of a maturity model, therefore, is to assess the maturity of a designated field and increase its capability based on a broad set of criteria (Ahern, Clouse and Turner, 2004; Hakes, 1997). In relation to this, Mettler and Rohner (2009) suggest that maturity models are "some-how in-between" methods and models due to the fact they combine state descriptions with activities. The concept of maturity assessment models is increasingly being applied within the field of information systems (IS) and management science, both as an informed approach for continuous improvement (Ahern, Clouse and Turner, 2004; Paulk et al., 1993) and as means of self or third-party assessment (Fraser, Moultrie, and Gregory, 2002; Hakes, 1997). For example, organizations use maturity models that assist with digital government (Gottschalk, 2009), IT management (Becker, Knackstedt, and Pöppelbuß, 2009; Hollis, 2007), business intelligence (Lahrmann et al., 2010) or knowledge management (Kulkarni and Freeze, 2004). In addition, in the field of business process management (BPM), several maturity assessment models have been proposed (Hammer, 2007; Lee, Lee, and Kang, 2007; Rohloff, 2009; Rosemann and De Bruin, 2005; Weber, Curtis and Gardiner, 2008). These models, as well as other normative models, have been strongly influenced by the Capability Maturity Model (CMM) (De Bruin et al., 2005; Mettler, 2011; Pries-Heje and Baskerville, 2003). The People CMM for example that was first designed and published in 1995, has been applied by companies such as Boeing, Ericsson, Lockheed Martin, Novo Nordisk IT A/S and Tata Consultancy Services and has successfully guided workforce improvement programs (Curtis and Thorhauge, 2000; Keeni, 2000; Martín-Vivaldi, 1999; Miller and Miller, 2000; Vu, 2007).

A characteristic of maturity is the ability to continuously achieve capabilities regardless of frequency (Chrissis, Konrad, and Shrum, 2011; Raschke and Ingraham, 2010). In relation to this, Ahlemann, Schroeder, and Teuteberg (2005) advise that maturity has to be defined in relation to the class of entities and application domain under study (Kohlegger, Maier, and Thalmann, 2009). Therefore, apart from defining constructs related to maturity and maturation, maturity models have to include definitions of central constructs related to the application domain. Furthermore, the basic theory of evolution and change in relation to the class of entities under investigation has to be clarified (King and Kraemer, 1984). This, among other things, includes taking into consideration the way change typically takes place in the specified application domain as well as drivers and barriers associated with maturation. Some of the widely recognized application-specific purposes of maturity models are: descriptive, prescriptive, and comparative (Becker, Knackstedt, and Pöppelbuß, 2009; de Bruin et al., 2005; Iversen, Nielsen and Norbjerg, 1999; Maier, Moultrie, and Clarkson, 2009). A maturity model serves a descriptive purpose of use when it is being applied for the assessment of the current capabilities of an entity (under investigation) with respect to given criteria (Becker, Knackstedt, and Pöppelbuß, 2009). In this case, the maturity model is used as a diagnostic tool for assigning a maturity level (Maier, Moultrie, and Clarkson, 2009). A maturity model, on the other hand, has a prescriptive purpose of use if it illustrates how to identify desirable maturity levels and offers direction for improvement (Becker, Knackstedt, and Pöppelbuß, 2009). In a prescriptive purpose of use, as Maier, Moultrie, and Clarkson (2009, p. 21) note, "Specific and detailed courses of action are suggested." Equally important, a maturity model serves a comparative purpose of use when provided with sufficient historical data, the maturity levels of similar business units and organizations can be compared, allowing for internal and external benchmarking (de Bruin et al., 2005; Maier, Moultrie, and Clarkson, 2009).

2.4.2 Design and Development of Maturity Assessment Models

Even though the literature on maturity models is extensive, the documentation available on how to design and develop theoretically comprehensive and broadly accepted maturity assessment models is significantly limited and problematic (De Bruin et al., 2005; Pöppelbuß and Röglinger, 2011). Mettler (2011) supports this view and through a systematic review of the relevant literature, highlights that a great deal of the developed maturity assessment models does not disclose its research method and the underlying design decisions and expands on this gap with the introduction of a phase model for both the development and application of such models. Mettler's (2011) phase model is based on the work of de Bruin et al. (2005). Taking into account that development and application are closely connected, different decision criteria are identified as being applicable in respect to rigor and relevance of the maturity models. Mettler (2011) identifies three different design methodologies for the development of a maturity model. Two of the methodologies use a top-down approach (Becker, Knackstedt, and Pöppelbuß, 2009; de Bruin et al. 2005; Knackstedt, Poeppelbuss, and Becker, 2009) while the third one uses a bottom-up approach (Mettler, 2010). Although these design methodologies are different in the details of the model definition, they are based more or less on common design steps (Mettler, 2011). Drawing from design science (e.g., Hevner et al., 2004), it is argued that a maturity model must have a design process that is clearly documented and communicated in an understandable manner (Becker, Knackstedt, and Pöppelbuß, 2009; de Bruin et al., 2005). Becker, Knackstedt, and Pöppelbuß (2009) develop requirements and a procedure model from Hevner's et al. (2004) guidelines on design science. They identify several phases that provide "a manual for the theoretically founded development and evaluation of maturity models" (Becker, Knackstedt, and Pöppelbuß, 2009 p. 221). On the other hand, by adopting a problem-oriented approach, Purao (2002) developed a maturity model cycle that consists of four phases: 1. Define scope, 2. Design model, 3. Evaluate design, and 4. Reflect evolution, and it is usually initiated by a 'need and require intention'.

Pöppelbuß and Röglinger (2011), based on existing literature, propose a framework that groups design principles into basic principles for descriptive and prescriptive purposes. The essential components included in Pöppelbuß's and Röglinger's (2011) framework, for designing a maturity model as listed by Fraser, Moultrie and Gregory (2002) are: ''levels, descriptors, descriptions for each level, dimensions, process areas, activities for each process area and a description of each activity as performed at a certain maturity level'' (Pöppelbuß and Röglinger, 2011 p. 5). In relation to this and drawing back to the application-specific purposes of maturity assessment models (discussed at the previous sub-section), De Bruin et al. (2005) propose a generic methodology for the development of maturity models in various domains. The generic methodology proposed provides organizations with a better understanding of existing domain capabilities, enables benchmarking against a range of competitors, allows greater efficiency in the utilization of resources in improving domain capabilities and presents an opportunity for improved success in the domain. The methodology contains six phases (aiming to guide the design of a descriptive maturity model and its advancement for prescriptive and comparative purposes): scope, design, populate, test, deploy, and maintain. Although these model types (descriptive, prescriptive, or comparative in nature) can be seen as separate, they actually represent evolutionary phases of a model's lifecycle. First, a model is descriptive in order to enable a deeper understanding of the 'as-is' domain situation (De Bruin et al., 2005). A model can then evolve from being descriptive into being prescriptive, stressing on the domain relationships to business performance. A prescriptive model specifies how maturity improvement should be approached in order to affect business value positively. Finally, a model can be comparatively used in order to attain sufficient data to enable valid comparison and facilitate benchmarking across industries or regions (De Bruin et al., 2005). A model with a comparative nature can provide a comparison between similar practices across organizations in order to benchmark maturity within different industries as well as to recognize that similar levels of maturity across industries may not translate to similar levels of business value.

2.4.3 Criticism on the Concept of Maturity Assessment

Regardless of its expanded reproduction (or perhaps because of it), the concept of maturity assessment has been exposed to considerable criticism (Mettler, 2011; Pöppelbuß and Röglinger, 2011). Indeed, several deficiencies have been reported in relation to both maturity models as design products and the design process of maturity models. Apart from the Capability Maturity Model CMM that has reached the level of a compliance standard (Mutafelija and Stromberg, 2003); most of the maturity models available, as De Bruin et al. (2005) argue, offer solely a way for positioning a selected unit under investigation on a pre-defined scale. The purpose of maturity assessment models is to identify gaps that can then be attained by succeeding improvement actions. Pfeffer and Sutton (1999) comment on a 'knowing-doing gap' and claim that many of the maturity assessment models developed do not demonstrate how to perform these improvement actions successfully (Mettler, 2011). A further criticism in relation to this, claims that maturity assessment models oversimplify reality; and for this reason, are characterized as "step-by-step recipes" that lack empirical foundation (Benbasat et al., 1984; de Bruin et al., 2005; King and Kraemer, 1984; McCormack et al., 2009). Biberoglu and Haddad (2002), on the other hand, extent on the weak theoretical foundation of maturity models. Mettler (2011), shares the same view and comments that maturity models lack a coherent definition and contextualization. Voivedich and Jones (2001) and Swanson (2012) complement this view and argue that the most important point worth of criticism is that while maturity assessment models are objective measures, there is no universally accepted measure for maturity.

Maturity models have also been criticized for rejecting the possible manifestation of multiple, equally advantageous paths (Teo and King, 1997). This is perhaps due to the fact maturity models give emphasis on the order of levels leading to a pre-defined "end state", instead of focusing on factors that drive evolution and change (King and Kraemer, 1984). Further criticism claims that since assessment data often depend on the people being asked (also referred to as key informant bias), being in line with a maturity assessment model cannot assure that an organization will reach success (Montoya-Weiss and Calantone, 1994). The causes for the ambiguous results of maturity assessment models, according to de Bruin et al. (2005), lies in inadequate emphasis on testing the models in terms of validity, reliability, and generalizability, in addition to the little documentation on how to develop and design such models. Indeed, although research has already demonstrated the design process, there is no holistic understanding of the design principles (form and function) that maturity models are ought to meet (Pöppelbuß and Röglinger, 2011). Additional criticism refers to the large number of almost identical maturity models (Becker, Knackstedt, and Pöppelbuß, 2009; Becker et al., 2010; Iversen, Nielsen, and Norbjerg, 1999).

2.4.4 Selected Maturity Assessment Models and their Relation to LoPHIEs

Risk Management Maturity Model

Risk capability, which is a function of risk capacity, involves the ability to record processes that entail risks as well as the maturity to handle them. An organization, therefore, needs to equally have the capacity and the maturity to manage risks (Anderson, 2011; Manoukian, 2016). This is called by the Institute of Risk Management IRM, the 'risk management maturity' of the organization. Risk management maturity is defined as ''the level of skills, knowledge, and attitudes displayed by people in the organization, combined with the level of sophistication of risk management processes and systems in managing risk within the organisation'' (Anderson, 2011, p.21). Many organizations have developed risk management maturity models that cover a variety of elements. Some are concerned with control processes and the maturity of risk management, reflected on the culture of the organization, while others contemplate the readiness of organizations to encounter disasters and emergencies (e.g., Gladden, 2012; Hoseini, Hertogh and Bosch-Rekveldt, 2019; Matsumoto and Shirasaka, 2016; van Biljon and Haasbroek, 2017; Wieczorek-Kosmala, 2014).

Kennet (2013) identifies five maturity ranking levels of risk management practices and notes that going up the ranks is both a managerial and a technological challenge. The 5 maturity levels identified are: (1) Intuitive - no official methods for risk management are used, (2) Qualitative - risk assessments are conducted based on expert opinions, (3) Quantitative - some data is collected and used to identify key risk indicators, (4) Semantic – unstructured data are being used for study and finally, (5) Integrated - data of various sources are unified into a coherent risk management system. Kenett and Tapiero (2010) and (Kenett, Zacks and Amberti, 2014), respectively, offer a similar quality ranking. In relation to this, a study conducted by (PricewaterhouseCoopers (PwC), 2013) on existing disaster risk management strategies among global corporations, shows that many of the corporations participated, exhibit low levels of maturity in relation to long-term risk reduction and prospective risk management.

Capability Maturity Model CMM

The Capability Maturity Model CMM was initially developed for software engineering in order to objectively evaluate the "ability to perform" and assess the maturity of the software development process (Raschke and Ingraham, 2010; Russell et al., 2010). Due to its general nature of capability maturity, that makes it appropriate for general application and allows it to prevent the temporal and finite limitations of other models the CMM, since its inception, has become a generalized model for capability maturity finding application in many areas beyond technology and engineering (Russell et al., 2010). Jones (2003) examines multiple continuous improvement models and selects the CMM to form the basis of a framework that enables the assessment of the emergency management performance and capability. The model provides key practices for activities in a given application area that enhance the process capability and subsequent outcome measures in the area of concern (Paulk et al., 1993).

The management of crises, disasters, and emergencies, is an area in which new knowledge and experience on risk continually arise. Thus, the CMM is particularly relevant for application in managing LoPHIEs. Its major advantage against the Risk Management Maturity Model is that it addresses double-loop learning, which ensures that a system continually evolves with new knowledge (Huffman and Whitman, 2011). This property, combined with CMM's generic nature, makes such models more inclusive as compared to the Risk Management Maturity Model that appears to be more restrictive and confined. According to Jones (2003), assessment based on other traditional methods focus on performance; that is proven by conducting emergency exercises. The main limitation with this approach is that assessing performance in one incident does not provide reliable indicators for future capability in dealing with a different incident or even the same incident at another time in the future. An additional reason, however, that makes the application of a CMM based approach, promising; relates to the concept of maturity. Based on an organization's current and previous levels of improvement, maturity can indicate how an organization is likely to develop in the future (Becker, Knackstedt, and Pöppelbuß, 2009; Gottschalk, 2009; Russell et al., 2010). Such output is highly valuable in an emergency management system, in order to assure the organization's capability and commitment to improvement.

Process Management Maturity Assessment Model PMMA and Business Process Maturity Model BPMM

The Process Management Maturity Assessment Model PMMA is based on the principal structure of Capability Maturity Management Integration CMMI (Rohloff, 2009). The CMMI is an approach used for assessing and improving development processes in general (Cindrić, 2009; Rohloff, 2009). Overall, most maturity models based on CMMI, outline five maturity levels in which a higher level is associated with a higher maturity and an improved organization performance. PMMA models provide a detailed analysis that helps identify strengths and weaknesses and enable to compare the performance of organizations in a differentiated manner and provide a comprehensive basis for best practice sharing (Mielcarek, 2017; Rohloff, 2009). An influential PMMA model introduced by Rohloff (2009) has been developed to assess the implementation of Process Management and the performance of organizations in this respect. The maturity model is based on the assessment of nine categories: program management, process management organization, process portfolio, and target setting system, process documentation, methods and tools, process performance controlling, process optimization, data management, and IT architecture. These categories comprehensively cover all aspects which impact the success of Process Management.

PMMA models fit into the overall Business Process Management implementation procedure of organizations and provide an important link to process management success (Rohloff, 2009). A number of maturity models for Business Process Management have been proposed over the years (e.g., Lee, Lee, and Kang, 2007; Rosemann and De Bruin, 2005; Smith and Fingar, 2004; Tarhan, Turetken and Reijers, 2016). Developed on the basis of the Capability Maturity Model (CMM), the Business Process Maturity Model BPMM usually has five levels of maturity: initial/ad-hoc; managed; standardized; predictable; and innovating. Beginning with an immature state (initial), which views processes as 'ad-hoc' the levels move through a mature state in which continuous improvement is enabled by feedback (Harmon, 2004). An empirical research conducted by Raschke and Ingraham (2010) suggests a correlation between process maturity and performance measures. From a process maturity perspective, the expectation is that as maturity increases a positive impact is visible on performance (Rosemann and De Bruin, 2005). Process efficiency and effectiveness are built-in indicators of process performance. Process outcomes are important to an organization because they are intermediate performance measures (Dehning and Richardson, 2002; Melville, Kraemer and Gurbaxani, 2004), and are documented in the literature as quality and efficiency (Matolcsy, Booth and Wieder, 2005; Melville, Kraemer and Gurbaxani, 2004; dispersed; Ray, Muhanna and Barney, 2005; Saeed, Malhotra and Grover, 2005; Wieder et al., 2006). Quality can be measured in terms of process results and can be determined by customer satisfaction (how effectively a process meets customers' needs). Such customer satisfaction indicators are often reflective of billing and shipping errors, on-time delivery, and customer complaints (Schneiderman, 1996).

People Capability Maturity Model P-CMM

The People Capability Maturity Model P-CMM is a tool that helps to successfully address the critical people issues in an organization and provides a framework for implementing advanced practices related to strategic human capital management (Becker, 1996; Mirvis, 1997). As Prahalad and Hamel (1990) notes, the model is an organizational change tool that provides a roadmap for transforming an organization by steadily improving its workforce practices. It promotes the continuous training of the workforce to meet the changing demands that address diversity issues, the implementation of formal performance monitoring programs, improved information sharing as well as the sufficient communication of the organization's mission (Wademan, Spuches and Doughty, 2008). Even though the model has been initially developed for application in knowledge intense organizations, with appropriate tailoring, it can be applied in almost any organizational setting. The main objective of the model is to improve the capability of the workforce (Hefley et al., 1995; Wademan, Spuches and Doughty, 2008). Workforce capability refers to the level of knowledge, skills, and process abilities available for performing an organization's business activities. The P-CMM consists of five maturity levels that form sequential foundations for continuously shaping the workforce needed to accomplish future business plans, by creating an environment in which teams can flourish and operate effectively, motivating performance that adds value and by proving individual competencies (Hefley et al., 1995). At each maturity level, a new system of practices is overlaid on those implemented at earlier levels. Each overlay of practices raises the level of sophistication through which the organization develops its workforce (Curtis, Hefley, and Miller, 2009). Each maturity level provides a layer in the foundation for continuous improvement and prepares the organization with increasingly powerful tools for developing the capability of its workforce. The P-CMM introduces gradually in this way, the best workforce practices. Each progressive level of the model generates a unique transformation in the organization's culture. Thus, the model establishes an integrated system of workforce practices that matures through increasing alignment with the organization's business objectives, performance, and changing needs (Curtis, Hefley and Miller, 2009).

Changing an organization's culture through staged improvements is a unique approach to organizational development. Although many process standards can transform an organization's culture, only a few include a roadmap for implementation. Consequently, organizations often fail to implement the standard effectively because they attempt to implement too much too soon and do not lay the right initial foundation of practices (Curtis, Hefley and Miller, 2009). By following the maturity framework of P-CMM, an organization can avoid introducing workforce practices that its employees are unprepared to implement effectively (Curtis, Hefley and Miller, 2009; Hefley et al., 1995). Since the P-CMM is an evolutionary framework, it guides organizations in selecting high priority improvement actions based on the current maturity of their workforce practices. The benefit of the model is in narrowing the scope of improvement activities to those vital few practices that provide the next foundational layer for developing an organization's workforce (Tripathi, 2014; Wademan, Spuches and Doughty, 2008). By concentrating on a specific set of practices and working towards installing them, organizations can steadily improve their workforce and make lasting gains in their performance and competitiveness (Curtis, Hefley and Miller, 2009).

2.5. Specific Research Questions

The systematic literature review conducted, presented in the previous sections of this Chapter, examined indicators included in Table 1 (see Chapter One, Section 1.4, page 7) for their relevance to the research objectives and enabled the identification of factors related to the maturation of CI in teams and Collective Performance. In addition, it enabled the development of the CIMA Model. For the evaluation of the proposed maturity model design, it was necessary to generate more specific questions in relation to the main research question and objectives that incorporate the factors identified in the literature.

Within the spectrum of the topic being explored by the current Thesis, the following specific research questions were generated:

R.Q. 1.1 Are personality traits positively correlated to social sensitivity (RME scores)?

R.Q. 1.2 Is there a statistical difference between each of the cognitive abilities (ability of understanding social causality and ability of spontaneously understanding the working of the physical world) and control or experimental mode participants?

R.Q. 1.3 Is there a statistical difference between the Control and Experimental group in relation to scores gained at each of the tasks?

R.Q. 1.4 Does collective problem-solving lead to improved performance outcomes?

R.Q. 1.5 Is there a relationship between the teams' demographic information (age and Risk Management Relevance) and CI?

R.Q. 1.6 Does CI predict the performance of teams?

R.Q. 1.7 Is high social reasoning (RME scores) positively correlated with the overall team performance outcomes?

R.Q. 1.8 Is there a relationship between personality traits and CI?

R.Q. 1.9 Is high Folk Physics scores positively related to CI?

R.Q. 1.10 What is the relationship between the teams' performance (scores gained at the tasks and overall performance outcomes) and: (a) Team Interaction and (b) CI?

R.Q. 1.11 Is the diversity in the teams' demographic information (age and Risk Management Relevance) correlated with: (a) the teams' performance outcomes and (b) CI?

R.Q. 1.12 Is the diversity in the teams' composition (examine each parameter individually) correlated with: (a) the teams' performance outcomes and (b) CI?

R.Q. 1.13 What is the relationship between the TMS developed in the teams and: (a) the scores gained at the tasks (b) the teams' overall performance outcomes (c) CI and (d) Team Interaction (examine each TMS component individually and collectively)?

The specific research questions have derived mainly from the literature reviewed concerning Collective Intelligence (refer to Section 2.3 of this Chapter). However, the literature reviewed in relation to the philosophical context of LoPHIEs (refer to Chapter One, Section 1.2) as well as the problem statement and research gap of the current Thesis have tailored the specific research questions to capture the complex relationships and forces occurring within teams and affect CI and Collective Performance, in relation to the management of LoPHIEs. Within the domain of LoPHIEs, the research gap identified is concerned with decision-making difficulties. Relevant literature has been reviewed in Section 2.2 of this Chapter.

2.6 Summary and Conclusions

The Chapter has layed out the theoretical dimensions of this Thesis. The second section, *Decision Making*, examined primarily two things; first, the concept of heuristics and cognitive biases, and second, the treatment of choice under uncertainty. In the beginning, the theoretical background of the heuristics and biases program has been introduced. The concept of the ‘‘two cognitive systems’’ has been examined; the concept supports the view that heuristics and biases emerge from the interplay between an Automatic and a Reflective System, that work simultaneously when humans make decisions. In a similar manner, it went on to consider a competing theory of human judgment, which differs on whether the use of heuristics is irrational; and examined the prospect of heuristics and cognitive biases as adaptive responses to situations. Furthermore, it reviewed some of the most prominent heuristics and cognitive biases affecting judgment. It looked at two closely related heuristics, the availability and the representativeness, both accountable, as the literature suggests, for the failure to guard against adverse events. Cognitive dissonance and hindsight bias have also been examined since they are found to influence judgment strongly. Their study clearly justifies why humans often find themselves being surprised by catastrophes lying outside of their anticipation and beyond their historical probability distributions. Within the decision-making domain, the focused study on understanding heuristics and biases arose mainly from the investigation of people’s judgment under conditions of ambiguity or uncertainty. Therefore, the focus then shifted on examining the treatment of choice under uncertainty. It began by looking at how differences in beliefs and preferences in situations that involve ambiguity or uncertainty influence judgment, as well as how the process of belief formation may explain how future expectations, using available information, are formed. Overconfidence, which is identified as one of the most evident psychological underpinnings of belief formation and which is heavily discussed in the literature on psychological and behavioral decision making in regards to choices under ambiguity and uncertainty, has also been examined. Attention has been drawn to the failure of specialist prognostication, and literature concerning the accuracy of expert predictions has been provided in a separate sub-section. The literature reviewed highlights that regardless of how well the concept of probability is understood and the range of the expertise possessed, humans are incapable of making accurate predictions far enough into the future. In addition, the literature points out that being uncomfortable to accept the world as complex and uncertain leads to exceptionally incorrect expert predictions. Furthermore, it has been illustrated that different intellectual approaches to probability may provide an additional explanation as to why expert predictions fail. Aiming to provide a comprehensive understanding of the treatment of choice under uncertainty, the distinction between risk and uncertainty has been addressed in detail. Conclusively, the section investigated rationality vs. bounded rationality in strategic decision making. It reviewed literature documenting numerous cognitive limitations in decision-making procedures and highlighted that high uncertainty levels, reduce rationality. In addition, it illustrated by referring to various research studies conducted in the field of strategic decision making, that humans engage in aspects of rational decision making only partially; and that decision makers' approaches to situations can be simultaneously rational and irrational.

The third section of this Chapter, *Collective Intelligence*, has examined four main themes: the g factor; the c factor; the concept of transactive memory systems; and crowdsourcing. It began by introducing the concept of intelligence and provided the definition, the theoretical origins, and the implications of intelligence at the individual level (general intelligence or ''g'' factor). It then moved on to examine its predictive validity. General intelligence, as illustrated through the literature reviewed, captures individuals' performance on a wide variety of different cognitive tasks providing substantial evidence for its existence as a mental or cognitive capacity; that can be used to distinguish the characteristic performance levels of different individuals and to predict which are likely to perform well on other tasks in the future. In a similar manner, it went on to examine collective intelligence (the ''c'' factor), its theoretical background and implications. The ''c'' factor, which has been addressed in a separate sub-section, is analogous to intelligence at the individual level. Jointly, the literature reviewed highlighted the importance of CI as a central construct for understanding the drivers of team performance and provided evidence that illustrates CI as the increase in performance by the collective group beyond what can be achieved by individuals.

Furthermore, it pointed to three factors significantly correlated with a group's CI: (1) the average social sensitivity of team members, (2) the proportion of females in the team, and (3) the equal distribution of conversational turn-taking and participation in team discussion. The three factors found to be significantly correlated with CI were investigated thoroughly. The predictive validity of CI has been also examined, and a strong correlation between CI and team learning has been identified. In addition, the different types of diversity have been addressed. Cognitive diversity, which is an aspect of group composition, is strongly related to CI since it is directly associated with team members' ability to communicate with each other. The relative importance of cognitive diversity and individual ability for collective decision making and problem-solving has been examined. The section then moved on to consider the different styles of thought that occur in teams during judgment and decision-making processes. In addition, literature stressing on the role of cognitive diversity in shaping performance has been reviewed, and several issues related to biased information-seeking processes and the incorporation of unshared information into the decision-making process were highlighted. Another important aspect in relation to collective decision making that has been examined is team strategic orientation and its influence on how individual members and the team as a whole respond to subsequent problems and decision making. Lastly, the role that confidence plays in the way in which team processes are shaped, as well as its influence on collective decision making, has been investigated. The concept of Transactive Memory Systems (TMS) has been addressed. The concept is of particular interest to this Thesis since it offers an effective way of understanding individual and group behavior through the examination of the style in which individuals and groups process and structure information. The components of Transactive Memory Systems, as well as the mechanism based on which such systems operate, have been investigated. In addition, the dimensions of Transactive Memory Systems: specialization, credibility, and coordination have been examined. Literature illustrating the role of interdependence between team members, in shaping transactive memory has been reviewed. Furthermore, the strong association between Transactive

Memory Systems and performance has been highlighted. Finally, the concept of crowdsourcing has been explored. Crowdsourcing is a special form of collective intelligence that takes advantage of the wisdom of crowds, and it can be broadly understood as the practice of acquiring ideas, information, or sources and services by inviting input from a large number of individuals. The potential of crowdsourcing in the management of adverse events has been investigated and literature that clearly illustrates crowdsourcing as a specific form of collaborative production of knowledge has been reviewed.

The fourth section, *Maturity Assessment Models*, began by introducing a generic model for maturity assessment and examined its origins, nature, and use. It addressed the theoretical importance of the notion of maturity and provided key arguments and discussion on the central constructs related to maturity and maturation. Furthermore, it reviewed literature on factors that have a strong dependency and effect on maturity and examined some of the widely recognized application-specific purposes of maturity models. The main objective of a maturity model is to assess the maturity of a designated field and increase its capabilities based on a sequence of levels that form an anticipated, desired, or logical maturation path. Different design methodologies for the development of a maturity model applicable to various domains have been investigated, and discussion in regards to raising concerns on the limited and problematic documentation in relation to the design and development of theoretically comprehensive and broadly accepted maturity assessment models has been provided. These concerns have been developed further in a separate sub-section that investigated additional limitations and criticism on the concept of maturity assessment. Finally, influential maturity assessment models, such as the Capability Maturity Model CMM, have been reviewed and their potential application in LoPHIEs settings has been critically examined.

Chapter 3 Research Methodology

3.1 Introduction

The Chapter seeks to justify the methodological foundation of the Thesis and to provide an understanding of the perspectives, processes, and methods of data collection and analysis involved. The Chapter begins by defining the nature of the study and its purpose. It then goes on to examine the different philosophical positions to social science and identifies the debate across the different schools of thought. The philosophical positioning most closely related to this research is discussed in detail. The research choice, which is one of the fundamental elements of the research design, is explored and the research strategies used throughout the whole development process of the CI Maturity Assessment (CIMA) Model, are discussed. A full cycle for the development of a maturity model consists of four phases: define scope; design model; evaluate design; reflect evolution. These phases are described in detail in Chapter Four. However, in this Chapter specific information is provided in relation to the verification and validation of the proposed maturity model. The aim is to make more than one iteration of the development cycle in order to increase the expressive power of the proposed model. The method used to apply the design of the proposed maturity model is outlined. Experimental Research Strategy justifies the methodological foundation based on which the design of the proposed maturity model, has been evolved. The experimental research strategy, as the main source of primary data collection in this Thesis, involving multiple experiments, is discussed. Criticism on the methodology selected for the evaluation of the design of the maturity model is addressed. The design of the multiple experiments conducted is detailed and the protocol followed for the experiments is discussed. In addition, the Chapter examines the characteristics of the sample selected. The internal and external validity of the experiments is also discussed. The design of each experiment is investigated separately, and justification for the selection of the material adopted, developed, and used is provided.

Furthermore, general information on the analysis of the primary data is provided. The Chapter justifies the decision for the quantification of all primary data collected from the experimentation process and explains the reasons for choosing R over other statistical software for the analysis of the data.

3.2 Research Nature and Purpose

The study has mainly an exploratory purpose and seeks knowledge that can be used to improve the management of LoPHIEs. Exploratory research is inherently flexible and enables the researcher to refocus the study and change its direction as new insights and data arise, allowing in this way the researcher to gradually narrow the focus of the study as the research progresses (Adams and Schvaneveldt, 1991; Saunders, Lewis and Thornhill, 2016). The exploratory purpose of the current study, especially at its early stages, where rigorous literature search took place, enabled the identification of the theoretical gap and the need for new theory development. In meeting the research objectives and addressing the multidisciplinary nature of the research topic, at different stages, the study is found to be also explanatory and descriptive. In relation to this, Robson (2002) and Saunders, Lewis and Thornhill (2016) support the view that as the research progresses, the purpose of a research may change, and therefore, multiple purposes may be identified in one study. The above, classify the current study as 'applied' and 'experimental'.

3.3 Philosophical Positioning

The research philosophy adopted when conducting research contains critical assumptions about the way the researcher views and understands the world, through which the research strategy and the methods selected, as part of that strategy, are underpinned (Saunders, Lewis and Thornhill, 2016). Hence, particular considerations in relation to what constitutes reality, influence the philosophy adopted significantly. The main influencing factor, however, remains the researcher's particular view of the relationship between knowledge and the process by which it is developed. Ontology is concerned with the nature of reality and deals with issues related to the researcher's assumptions about the way the world operates and the personal commitment held to particular views. Subjectivism and Objectivism are the two aspects of ontology. Both, as Saunders, Lewis, and Thornhill (2016) note, are widely accepted by many researchers, for producing valid knowledge.

Subjectivism embraces the idea that social phenomena are shaped from the perceptions and consequent actions of social actors, in a way that a situation of continual process of social interaction is formed, in which social phenomena are being constantly under revision (Merlo, 2016). Subjectivism is associated with the term constructionism, or social constructionism, which follows from the interpretivist position. Interpretivism is an epistemological stance that supports the view that reality is being socially constructed and shaped by the various ways individuals perceive different situations as a result of their own view of the world (Baert and Rubio, 2009). The different ways individuals interpret situations, affect their actions, and the way in which social interaction with others takes place. Scholars, who favor this approach, seek to understand the subjective reality of the individuals being studied and capture the rich complexity of social situations in order to make sense of and understand the motives, actions, and intentions of individuals in a way that it is meaningful (Alizade and Sarmadi, 2015; Benton and Craib, 2011). Concerning this, it may be argued that the investigator's personal involvement in the data collection process is unavoidable. Entering the reality of the research subjects and understanding the world from their point of view poses a challenge, and therefore, the generalizability of the research findings becomes difficult (Baert and Rubio, 2009). Qualitative methods of data collection and analysis are more likely to be employed, when adopting this specific approach, although quantitative methods may also be employed (Clark, 1998; Crotty, 2015). Objectivism, on the other hand, which follows from the positivist approach to research, holds the view that social entities exist in reality externally to the researcher, and as such, the world and any properties occurring within it should be measured in an objective manner (Holden and Lynch, 2004). Reliable data, according to the positivist approach, can be obtained only through phenomena that can be observed. Equally important, positivism claims that true knowledge can only be based on facts (Turner, 2001). Therefore, in contrast to the interpretivist approach to research, the positivist approach is concerned with facts (consistent with the notion of 'observable social reality'), rather than impressions. In this manner, positivists aim for the development of law-like generalizations, while they maintain an external position to the data collection process (Remenyi et al., 1998). In relation to this, Remenyi et al. (1998, p. 33) note that 'the researcher is independent of and neither affects nor is affected by the subject of the research''. For these reasons, scholars who favor this approach employ quantitative methods for the collection and analyses of data, while emphasis is given on quantifiable observations that can be statistically analyzed.

The researcher identifies with both aspects of ontology. On the one hand, the researcher supports the view of subjectivism and considers individuals' reality to be the construct of social interaction. The researcher holds that reality, as it is seen by each one of us individually, is under a constant state of revision, and this is due to the fact, we, as humans continually interpret the world around us as well as the actions of others, we interact with. This interpretation, in turn, leads to alternations of our own meanings and actions, and therefore, in understanding the complex social situations, efforts should be made in understanding the unique and exclusive reality of individuals. On the other hand, however, the researcher also identifies with objectivism and holds the position that interaction between individuals is performed on the basis of a grant plan, over which individuals have no control and in which timing/synchronicity plays a significant role. Social interaction through which reality is constructed may be characterized by the researcher to be chaotic; having attributes of non-linearity. Nevertheless, the researcher considers that there is, after all, some order in the chaos of social interaction and that therefore, the world and any properties occurring within it should also be measured in an objective and quantifiable manner. The researcher's view of how the world operates, what constitutes reality and how knowledge is developed, is consistent with pragmatism's arguments that the most crucial determinant of the research philosophy adopted is the research question itself and that (due to this) it is perfectly possible to work with both philosophies of objectivism and subjectivism. In relation to this, Tashakkori and Teddlie

(2016) suggest that it is more suitable for the researcher to think of the philosophy adopted in a particular study as a continuum rather than conflicting positions. Furthermore, they note that ‘‘at some points the knower and the known must be interactive, while at others, one may more easily stand apart from what one is studying’’ (Tashakkori and Teddlie, 2016, p. 26). To this end, mixed methods, both qualitative and quantitative, are possible, and possibly highly suitable, within one study. In fact, the multidisciplinary nature of the specified research topic necessitates the use of mixed methods.

Pragmatism is identified to be one of the four leading paradigms across the debate on mixed methods research, and it has obtained considerable support as a stance for mixed methods researchers (Feilzer, 2009; Johnson and Onwuegbuzie, 2004; Maxcy, 2003; Morgan, 2007). This is due to the fact that it is concerned with solving practical problems in the “real world”, rather than with assumptions about the nature of knowledge (Feilzer, 2009; Mitchell, 2018). As it has been argued, however, sufficient rationale in the case of mixed methods research, cannot be provided through a single paradigm, as serious limitations arise. The researcher argues that a realist perspective, as a complementary paradigm, provides the means to overcome these limitations (Maarouf, 2019). While being an ontological position usually associated with positivism and post-positivism, realism is by no means confined to these positions. As Lipscomb (2010) notes, a realist-pragmatism approach has proven to be appealing to realist mixed-methods researchers (Downward and Mearman, 2007; Lipscomb, 2008; McEvoy and Richards, 2006) as well as to those interested in pragmatism (Rescher, 2000, 2003, 2007), as it allows freedom in the choice of investigative techniques. The researcher identifies more with critical realism, which claims that there are two steps to experiencing the world. The first step involves the thing itself and the sensations it conveys while the second step involves accepting that there is also the mental processing that goes on sometime after that sensation meets our senses (Ackroyd, 2004). Direct realism, which forms the second type of realism, claims that the first step is enough. The researcher argues that combining pragmatism with a critical realist ontology offers an interesting and potentially productive philosophic frame for the current Thesis.

3.4 Research Design: Research Choice

The research choice is concerned with the way in which the researcher decides to combine quantitative and qualitative techniques and procedures for the collection and analysis of data (Saunders, Lewis and Thornhill, 2016). Mono-method uses a single technique for the collection of data and related analysis procedures, while multiple methods use more than one data collection technique and analysis procedures to answer the research question/s. The choice of multiple methods, as Curran and Blackburn (2001) note, is increasingly advocated within business and management research.

Based on several considerations, including the nature, the purpose of the study, and the main research question, including the specific questions formulated in relation to the main research question, the Thesis employs multiple methods. Having clear research questions and objectives is vital for ensuring that the research methods and strategies selected will enable to meet them (Saunders, Lewis and Thornhill, 2016). The choice of multiple methods provided better opportunities for answering the main research question and meeting the objectives of this Thesis. Also, it enabled an enhanced evaluation of the extent to which the research findings can be trusted. More specifically, the study employed mixed methods. This is due to the fact, multi-methods were found to be restricting, in the sense that while they allow the use of more than one data collection technique and corresponding analysis procedures, the mix of quantitative and qualitative techniques and procedures is not possible. A multi-method study can be either multi-method quantitative or multi-method qualitative (Tashakkori and Teddlie, 2010). Mixed methods, on the other hand, allowed the use of different research methods, for different purposes in the study and enabled triangulation to take place. Both quantitative and qualitative data collection techniques and analysis procedures were used (Saunders, Lewis and Thornhill, 2016; Tashakkori and Teddlie, 2010).

Mixed methods research is a rising methodological choice for many academics and researchers from across a variety of disciplines. The growth of mixed methods research has been led by a discussion over the justification for combining what has been previously regarded as incompatible methodologies. As Teddlie and Tashakkori (2010) argue, mixed methods research has been established as a third methodological movement, complementing the existing traditions of quantitative and qualitative movements (Greene, 2007; Tashakkori and Teddlie, 2010; Teddlie and Tashakkori, 2010). A comprehensive definition is given by Creswell and Plano Clark (2018, p. 5) who define mixed methods research as “a research design with philosophical assumptions as well as methods of inquiry. As a methodology, it involves philosophical assumptions that guide the direction of the collection and analysis of data and the mixture of qualitative and quantitative data in a single study or series of studies. Its central premise is that the use of quantitative and qualitative approaches in combination provides a better understanding of research problems that either approach alone”.

Mixed-method research and mixed-model research fall under the category of mixed methods. In mixed-method research, quantitative and qualitative data collection techniques and analysis procedures can be used either at the same time or one after the other but cannot be combined. The multi-purpose and multi-disciplinary nature of the specified research study required the combination of quantitative and qualitative data collection techniques and analysis procedures as well as the combination of quantitative and qualitative approaches, and such combination was able with the use of mixed-model research.

3.5 Research Design: Horizontal Research Strategies for the CIMA Model

The aim of the Thesis is to materialize a CI maturity model for the assessment of teams’ preparedness and resilience towards LoPHIEs. The development of such a model, as explained in Chapter One of the Thesis, is of paramount importance as it can offer decision support to teams tasked with the management of LoPHIEs, guiding the strategic decision making required for successful and sustainable management. Models are one of the prime instruments of modern science and are of central importance in many scientific disciplines. Models perform two essentially different representational functions. A model can be, on the one hand, a representation of a selected ‘target system’. Such models, depending on the nature of the target, are either models of data (Suppes, 1962) or models of phenomena (Frigg and Hartmann, 2018). On the other hand, a model can be a representation of a theory in the sense that it provides interpretations of the laws and axioms of that theory (Hodges, 2003). These two functions are not mutually exclusive as scientific models can be representations in both senses at the same time (Frigg and Hartmann, 2018). Models are vehicles for learning about the world and are employed to explain and predict the behavior of systems or real objects. In summary, as Swoyer (1991) argues, models, allow for surrogative reasoning. Several scholars further suggest that scientific models give rise to a new style of reasoning, called 'model based reasoning' (e.g., Magnani, 2012; Magnani and Nersessian, 2002).

The researcher has adopted Mettler's (2010) design science research approach, a methodology that has established a helpful framework for building the proposed model of Collective Intelligence Maturity Assessment (CIMA). Figure 1, adapted from Mettler (2011), presents the development cycle of a maturity assessment model. Since Design Science Research is a problem-oriented approach, the development cycle is initiated by a 'need and require intention' (Purao, 2002). The complete development cycle, as shown in Figure 1, consists of four phases: 1. define scope, 2. design model, 3. evaluate design, 4. reflect evolution.

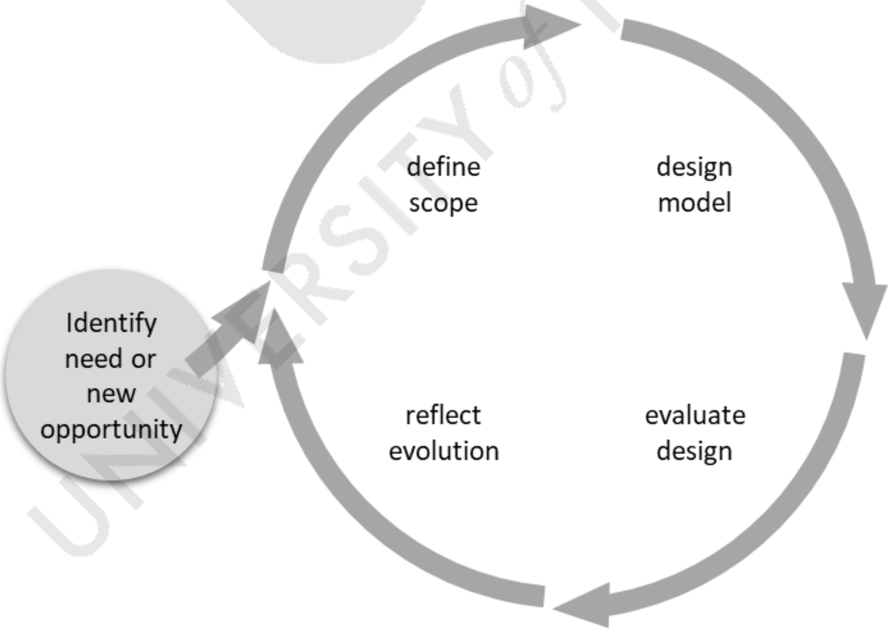


Figure 1: *Initiating a Maturity Model Development Cycle (adapted from Mettler, 2011)*

The development of maturity models by conducting design-oriented research means arriving to solution patterns for critical unsolved problems or providing guidance in resolving issues in more efficient and effective ways (Hevner et al., 2004). Therefore, as previously mentioned, the development cycle of a maturity assessment model is initiated with a need identified or new opportunity. The need and opportunity for the development of a CI Maturity Assessment Model have been addressed in general at Chapter One of the Thesis, in which the statement of the problem and the aim and scope of the study have been examined. In addition, the need for the development of such a model has been investigated in detail in Section 2.2 *Decision Making* of Chapter Two, and the opportunity for the development of the model has been examined thoroughly in Section 2.3, Collective Intelligence (CI).

In the context of this Thesis, the research approach relies on both deductive and inductive reasoning methods. Secondary data are collected through a systematic review of the theory and literature using the deductive method. The systematic literature review (presented in Chapter Two) enabled the identification of factors related to the maturation of CI in teams and, in turn, allowed the design of an initial CI Maturity Assessment (CIMA) Model (refer to Chapter Four, Section 4.3.1). Primary data are collected with the implementation of an experimental research strategy involving multiple experiments. By conducting the experiments, the initial maturity model designed will be applied and evaluated. More specifically, three interconnected experiments are conducted, each with a different focus but all contributing to answering the main research question and sub-questions and meeting the objectives of the study. Expert opinion is also acquired at different stages of the study as the research progresses, by specialists in the field. Expert opinion assists with narrowing the research focus, the selection of best research strategies and methods for the investigation of the problem addressed by the Thesis, the development of the CI Maturity Assessment (CIMA) Model and the multiple experiments for the evaluation of the model, as well as best techniques for data analysis. From the data collected (both secondary and primary), the gradual improvement of the design of the proposed model takes place.

Table 2 aligns the research questions and objectives with the research strategies and techniques employed for data collection.

Table 2: *Research Questions, Objectives, Strategies and Techniques*

MAIN RESEARCH QUESTION	
What are the significant factors that need to be included in a CI maturity assessment model examining the preparedness of organizations for managing LoPHIEs?	
SPECIFIC RESEARCH QUESTIONS	
R.Q. 1.1 - Are personality traits positively correlated to social sensitivity (RME scores)? R.Q. 1.2 - Is there a statistical difference between each of the cognitive abilities (ability of understanding social causality and ability of spontaneously understanding the working of the physical world) and control or experimental mode participants? R.Q. 1.3 - Is there a statistical difference between the Control and Experimental group, in relation to scores gained at each of the tasks? R.Q. 1.4 - Does collective problem-solving lead to improved performance outcomes? R.Q. 1.5 - Is there a relationship between the teams' demographic information (age and Risk Management Relevance) and CI? R.Q. 1.6 - Does CI predict the performance of teams? R.Q. 1.7 - Is high social reasoning (RME scores) positively correlated with the overall team performance outcomes? R.Q. 1.8 - Is there a relationship between personality traits and CI? R.Q. 1.9 - Is high Folk Physics scores positively related to CI? R.Q. 1.10 - What is the relationship between the teams' performance (scores gained at the tasks and overall performance outcomes) and: (a) Team Interaction and (b) CI? R.Q. 1.11 - Is the diversity in the teams' demographic information (age and Risk Management Relevance) correlated with: (a) the teams' performance outcomes and (b) CI? R.Q. 1.12 - Is the diversity in the teams' composition (examine each parameter individually) correlated with: (a) the teams' performance outcomes and (b) CI? R.Q. 1.13 - What is the relationship between the TMS developed in the teams and: (a) the scores gained at the tasks (b) the teams' overall performance outcomes (c) CI and (d) Team Interaction (examine each TMS component individually and collectively)?	
RESEARCH OBJECTIVES	**RESEARCH STRATEGIES & TECHNIQUES**

R.O. 1 - Identify indicators related to the management of LoPHIEs.	➢ Secondary Data Collection / Literature Review
R.O. 2 - Explore indicators related to the management of LoPHIEs in the presence of CI-supported decision making.	➢ Secondary Data Collection / Literature Review ➢ Multiple Experiments
R.O. 3 - Design and develop a CI maturity assessment model.	➢ Secondary Data Collection / Literature Review ➢ Expert Opinion ➢ Multiple Experiments
R.O. 4 - Validate how the proposed CI maturity assessment model can be applied to assess teams' maturity levels in dealing with LoPHIEs.	➢ Multiple Experiments

3.5.1 Experimental Research Strategy

The experimental methodology has a rich tradition in the natural sciences. Social sciences, especially psychology and economics, also use the methodology in order to develop and test theories of behavior. To this end, psychology has historically relied on laboratory experiments. Management domains, related to psychology and especially research in organizational behavior, relies heavily on the experimental method for generating and testing new theories in the organizational context. For example, numerous studies have investigated group performance and decision-making using experimental methods (e.g., Bhappu, Griffith and Northcraft, 1997; Knez and Camerer, 1994; Thomas-Hunt, Ogden and Neale, 2003). Significant advancements in economics have also resulted from the application of experimental methods in the field (see Davis and Holt, 1993; Kagel and Roth, 1995, for reviews).

Experiments examine whether a change in one independent variable causes a change in another dependent variable. The aim of an experiment is, therefore, to study causal links. Simple experiments investigate whether there is a link between two variables (Shadish, Cook and Campbell, 2002). Complex experiments, on the other hand, also consider the magnitude of the change and the comparative importance of two or more independent variables (Bandiera, Barankay and Rasul, 2011; Cook and

Campbell, 1979; Croson, Anand and Agarwal, 2007). Experiments, therefore, are mostly used in exploratory and explanatory research to answer 'how' and 'why' questions (van Oudenhoven and de Boer, 1995). Classic experiments involve the establishment of two groups, and members are assigned to each group randomly. The two groups are precisely similar in all aspects relevant to the research, with the only difference concerning whether or not they are exposed to a planned intervention or manipulation. In the experimental group, some form of planned intervention or manipulation is made purposefully. In the control group, no such intervention is made (Bell and Peck, 2012). The experimental research strategy provides clean measures of independent and dependent variables (Schweiger and Goulet, 2000, Spencer, Zanna and Fong, 2005), and as Gay (1992, p. 298) notes "The experimental method is the only method of research that can truly test hypotheses concerning cause-and-effect relationships". This view is supported by Moore and McCabe (1993, p. 202), who note that "The best method — indeed the only fully compelling method — of establishing causation is to conduct a carefully designed experiment in which the effects of possible lurking variables are controlled. To experiment means to actively change x and to observe the response in y". Unlike real-world data, which in most cases are noisy, experiments provide clean, observable, dependent measures. Furthermore, experiments are replicable; other researchers can reproduce the experiment and verify the findings independently (Cook and Campbell, 1979). Based on these advantages, experiments are suitable for testing predictions of theories or estimating theories' parameters. Many researchers would agree on the view that the foundations of scientific advancement lay in the combination of inductive and deductive reasoning. Experiments that address theory have, therefore, an important place in the dialectic of the scientific method. After a theory is inductively formulated and hypotheses are developed from it deductively, the conduction of an experiment can, in fact, test these hypotheses and provide insights as to whether the theory needs to be refined (Cook and Campbell, 1979; Harrison and List, 2004).

3.5.2 Criticism on the Experimental Research Methodology

Despite the conceptual advantage of the experimental design in establishing a causal link between intervention and impact, experiments are often criticized on a variety of factors concerning the validity, quality of data, scientific integrity, and practical feasibility (Bell and Peck, 2012). The limited sample sizes often achieved in experiments are an issue heavily criticized on the basis of the practical feasibility of the experimental research strategy (Shadish and Cook, 2009). The problem is created due to the fact that often people are not willing to participate in experiments, and so those who volunteer may not be representative (Bell and Peck, 2012; Lynch and John, 1982). Because of this, the experiment strategy is often used only on captive populations such as university students. The design requirements of an experiment often mean that samples selected are both small and atypical, leading to problems of external validity. In relation to this, it is noted that while a large and representative sample may overcome such problems, this is likely to be both complicated and costly (Harrison and List, 2004; Levitt and List, 2009).

Another issue leading to problems in external validity is the fact that experiments, including also those in domains linked closely with business and management such as organizational psychology, are conducted in laboratories rather than in the field. Laboratory experiments offer greater control over aspects of the research process, such as the settings within which the experiment takes place and enable the implementation of unusual or rarely-observed parametric values or treatments in a way that it would not be feasible using naturally-occurring data. Consequently, a well thought experimental design can distinguish theories that cannot be notable otherwise (Kirk, 2013). While on the one hand, this improves the internal validity of the experiment, especially the extent to which the findings can be attributed to the interventions rather than any flaws in the research design; on the other hand, external validity is likely to be more challenging to achieve. The argument is based on the fact that since laboratory settings are abstract and unrealistic, in the way that fewer considerations, dimensions, and confounds are contained as compared to the real world, the extent to which the findings from a laboratory experiment can be generalized is likely to be lower than the results from a field-based experiment. The issue of external validity in experiments is discussed in depth by Zelditch (1969) who even though acknowledges that laboratory settings are different than any naturally-occurring, real-world setting, argues that the bridge between the lab and the real world is the theory being developed to predict and explain real-world observations; and should also predict and explain behavior in laboratory settings. In case the opposite occurs, as Zelditch (1969) explains, it is not due to the experiment settings, but due to a lack in the theory being developed. Plott (1991) supports this view and notes that, in fact, since confounding factors not incorporated in the theory are absent in a laboratory setting, the theory should perform better in the lab. Meaning that if the theory cannot be verified in the uncomplicated and clean environment of a lab, it is not likely to be verified in the noisy, confounded environment of the field either.

3.5.3 Multiple Experiments Design - Materials and Methods

Protocol

Three interlinked experiments, each with a different focus, were conducted in total. The focus of the first experiment was the assessment of individual intelligence and included three psychometric tests which all participants were required to complete individually. Following the completion of the first experiment, the sample was split in half. Fifty percent of the participants were based on convenience selected to proceed to the second experiment continuing to work individually. These participants formed the control group. The other fifty percent of the participants formed the experimental group and proceeded to the second experiment, working in teams. The allocation of the participants to the Control and Experimental groups was carried out based on convenience due to the fact that most participants were professionals with limited time available. Fourteen teams of three to four members were created within the Experimental group. The allocation of the experimental group participants to the teams was random. The second experiment aimed to assess collective intelligence in the context of LoPHIEs and included three tasks that participants were required to complete either working individually (control mode) or in teams (experimental mode). Two of the tasks were related to the management of LoPHIEs, and one focused on assessing the participants' ability of spontaneously understanding the working of the physical world when addressing the task individually (control group) and collectively (experimental group). Even though the content of the specific task was not related to the management of LoPHIEs, it assessed analytic, and accuracy skills that are vital in processing the volume of the information received throughout the management adverse events. While conducting the second experiment, the control group was exposed to precisely the same external influences as the experimental group, apart from the planned intervention. Therefore, the only explanation for any changes to the dependent variable is the planned intervention made, which in the context of this Thesis is the emergence of collective intelligence that can only be achieved through the interaction between a number of individuals. After the completion of the second experiment, only those participants who were selected to work in teams (experimental group) during the second experiment, have been asked to proceed to the third experiment. This was due to the fact that the aim of the third experiment was to assess Transactive Memory System (TMS) measures. As previously seen in the literature review, Transactive Memory Systems, just as collective intelligence, emerge only in teams. To the best of the researcher's knowledge, the current study is the first to examine transactive memory systems in relation to collective intelligence. The dimensions of the transactive memory systems developed in the teams during conducting the second experiment were measured in the third experiment with participants being asked to complete individually, a TMS scale, developed by Lewis (2003). Throughout the experimentation process, observational techniques were employed to document team interaction levels and conversational turn-taking (speaking turn variance in the experimental group).

Participants

One hundred fifty-four participants, including professionals and students, were initially recruited to participate in the experiments. However, fifty-seven participants were excluded due to failure to attend the whole experiment protocol, and their exclusion from the sample was necessary in order to maintain the consistency of the experiments and the accuracy of the results. Then, three more participants were recruited to achieve a sample of one hundred. From those one hundred participants, forty-nine were female, and fifty-one were male, ranged in age from twenty to fifty-seven, covering nine nationalities. In total, sixty-five participants were professionals, of which twenty-nine with high risk management relevant occupations, eight with medium to high risk management relevant occupations, eleven with medium risk management relevant professions, and seventeen with low to medium risk management relevant occupations. The other thirty-five participants were senior students (i.e., at their fourth year of study) or postgraduate students and are considered to have low relevance to risk management. It is anticipated that the sample selected comprises a mix of people with all different ranges of exposure to risk management.

Internal and External Validity of the Experiments

The internal and external validity of the experiments has been achieved with the use of validated tests and a set of tasks based on established and validated taxonomies. In addition, the inclusion to the sample of both professionals with high to low-medium relevance to risk management and students with low relevance to risk management has further minimized threats to the validity of the multiple experiments conducted.

Experiment 1 – Measuring Individual Intelligence

The experiment involved the completion of three tests (Reading the Mind in the Eyes Test, Folk Physics Test Part I, and Big Five Personality Test) that are widely used in the field of CI and psychology, aiming to assess the individual intelligence of participants. The tests were completed individually by all participants.

Justification for the Selection of the Tests

The framework of evolutionary psychology holds the view that the human mind must be measured in terms of its evolved adaptedness to the environment (Karmiloff-Smith et al., 1995). Intuitive (or folk) psychology, for understanding social causality and intuitive (or folk) physics, for understanding physical causality, are considered to be key neurocognitive adaptations of the human mind.

Folk psychology is concerned with Emotional Intelligence EI, which is defined as the capacity to reason about emotions and to use emotions to enhance thinking (Johnson, 2000; Leslie, 1987). It includes abilities such as understanding emotional knowledge (Baron-Cohen, 1993; Premack, 1990), being able to perceive emotions in others accurately (Harris et al., 1989), accessing and generating emotions so as to support thought (Premack, 1990; Yirmiya et al., 1992;) and the reflective control of emotions so as to stimulate intellectual and emotional growth (Mayer, Caruso and Salovey, 2000; Mayer and Salovey, 1993; Mundy and Crowson, 1997; Scaife and Bruner, 1975; Tomasello, 1988). A specific subset of these skills, related to the perception of emotions and mental states, has been studied under the term “theory of mind” (ToM), which refers to the cognitive capacity to attribute mental states to self and others (Apperly, 2012; Baron-Cohen et al., 2001b; Flavell, 1999; Premack and Woodruff, 1978; Saxe, 2009). Other names for the same capacity include “mentalizing”, “naïve psychology”, “common-sense psychology” and “folk (or intuitive) psychology” (Apperly, 2012; Baron-Cohen et al., 2001b; Flavell, 1999; Heyes and Frith, 2014; Premack and Woodruff, 1978; Saxe and Powell, 2006).

Theory of mind appears to be the component of EI with the greatest relevance to studies of collective intelligence due to the fact it encompasses the accurate representation and processing of information about the mental states of other people, also known as “mentalizing ability” (Baron-Cohen et al., 2001a), which contribute to successful interaction with others. Indeed, there is a general consensus that EI and related abilities improve group performance (e.g., Ashkanasy and Daus, 2005; Barsade and Gibson, 2007; Druskat and Wolff, 2008 and 2001; Elfenbein, Polzer and Ambady, 2007; Elfenbein, 2006; Feyerherm and Rice, 2002; Jordan et al., 2002). A study conducted by Woolley et al. (2010) found that groups whose members had higher average ToM scores (as measured by the “Reading the Mind in the Eyes” (RME) test, Baron-Cohen et al., 2001b) also had significantly higher collective intelligence. In fact, average ToM scores remained the only significant predictor of collective intelligence even when individual intelligence or other group composition or process variables (such as the proportion of women in a group or the distribution of communication), were controlled. Therefore, this places Theory of mind, among the small group of abilities within the board category of EI that can be most reliably measured.

Folk physics, on the other hand, is concerned with how physical-causality is perceived and understood. It refers broadly to skills developed for understanding expectations concerning the motion and properties of physical objects (Leslie and Keeble, 1987) as well as concepts related to mechanics (Karmiloff-Smith, 1999). Folk psychology appears to be present from at least 12 months of age (Baron-Cohen, 1993; Premack, 1990). Folk physics is also present very early in human ontogeny, and it is manifested in infants’ sensitivity to apparent violations of the laws of physics. For example, larger objects going into smaller ones or one object passing through another (e.g., Baillargeon, Kotovsky and Needham, 1995; Leslie and Keeble, 1987; Karmiloff-Smith, 1999; Spelke, Phillips and Woodward, 1995). Based on seven shared features, both folk physics and folk psychology are considered as "core domains of human cognition" (Carey, 1987; Gelman and Hirschfield, 1994; Sperber, Premack and Premack, 1995; Wellman and Inagaki, 1997). Both domains: 1. are aspects of our causal cognition, 2. are adaptive, 3. demonstrate maturity in human infancy, 4. are acquired or develop universally, 5. have a specific but universal ontogenesis, 6. show little if any cultural variability and 7. may be open to neurological dissociation.

Due to the nature of the specified study and since sustainable management for LoPHIEs requires those affected or involved in the management of such events, to demonstrate an ability to manage uncertainty and adapt to rapid change, the researcher has concluded that both folk psychology and folk physics, as key neurocognitive adaptations of the human mind, should be measured in the multiple experiments conducted. Understanding of social causality is measured in the first experiment by the ''Reading the Mind in the Eyes'' test. The ''Reading the Mind in the Eyes'' test is considered as an 'advanced theory of mind test' which gauges the ability to attribute mental states to oneself or another person. The test has been shown to have satisfactory test-retest reliability (Hallerbäck et al., 2009) and several studies suggest that it measures a fundamental property of individual brain function (e.g., Baron-Cohen et al., 2001b; Chapman et al., 2006; Domes et al., 2007). On the other hand, understanding of physical causality is measured in the experiment by a folk physics test, developed and validated by Baron-Cohen et al. (2001b). The above tests measure attributes of individual intelligence, and their inclusion in the experiment helped to explore the degree to which both folk physics and folk psychology play a role in facilitating collective intelligence in LoPHIEs settings.

Individual personality traits were also measured in the experiment by the Big Five Personality Test in order to: (1) determine whether personality traits are positively correlated with human's ability to make inferences about notions of the physical world as well as their capacity to explain and predict the mental state of other people, (2) explore the relationship between personality traits and CI in the context LoPHIEs.

Personality has been conceptualized as a multi-level concept (McAdams, 1995), in which each level advances the understanding in relation to different human behaviors and experiences (John and Srivastav, 1999). While there seem to be limitless personality variables, the general consensus in academic psychology suggests that there are five fundamental personality traits that stand out in terms of explaining an individual's personality. These traits are: extraversion, agreeableness, conscientiousness, emotional stability, and intellect or imagination. The Big Five model is the most accepted and commonly used model of personality, and it is persistently used widely in numerous research contexts and domains (Block, 1995). Previous studies have shown that personality traits are significant predictors for adjustment and success in various contexts (Downes et al., 2010; Kim and Slocum, 2008; Ramalu, Wei and Rose, 2011) and are associated to a range of behaviors (Ozer and Benet-Martinez, 2006), including leadership, job performance (Mount, Barrick, and Stewart, 1998) and academic achievement (e.g., Fairweather, 2012; Heckman, Stixrud and Urzua, 2006; John and Srivastava, 1999; Judge et al., 2007; Singh, 2012). The results of a study conducted by Nye, Orel, and Kochergina (2013) indicate that the importance of different Big Five traits may vary in different team settings. The Big Five Personality Test measures the big five personality traits using the IPIP Big-Five Factor Markers from the International Personality Item Pool, developed by Goldberg (1992).

Test 1 - Reading the Mind in the Eyes (RME) – Social Sensitivity

All participants completed individually the ''Reading the Mind in the Eyes'' test in which they were presented with a series of 36 photographs of the eye region of the face of different actors and actresses, and were asked to choose among four words (possible mental states) to describe what the person in the photograph is thinking or feeling. The options of the words included in the test are complex mental states (e.g., shame, guilt, curiosity, desire) rather than simple emotions (e.g., happiness, anger). Participants earned 1 point for each item answered correctly. Individual scores for participants selected to proceed to the second experiment working in teams (experimental group), were averaged for the team as a whole.

An example from the ''Reading the Mind in the Eyes'' test is given below. A copy of the full test can be found in Appendix IV.

Figure 2: *The ''Reading the Mind in the Eyes'' test – An Example*

Test 2 - Folk Physics Test (Part I)

As mentioned earlier, the test was adapted from Baron-Cohen et al. (2001b), and it comprises 20 items/problems in multiple-choice format, drawn from a variety of sources. All the items/problems can be solved from everyday real-world experience of the physical-causal world. For the first experiment, participants were asked to individually solve only the first ten items/problems of the test and earned 1 point for each item answered correctly. Individual scores for participants selected to proceed to the second experiment working in teams (experimental group), were averaged for the team as a whole. An example from the Folk Physics Test is given below. A copy of the full test can be found in Appendix V.

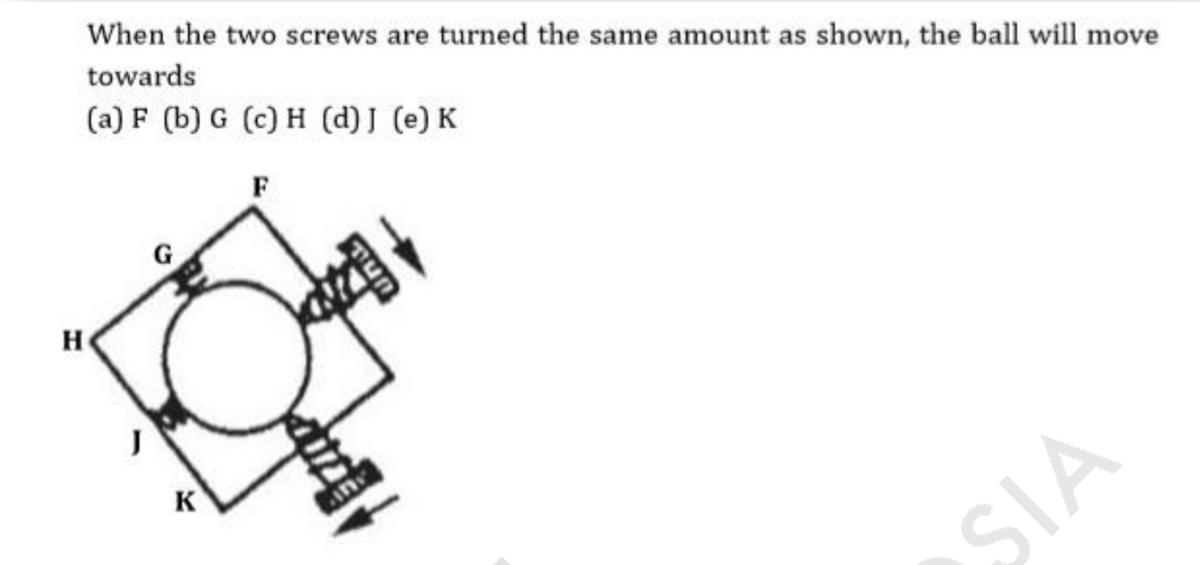


Figure 3: *The "Folk Physics" test – An Example*

Test 3 - Big Five Personality Test (Individual Personality Traits)

Participants completed the Big Five Personality Test (Woodley and Bell, 2011), which measures the five primary dimensions of adult personality: Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Intellect or Imagination. An example from the Big Five Personality Test is given below. A copy of the full test can be found in Appendix VI. Fifty items are responded to on a 1 to 5 scale; the mean for each scale was calculated for each participant. Individual scores on each mean for participants selected to proceed to the second experiment working in teams (experimental group), were averaged for the team as a whole and analyzed in relation to collective intelligence, RME test (Devine and Phillips, 2001) and Folk Physics Test.

	Very Inaccurate	Moderately Inaccurate	Neither Accurate Nor Inaccurate	Moderately Accurate	Very Accurate
Am interested in people.	○	○	○	○	○
Leave my belongings around.	○	○	○	○	○
Am relaxed most of the time.	○	○	○	○	○
Have difficulty understanding abstract ideas.	○	○	○	○	○

Figure 4: *The "Big Five Personality" test – An Example*

Experiment 2 – Measuring Collective Intelligence

The experiment involved the completion of three tasks, aiming to assess collective intelligence. The tasks were completed by all participants, either working in teams (experimental group) or individually (control group).

Justification for the Development of the Tasks

The set of the tasks used in the experiment was based on established taxonomies of team tasks (Larson, 2010; McGrath, 1984) and similar tasks used in prior studies in the field of collective intelligence (e.g. Engel et al., 2014; Engel et al., 2015; Woolley et al., 2010; Woolley et al., 2013). More specifically, the tasks developed or adopted are based on the McGrath Task Circumplex (McGrath, 1984), an established and validated taxonomy characterizing tasks according to the dominant coordination process required for its accomplishment by a team (refer to Figure 5, page 93). The Taxonomy identifies four main types of tasks: (1) Quadrant I, contains ''Generate'' tasks which include brainstorming tasks and anything involving the development of new ideas or information; (2) Quadrant II, includes ''Choose'' tasks which involve deciding about issues that either have a correct answer or which are matters of judgment, with some research noting important distinctions among intellective and judgemental tasks (Larson, 2010); (3) Quadrant III, includes ‘‘Negotiate’’ tasks which involve resolving conflicts of interest or points of view; and (4) Quadrant IV, contains ‘‘Execute’’ tasks which involve performance and psychomotor tasks. Material for two of the tasks was adopted from credible organizations with noteworthy and long involvement in the management of crises, disasters, and emergencies. The tasks are described below:

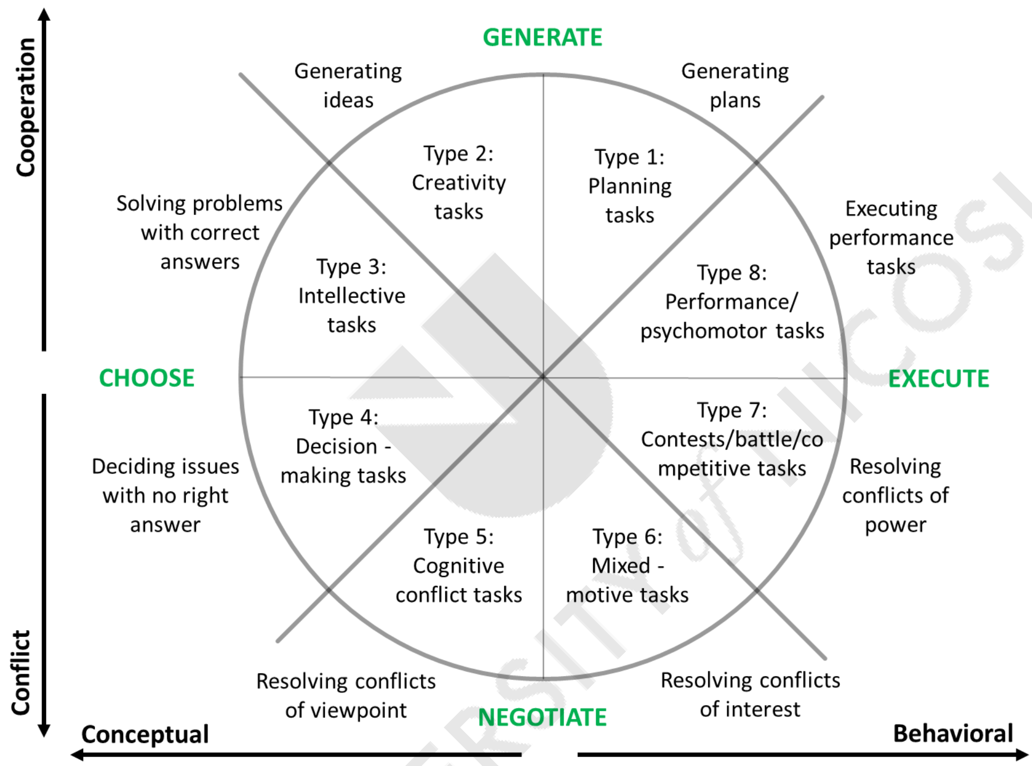


Figure 5: *McGrath Task Circumplex (adopted from McGrath, 1984)*

Task 1 – Emergency Planning Activity – Case Study (Quadrant I)

The task was designed based on material obtained from a course offered by The Federal Emergency Management Agency’s (FEMA’s) Independent Study Program. The Federal Emergency Management Agency is a division of the United States Department of Homeland Security, committed in helping people before, during, and after disasters. The course has been developed for emergency management personnel involved in developing efficient emergency planning systems and offers training in the fundamentals of the emergency planning process.

Participants were required to answer two open-ended questions and two multiple-choice questions (with only one correct answer), based on a case study on Emergency Planning. Supporting Material was provided to all participants, covering topics on the emergency planning process, the main steps of emergency planning, and the parties involved in the process. Participants were given twenty minutes to complete the task. For the two open-ended questions, the individuals (control group) or teams (experimental group) earned 1 point for each issue relevant to the question, covered in their answer; and 1 point for each multiple-choice question answered correctly. A copy of the task can be found in Appendix VII.

Task 2 - Folk Physics Test Part II (Quadrant II)

The task required participants to solve the remaining ten items/problems included in the Folk Physics test described in the first experiment and were given 10 minutes to complete the task. The individuals (control group) and teams (experimental group) earned 1 point for each item answered correctly. A copy of the test can be found in Appendix V.

Task 3 - Tsunami Disaster Scenario (Quadrants III & IV)

The task was designed based on material adopted by Stop Disasters! a resource management and strategy game developed to educate about the warning signs of disasters and the methods of reducing casualties and impact as a result of natural catastrophes. The game has been launched by the United Nations International Strategy for Disaster Reduction and many organizations such as the International Federation of Red Cross and the Center for Research on the Epidemiology of Disasters as well as experts on education, emergency management scenario development and disaster risk reduction, have participated in the development of its contents and the making of the game.

The participants of the experiment were given 20 minutes in total to complete a task on a tsunami disaster scenario, which included three activities. To help solve the activities, all participants were initially provided with Fast Facts about tsunamis, including information about what a tsunami is, the elements most at risk during a tsunami, and how communities can become more resilient. Participants were given 10 minutes to read the Fast Facts sheet and were asked to remember as must information as possible, as they were not allowed to take notes of any kind, on the information provided on tsunamis. For participants working in teams (experimental group), this meant that information could be separated and allocated between the team members for maximum results. Subsequently, the participants were given 10 minutes to complete the activities and were presented with a map, which was an overview of the current area they were requested to work on that encompassed five levels of risk exposure.

For the first activity, participants were required to identify the factor/s based on which the map (presented in color in Appendix VIII) was separated into different levels of risk. Individuals (control group) and teams (experimental group) earned 1 point for each relevant to the question issue, covered in their answer.

For the second activity, participants were asked to indicate the level of risk each tile in the map (presented in grayscale in Appendix VIII), is exposed to, using coloring pencils. The map included five levels of risk, and different colors were indicative for each level of risk exposure. Individuals (control group) and teams (experimental group) were given 1 point for each tile indicated with the correct risk level exposure color.

For the third activity, participants were required to indicate with ‘’ X ’’ the best location (tile) on the map (presented in color in Appendix VIII), to build a hospital and were asked to justify their decision. Individuals (control group) and teams (experimental group) were given 1 point for placing the hospital at tiles of minimum risk level exposure. In addition, they earned 1 point for each reasonable justification provided for the selection of the hospital’s location. A copy of the task can be found in Appendix VIII.

Experiment 3 – Measuring the Construct of Transactive Memory System (TMS)

The third experiment aimed to assess Transactive Memory System (TMS) measures and only the participants who were selected to work in teams (experimental group), during the second experiment, were required to participate in the third experiment. Participants were asked to complete individually, a TMS scale, developed by Lewis (2003). The TMS measurement model used for the experiment can be found in Appendix IX. The three dimensions of a Transactive Memory System: Specialization, Credibility, and Coordination, are measured in the model by five items each. All items respond to a 5-point disagree-agree format, in which 1 = *strongly disagree*, 2 = *disagree*, 3 = *neutral*, 4 = *agree* and 5 = *strongly agree*.

3.6 Analysis of Primary Data

The three interlinked experiments designed for the purposes of the Thesis collect both qualitative and quantitative data. However, all qualitative data was quantified, and the analysis was quantitative in nature. The decision to quantify all primary data relates mainly to the different focus and objective of each experiment. The first experiment measures Individual Intelligence, the second experiment measures Collective Intelligence while the third experiment measures the Construct of Transactive Memory System (TMS). Despite their different focus and objective, however, all three experiments collectively contribute in answering the main research question of the Thesis (including sub-questions) and meeting the research objectives; a fact that raises the need for a unified mechanism of data analysis that will allow to extract maximum benefit from subjective information. The quantification of the qualitative data, therefore, enables the researcher to draw associations, identify correlations, and make comparisons between variables examined separately in each experiment. Such quantification of qualitative data is considered by Rahman and Areni (2016) as an innovative approach to knowledge creation.

3.6.1 Statistical Analysis

Statistical analysis was performed in R, a programming language and software environment for statistical computing and graphical display available under an open-source license (De Vries and Meys, 2019).

R was preferred over other statistical software packages because it is actively maintained, having functional connectivity to various types of data and other systems, and it is versatile enough to solve problems in many domains (De Vries and Meys, 2015). In addition, it is highly extensible in the sense that users can contribute new statistical methods, as well as improvements and fixes to the R code (De Vries and Meys, 2015; NewGenApps, 2017). This is something that makes R very stable and reliable in regards to data processing and statistical modeling since developments are happening at a rapid scale. It contains an extensive library of tools for database manipulation and data wrangling that allow advance processes of cleaning messy and complex data sets to enable convenient consumption and further analysis (De Vries and Meys, 2019; NewGenApps, 2017). An additional reason for selecting R over other statistical software packages is that it offers many tools and graphical techniques that can help in data visualization and representation. The dynamic and flexible data visualization offered allows data analysis from diverse angles (De Vries and Meys, 2015).

3.7 Summary and Conclusions

The Chapter presented the methodological foundation of the Thesis. It has been concerned with the nature and purpose of the research. The current study has been classified as 'applied' and 'experimental' with mainly an exploratory purpose. However, it has been acknowledged that in meeting the research objectives and addressing the multidisciplinary nature of the research topic, at different stages, the study is found to be also explanatory and descriptive. It examined the different philosophical positions to social science and discussed in detail the philosophical positioning most closely related to this research. The research identifies with both aspects of ontology (objectivism and subjectivism). The researcher adopts a realist perspective, as a complementary paradigm, in order to overcome limitations that arise from the use of a single paradigm in the conduction of mixed methods research and argues that combining pragmatism with a critical realist ontology offers an interesting and potentially productive philosophic frame for the current Thesis.

In addition, the Chapter dealt with the two fundamental elements of the research design: the Research Choice, and the Research Strategies over which the study was undertaken. The Research Choice is concerned with the way in which the researcher decides to combine quantitative and qualitative techniques and procedures for data collection and analysis. Based on several considerations including the nature, the purpose of the study and the main research question, the Thesis employed multiple methods for the collection and analysis of data. More specifically, the study employed mixed methods. Mixed methods, allowed the use of different research methods, for different purposes in the study and enabled triangulation to take place. Within the spectrum of mixed methods, a mixed-model research approach was adopted, that allowed the combination of quantitative and qualitative data collection techniques and analysis procedures as well as the combination of quantitative and qualitative approaches. The Chapter presented the development process used to arrive to the proposed CI Maturity Assessment (CIMA) Model and discussed the research strategies used throughout the whole development process. The research strategies employed relied on both deductive and inductive reasoning. Secondary data were collected through an extensive review of the theory and literature using the deductive method. Primary data were collected with the implementation of an experimental research strategy during the 'evaluate design' phase of the maturity model development cycle, that involved multiple experiments. Furthermore, the contribution of expert opinion acquired at different stages of the study as the research progressed, by specialists in the field, has been highlighted. Expert opinion provided support in narrowing the research focus, the selection of best research strategies and methods for the investigation of the problem addressed by the Thesis, the design of the CI Maturity Assessment (CIMA) Model and the multiple experiments for the evaluation of the model, as well as best techniques for data analysis.

Within the maturity model development process, focusing exclusively on the 'evaluate design' phase of the first development cycle of the proposed model, the Chapter justified the methodological foundation based on which the design of the proposed maturity model, has been evolved. The experimental research strategy as the main source of primary data collection in this Thesis with the conduction of the multiple experiments has been discussed, and criticism on the methodology selected for the evaluation of the proposed maturity model has been presented. The design of the multiple experiments conducted and the experiments' protocol have been detailed. Furthermore, the characteristics of the sample selected, have been reviewed. The internal and external validity of the experiments has been also discussed. Each experiment has been investigated separately, and justification for the selection of the material adopted, developed, and used has been provided.

General information on how the analysis of primary data was conducted have been given. The three interlinked experiments collected both qualitative and quantitative data. However, all qualitative data collected were quantified, and the analysis was quantitative in nature. The decision to quantify all primary data collected throughout the experimentation process has been justified. In addition, the reasons R was preferred over other statistical software for the analysis of the data, have also been explained.

Chapter 4 CIMA Model Development Process – Research Findings

4.1 Introduction

The current Chapter details the complete process followed for the development of the Collective Intelligence Maturity Assessment (CIMA) Model and constitutes an analysis of the data gathered through the conduction of the three interlinked experiments, in order to assess the design of the proposed maturity model. A complete maturity model development cycle, as previously seen, consists of four phases, and it is usually initiated by a 'need and require intention'. Two iterations of the development cycle have been performed to arrive to the proposed maturity model. This has gradually increased the expressive power of the model. Throughout the Chapter, it is examined whether the specific research questions are answered.

The Chapter is initially concerned with the first development cycle in which an initial design of the CIMA Model is proposed. The form and function of the initial design are discussed. In addition, during the first development cycle, an initial analysis of the primary data collected through the three interlinked experiments is performed. After the completion of the first development cycle, the Chapter proceeds to examine the second development cycle in which an improved design of the CIMA Model is presented. Furthermore, during the second development cycle, a complete analysis of the primary data is conducted.

The analysis is initially concerned with the data gathered through the conduction of the first experiment, in which the individual intelligence of the participants was measured. Descriptive statistics for the 100 participants on the three tests used to assess individual intelligence are presented. The three tests measured the participants' personality (Big Five Personality Test), their ability of spontaneously understanding the workings of the physical world (Folk Physics Test – Part I), and their ability to understand social causality (Reading the Mind in the Eyes Test - RME). The correlations between these measures are examined. The analysis then focuses on the data collected through the second experiment, in which Collective Intelligence was measured. The experiment involved the completion of three tasks. A comparison between the Control and Experimental groups is provided and demographic differences between the two are identified. Furthermore, the performance of each group (Control and Experimental) on each of the three tasks is examined thoroughly and a comparative analysis is provided. The Experimental group is examined in detail by providing statistics on the demographic characteristics by team. In addition, associations of the Total Task Score (average of the Task 1, Task 2 and Task 3 scores) and Collective Intelligence in relation to the teams' demographic composition and Experiment 1 measurements (participants' personality traits, individual ability of spontaneously understanding the workings of the physical world and ability of understanding social causality), are explored. Moreover, the performance of the teams in each of the three tasks, in relation to Team Interaction and Collective Intelligence, is explored, and correlations are highlighted. It is also explored whether the diversity in the sample's demographic information and Experiment 1 measurements (composition of teams) are associated with the Total Task Score (indicative of the overall performance outcome of the teams) and Collective Intelligence. The data collected through the third experiment, which measured the construct of Transactive Memory Systems developed in the teams during the conduction of Experiment 2, are also examined. Descriptive statistics on the TMS components (Coordination, Credibility, and Specialisation) and TMS Total Scale for the 50 Experimental group participants (only individuals who worked in teams at Experiment 2, have participated in Experiment 3) are provided. Correlations between TMS and task scores, Collective Intelligence, and Team Interaction are explored. Additional research findings considering the total sample (N=100) of participants are discussed. A multiple linear regression model fitted to regulate the multivariate effect of the Experiment 1 measures, including demographic characteristics to the Total Task Score (TTS) obtained in Experiment 2, is presented. The model takes account of whether the participants took place in Experiment 2 individually or as a member of a team. Furthermore, a draft model for predicting team interaction, that was developed for exploratory purposes, is presented.

In the last phase of the second development cycle, the results of the data analysis are taken into consideration and several changes in regards to the form and function of the improved CIMA Model are made. The final design of the CIMA Model is presented and its form and function are discussed in detail. The final design of the CIMA Model integrates in full the maturity of the phenomenon under study.

4.2 CIMA Model - First Cycle: Define Scope Phase

The first phase in developing a maturity model, as shown in the maturity model development process adapted from Mettler (2011), is to define the scope of the proposed model (refer to Figure 6). Several decisions concerning the scope of the proposed model and their combination influence all the remaining phases of the development cycle (de Bruin et al., 2005; Mettler, 2009).

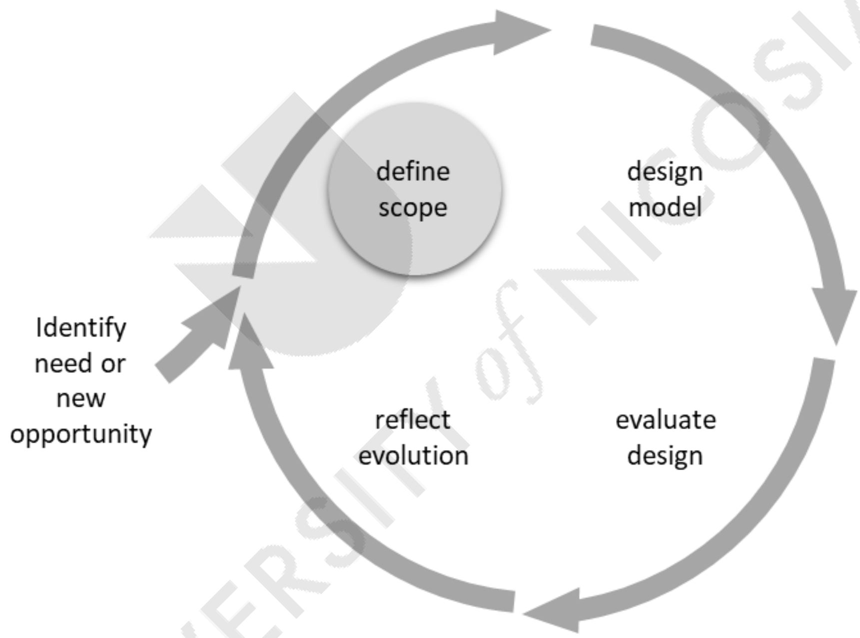


Figure 6: *Maturity Model Development Process: Cycle 1 – Phase 1 (adapted from Mettler, 2011)*

Table 3 (see page 103), adopted from Mettler (2009), presents the phases involved in the development cycle in relation to decision parameters that should be taken into account during the development of a maturity assessment model. Within the 'define scope' phase, the most important decision to be made is concerned with the focus of the model. Focus refers to which domain the maturity model would be targeted and applied (de Bruin and Rosemann, 2005; Mettler, 2009).

Table 3: *Decision parameters during maturity model development (from Mettler, 2009)*

Phase	Decision parameter	Characteristic			
Define scope	Focus/breadth	General issue	Specific issue		
	Level of analysis/ depth	Group decision-making	Organisational considerations	Inter-org. considerations	Global & societal considerations
	Novelty	Emerging	Pacing	Disruptive	Mature
	Audience	Management-oriented	Technology-oriented	Both	
	Dissemination	Open	Exclusive		
Design model	Maturity definition	Process-focussed	Object-focussed	People-foccused	Combination
	Goal functioning	One-dimensional	Multi-dimensional		
	Design process	Theory-driven	Practitioner-based	Combination	
	Design product	Textual description of form	Textual description of form and functioning	Instantiation (assessment tool)	
	Application method	Self-assessment	Third-party assisted	Certified professionals	
	Responders	Management	Staff	Business partners	Combination
Evaluate design	Subject of evaluation	Design process	Design product	Both	
	Time-frame	Ex-ante	Ex-post	Both	
	Evaluate method	Naturalistic	Artificial		
Reflect evolution	Subject of change	None	Form	Functioning	Form and functioning
	Frequency	Non-recurring	Continuous		
	Structure of change	External / open	Internal / exclusive		

The focus of the proposed CI Maturity Assessment Model is domain-specific addressed to both the academia and practitioners. Focusing on the Low Probability High Impact Events (LoPHIEs) domain and within this specified domain, focusing the model further, with the integration of the concept of CI distinguishes the proposed model from other existing models and has determined the specificity and extensibility of the model. The overall scope of the proposed model and other decisions related to the 'define scope' phase, such as the novelty of the subject, the audience, and dissemination of the model (Hevner et al., 2004), have been addressed in Chapter One of the Thesis and in Sections 2.2 and 2.3 of Chapter Two.

Table 4 presents a framework of general design principles for maturity models developed by Pöppelbuß and Röglinger (2011) and adopted accordingly for the purposes of the current study in order to help respond to specific information in regards to the proposed maturity model. Thinking of the framework (refer to Table 4) in relation to Mettler's (2011) development cycle, items (a) to (e) in regards to the *Basic information*, correspond to the 'define scope' phase. According to Pöppelbuß and Röglinger (2011) attending to the items presented in the basic information section of the framework, enables to sharpen the field of work and provide support in the classification of the model (Ahlemann, Schroeder and Teuteberg, 2005; Becker, Knackstedt and Pöppelbuß, 2009; Benbasat et al., 1984; de Bruin et al., 2005; Hevner et al., 2004; Solli-Sæther and Gottschalk, 2010).

Table 4: *General design principles for maturity models (adopted from Pöppelbuß and Röglinger, 2011)*

Group		Design Principles
BASIC	**1.1**	**Basic information** a) Application domain and prerequisites for applicability b) Purpose of use c) Target group d) Class of entities under investigation e) Differentiation from related maturity models f) Design process and extent of empirical validation
	1.2	**Definition of central constructs related to maturity and maturation** a) Maturity and dimensions of maturity b) Maturity levels and maturation paths c) Available levels of granularity of maturation d) Underpinning theoretical foundations with respect to evolution and change
	1.3	**Definition of central constructs related to the application domain**

In regards to the items (a) to (e) of the *Basic information*, the proposed model is: (a) to be applied in the Low Probability High Impact Events (LoPHIEs) domain (the gap identified within this domain is concerned with decision-making difficulties), (b) to be used to provide decision support to teams tasked with the management of LoPHIEs, guiding the strategic decision making required for successful and sustainable management, (c) targeted to those affected or involved in the management of an adverse event, (d) entities from both the LoPHIEs and CI domains are investigated (e) focusses on the assessment of CI maturity. CI has not been previously considered as a systemic dimension that can provide collectives with a methodological assessment of their maturity levels in dealing with LoPHIEs.

4.3 CIMA Model - First Cycle: Design Model Phase

Drawing back to the maturity model development process adapted from Mettler (2011), the second phase of developing a maturity assessment model, is concerned with the design of the model (refer to *Figure 7*).

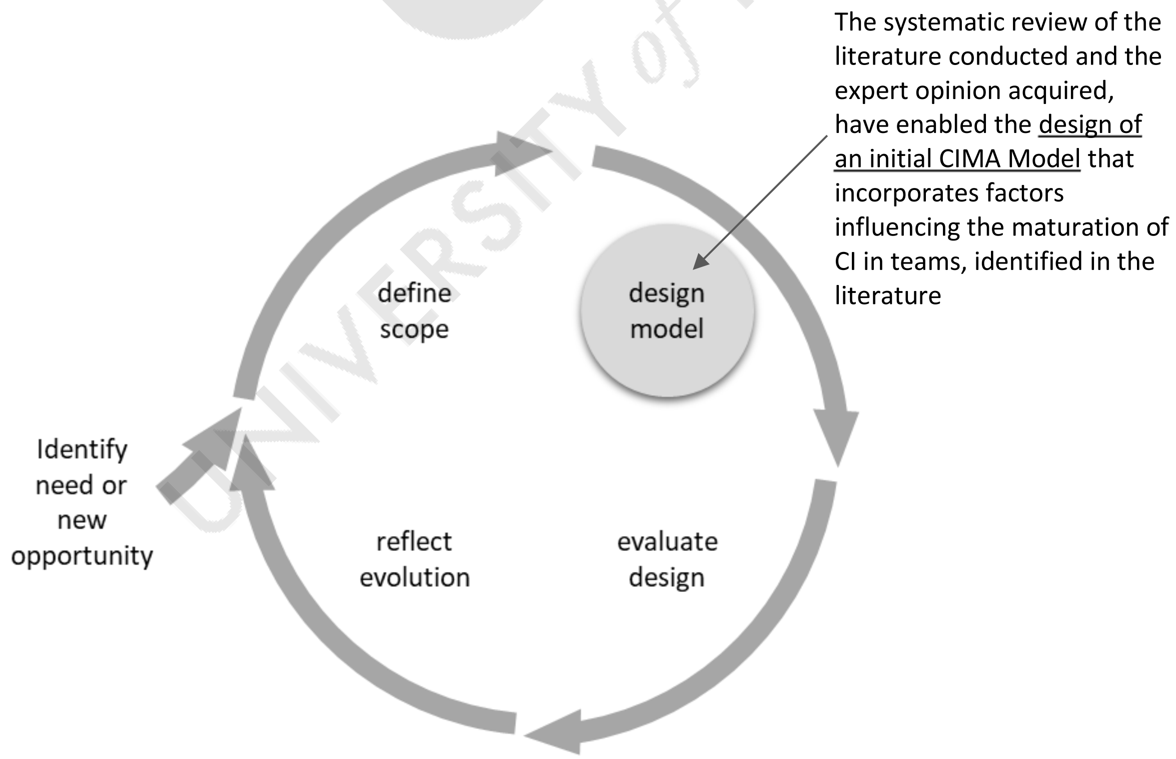


Figure 7: *Maturity Model Development Process: Cycle 1 – Phase 2 (adapted from Mettler, 2011)*

Within the 'design model' phase, it is very important to have a clear understanding of what 'maturity' means in the domain of application. Thinking of Pöppelbuß's and Röglinger's (2011) framework of general design principles for maturity models (refer to Table 4, Section 4.2, page 104), in relation to Mettler's (2011) maturity models development cycle, items (a) to (d) in regards to the *Definition of central constructs related to maturity and maturation*, correspond to the 'design model' phase. Based on the above, it is necessary to define central constructs concerning maturity and maturation (Becker et al. 2010). Drawing back to Mettler's (2009) decision parameters during maturity model development (refer to Table 3, Section 4.2, page 103), thinking of maturity in terms of processes/structures, objects/technology, people/culture or a combination of these, can help arrive to a comprehensive definition of maturity. A process-focused understanding of maturity necessitates focusing on activities and work practices, such as inputs and outputs of particular tasks, in order to establish more effective procedures. With an object-focused understanding, the features of work products (for example, functional and non-functional standards) are studied with the intention to improve their mode of operation. Having a people-focused understanding of maturity, focusing on people's skills and proficiency, requires to stress on soft capabilities, such as people's feelings and behavior. Drawing back to the literature provided in regards to LoPHIEs, the management of such events, is a set of factors that form a process (Coombs and Holladay, 2010), which is usually distinguished into three phases, namely methods that are introduced *before* the event for prevention and preparation; methods that are initiated *during* the event to limit damage and methods that examine the aftermaths (Bernstein, 2011; Coombs and Holladay, 2010; Coombs, 2007). These phases do not stand alone but interlock. Throughout these phases, the management of LoPHIEs involves the coordination of many different types of multi-faceted processes, ranging from highly structured and predefined processes guided by protocols and emergency operating procedures; to highly ad-hoc and emergent processes that are designed and managed as they evolve (Labadie, 2008; Lettieri, Masella and Radaelli, 2009; Lin Moe and Pathranarakul, 2006).

On the other hand, in regards to CI, drawing on the literature provided in Section 2.3 of Chapter Two, a group's CI is greatly influenced by two facts: (1) Group Composition, such as the individual skills of team members, cognitive diversity and individual intelligence and (2) Group Interaction, such as structures, processes and norms that regulate collective behavior in ways that enhance the quality of coordination and collaboration. Therefore, considering the above, the definition of maturity within the bounds of the current study, based on which the proposed CI Maturity Assessment Model is developed, incorporates a combination of two dimensions: 1. processes/structures (process-focused understanding of maturity) and 2. People/culture (people-focused understanding of maturity). Through this clarification of 'maturity', the goal function of the model - that is, the way maturity progresses, is tacitly influenced. In relation to this, according to Mettler (2009), it is important to consider whether the progress of maturity is one-dimensional (focusing solely on one target measure) or multi-dimensional (focusing on multiple target measures, frequently on divergent goals or competitive bases). The progress of maturity within the bounds of the current study is multi-dimensional. A multi-dimensional approach according to De Bruin et al. (2005), facilitates the definition of assessment criteria and the classification of improvement measures. The extensive scope of elements reviewed and incorporated in the model has been demanded by the very nature of the specified research problem, which necessitates a comprehensive approach involving all potential factors affecting CI and its maturation within the specified application domain.

Maturity is commonly represented within existing maturity models, as a number of cumulative levels. Based on this design principle, higher levels build on the requirements of lower levels with 5 representing high maturity and 1 representing low maturity. The number of levels, however, can differ depending on the case. This practice according to De Bruin et al. (2005), was made popular by the Capability Maturity Model CMM and appears to have extensive practical acceptance. Level definitions should be developed and provide a summary of the major requirements and measures. The maturity levels defined for the proposed maturity model, are discussed at a later point in relation to the initial Collective Intelligence Maturity Assessment (CIMA) Model.

One of the main difficulties faced with while defining the maturity levels for the CIMA Model was that the proposed maturity model is developed for a highly unexplored phenomenon. Even though both the domain of LoPHIEs and the domain of CI study independently a mature phenomenon, this is the first time, to the best of the researcher's knowledge that both are studied jointly, in an attempt to provide a more efficient solution to the problem under investigation. When developing a maturity assessment model for a highly innovative phenomenon, the justificatory knowledge to be based on is weak or missing. In addition, principles of form and function are vague due to the absence of a dominant design (Mettler, 2009). Furthermore, as Mettler (2011, p. 88) notes, when building a maturity model for a highly innovative phenomenon, ''the required cases to derive the maturity levels and recommendations may be missing as well''. In order to overcome the above difficulties, a top-down approach was eventually used for defining the maturity levels for the CIMA model. The specific approach according to De Bruin et al. (2005), works well when the domain of application is rather new, and there is little evidence of what is thought to represent maturity. This is because the top-down approach gives emphasis first on what represents maturity and then on how maturity can be measured.

Drawing back to Table 4 (see page 104), it is of significant importance that a maturity model explicates the basic theory of evolution and change in relation to the class of entities under investigation – refer to item (d) in the *Definition of central constructs related to maturity and maturation* (Benbasat et al. 1984, King and Kraemer 1984). This includes taking into consideration the way change typically takes place in the specified application domain, as well as addressing drivers and barriers associated with maturation. The dimensions of the conceptual definition of LoPHIEs, in regards to the statement of the problem being addressed by the current study, provided in Chapter One, form the foundations of the basic theory of evolution and change in the specified field. These dimensions are: 1) Threat 2) Decision time 3) Awareness (surprise). The specific ways in which the notions of risks and uncertainty are conceptualized also contribute to the basic theory of evolution and change within the concept of managing LoPHIEs. In regards to CI, underpinning theoretical foundations of evolution and change may be traced to the concept's people-focussed understanding of maturity. The evolution and change of CI within teams are greatly influenced by the individual skills of team members, cognitive diversity, and individual intelligence (group composition) as well as by the structures, processes, and norms that regulate collective behavior (group interaction). When sufficient understanding of their influence on performance is achieved, the combination of these same factors, become drivers of the maturation of CI. On the other hand, failure to comprehend sufficiently the individual and collective impact of these factors on performance prohibits the maturation of CI in teams.

Decisions related to the nature of the design process have to also be taken at the ‘design model’ phase. Considering whether the desired model is theory-driven, practitioner-based, or a combination of both will help identify the knowledge base for deriving the maturity levels, the metrics, and the related improvement suggestions. Deciding on the nature of the design process is of particular importance as this influences greatly the choice of the research methods to be used. For example, whether the model has been constructed by undertaking a systematic literature review (theory-driven) versus arriving to the model by carrying out industry focus group discussions (practitioner-based). Decisions concerning the nature of the design process can also influence the scientific and practical quality of the resulting design product. The quality of the resulting product, according to Mettler (2011), is also determined by its shape, whether it is a pure textual description of the form and functioning of the maturity model or if it is, for example, instantiated as a software assessment tool. In addition, the application method (whether the data collection is based upon a self or a third-party assessment) and the setting of the respondents for data collection (e.g., management, staff, business partners, or a combination), also affect the quality of the maturity model. Undoubtedly, the design process and the actual maturity model are also strongly influenced by the skills of the developer (e.g., research and programming skills) and the resources available for the development of the model (e.g., academic and business partners).

4.3.1 CIMA Model – Initial Design

With reference to Pöppelbuß’s and Röglinger’s (2011) framework of general design principles for maturity models (refer to Table 4, Section 4.2, page 104), item (f) of the *Basic information*, by adopting a combination of theory-driven and practitioner-based design process, an initial CI Maturity Assessment Model was designed through systematic literature review and expert opinion. The systematic literature review helped identify factors that influence the maturation of CI in teams. These factors are ultimately compiled through the design of the initial CI Maturity Assessment Model. Building on the theoretical foundations of maturity assessment models, the initial model designed takes into consideration underpinning theoretical foundations of evolution and change in regards to CI. These have been examined in depth in Section 2.3 of Chapter Two. Definitions of central constructs related to the specified application domain and considerations in regards to the way evolution and change typically take place in the domain of LoPHIEs (these have been examined in depth at Chapter One and in Section 2.2 of Chapter Two) have been incorporated in the design of the multiple experiments. The initial CI Maturity Assessment Model is depicted in Figure 8.

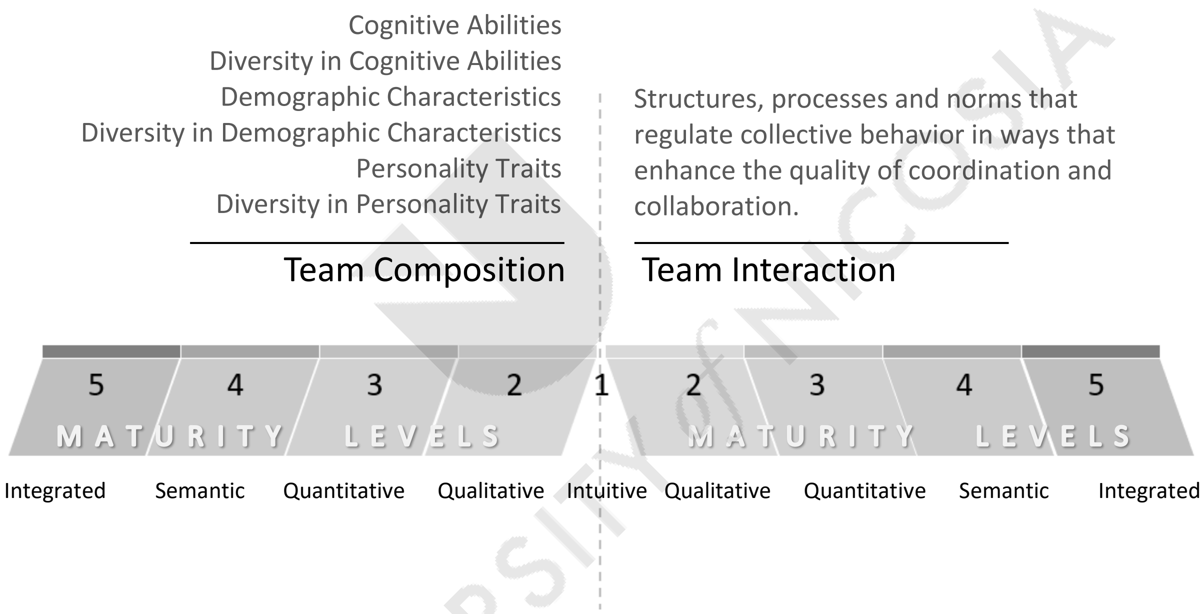


Figure 8: *CIMA Model – Initial Design*

As seen in Figure 8, the initial design of the CIMA model incorporates two dimensions: 1. Team Composition, and 2. Team Interaction. Both dimensions mature in five levels, from an intuitive to an integrated stage. Within the dimension of *Team Composition*, the factors included correspond to six categories that have been identified in the literature to influence the maturation of CI in teams. These categories are: 1. Cognitive abilities (includes: the ability of understanding social causality, as measured by the Reading the Mind in the Eyes RME test and the ability of spontaneously understanding the workings of the physical world – understanding physical causality, as measured by the Folk Physics test), 2. Diversity in cognitive abilities (includes: the diversity in the ability of understanding of social causality and the diversity in the ability of understanding of physical causality), 3. Demographic characteristics (includes: age and Risk Management Relevance - RMR), 4. Diversity in demographic characteristics (includes: diversity in age and diversity in Risk Management Relevance – RMR), 5. Personality traits (includes the five primary dimensions of adult personality, as measured by the Big Five Personality Test: Extraversion, Agreeableness, Conscientiousness, Emotional Stability and Intellect or Imagination, 6. Diversity in personality traits (includes: the diversity in the five primary dimensions of adult personality). The dimension of Team Interaction incorporates structures, processes, and norms that regulate collective behavior in ways that enhance the quality of coordination and collaboration. The definitions developed for the maturity levels for each dimension have been derived based on secondary data and expert opinion. The definitions of the maturity levels are shown below:

Maturity level 1: Intuitive

Team Composition:

Teams are formed with complete ignorance of how team composition dimensions influence performance. There is a lack of formal tools to measure dimensions of team composition (individual and collective intelligence as well as demographic characteristics in teams).

Team Interaction:

Team interaction is at a low level, with no presence of knowledge sharing. There is complete ignorance of how structures, processes, and norms regulate collective behavior in ways that enhance the quality of coordination and collaboration. Formal tools to measure team interaction levels are absent.

Maturity level 2: Qualitative

Team Composition:

Team composition dimensions are intuitively assessed and analyzed. However, there is still a lack of formal tools to measure dimensions of team composition (individual and collective intelligence as well as demographic characteristics in teams).

Team Interaction:

Team interaction is at low – medium level, with limited knowledge sharing. The team interaction level is intuitively assessed, but formal tools to perform a comprehensive assessment are absent. Structures, processes, and norms that regulate collective behavior are intuitively being considered.

Maturity Level 3: Quantitative

Team Composition:

Plans are developed to assess and analyze team composition dimensions and assist in ways that positively influence performance. There is some awareness of diversity (in terms of personality traits, cognitive abilities, social category diversity, and demographic characteristics) and how it influences team performance. Some supporting tools to measure dimensions of team composition are in place, offering some reporting and metrics.

Team Interaction:

Team interaction is at a medium level, with improved knowledge sharing and interaction style. Some supporting tools to measure team interaction levels are in place, offering some reporting and metrics. There is a limited understanding of how structures, processes, and norms regulate collective behavior in ways that enhance the quality of coordination and collaboration.

Maturity Level 4: Semantic

Team Composition:

Intuitive team modification based on team composition dimensions and awareness of diversity, with limited understanding of how these dimensions influence team performance. Supporting tools to measure dimensions of team composition are in place, offering advanced reporting and metrics.

Team Interaction:

Team interaction is at medium-high level, with extensive knowledge sharing. There is improved understanding of the structures, processes, and norms that regulate collective behavior in ways that enhance the quality of coordination and collaboration. Supporting tools to measure team interaction are in place, offering advanced reporting and metrics.

Maturity Level 5: Integrated

Team Composition:

There is informed team modification based on team composition dimensions and awareness of diversity, with a comprehensive understanding of how these dimensions influence team performance. Extensive supportive tools to measure dimensions of team composition are in place, offering measurable results.

Team Interaction:

Team interaction is at a high level, with broad knowledge sharing. There is a comprehensive understanding of how the structures, processes, and norms that regulate collective behavior in ways that enhance the quality of coordination and collaboration. Extensive supporting tools to measure team interaction levels are in place, offering measurable results.

4.4 CIMA Model - First Cycle: Evaluate Design Phase

Drawing back to the maturity model development process adapted from Mettler (2011), this section examines the 'evaluate design' phase (refer to Figure 9).

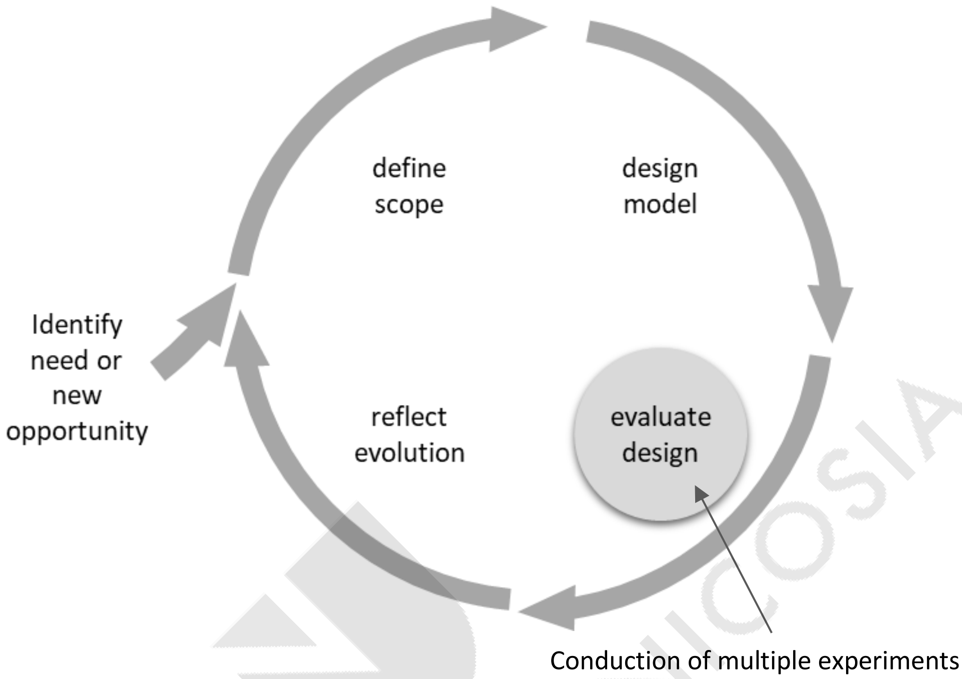


Figure 9: *Maturity Model Development Process: Cycle 1 – Phase 3 (adapted from Mettler, 2011)*

The 'evaluate design' phase, is concerned with the verification and the validation of the designed maturity model. Consistent with Conwell, Enright and Stutzman (2000), Mettler (2011, p. 92) notes that ''verification is the process of determining that a maturity model represents the developer's conceptual description and specifications with sufficient accuracy and validation is the degree to which a maturity model is an accurate representation of the real world from the perspective of the intended users of the model.''

The decisions needed to be taken in the 'evaluate design' phase (refer to Table 3, Section 4.2, page 103), according to Pries-Heje, Baskerville and Venable (2008) can be reflected in: *what* is the subject of evaluation, *when* is the subject evaluated (time-frame) and *how* the subject is evaluated. In regards to defining the subject of evaluation, this can be the design process (the way the model was constructed) or the actual design product (the model itself) (Pries-Heje, Baskerville and Venable, 2008) or according to Mettler (2009) both (the design process and the actual design product) can and should be subject to evaluation. Regarding decisions concerning the point in time of evaluation, it should be resolved whether this will be ex-ante versus ex-post. In other words, deciding whether the evaluation will be based on forecasts rather than actual results (ex-ante) or whether it will be based on actual results rather than forecasts (ex-post). Decisions about the time-frame influence the method of evaluation. This is whether the evaluation will be conducted on the basis of naturalistic methods or on the basis of artificial methods.

In the case of the current study, only the actual design product is being evaluated during the ‘evaluate design’ phase. The evaluation process aims to arrive to wholistic improvements in regards to the final model proposed. The initial model designed is assessed with the three interlinked experiments that have produced actual results, and therefore the evaluation is not based on forecasts (ex-post time-frame). The results produced through the experimentation process have informed in regards to new parameters and factors that are needed to be integrated into the model design and have led to the development of the proposed maturity assessment model. The reader may find complementary information in regards to the ‘evaluate design’ phase of the first development cycle in Section 3.5 of Chapter Three.

4.5 CIMA Model - First Cycle: Reflect Evolution Phase

This section examines the last phase of the first development cycle of the proposed maturity model, ‘reflect evolution’ in which the design resilience of the initial maturity model is being considered (refer to Figure 10, page 116).

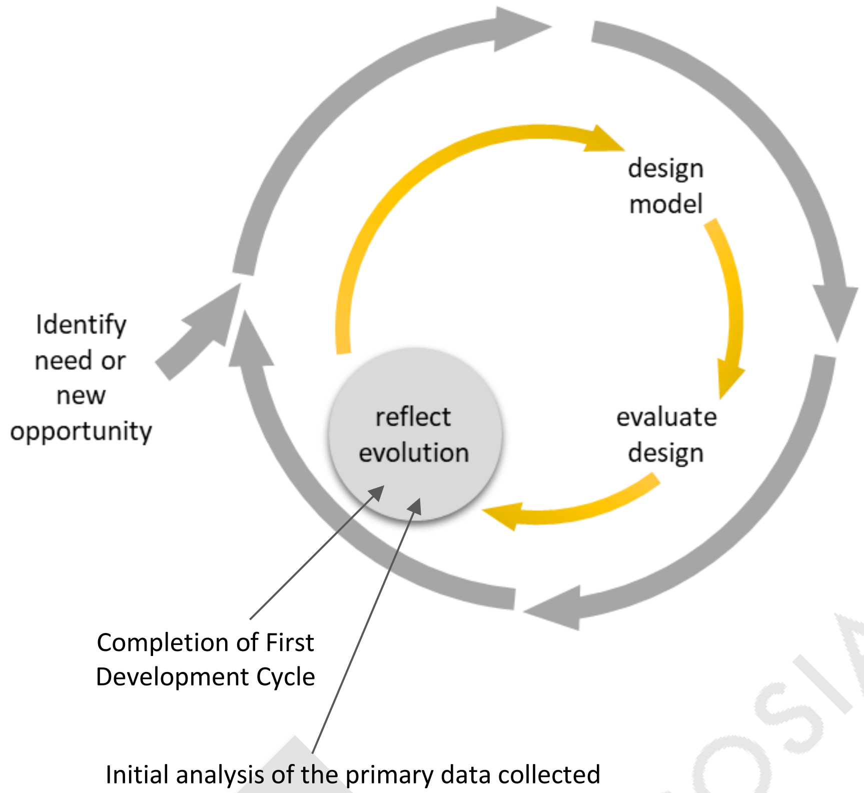


***Figure 10:** Maturity Model Development Process: Cycle 1 – Phase 4 (adapted from Mettler, 2011)*

The application during the 'evaluate design' phase of the initial design of the CI Maturity Assessment (CIMA) Model and the initial analysis of the primary data collected throughout the three interlinked experiments, in relation to the specific research questions (incorporating the factors influencing the maturation of CI, identified through the systematic review of the literature), have led to the identification of additional factors that play a significant role in the maturation of CI in teams. These factors are related to task classification. In addition, the initial analysis of the primary data collected and the identification of the additional factors related to the maturation of CI in teams, have led the researcher to examine the tasks included in the second experiment in relation to additional task taxonomies and have created the need for further literature review for the interpretation of the research findings.

Table 5 presents descriptive information on the tasks developed or adopted for the second experiment, focusing on the characteristics of each task. It provides information on the task type (whether it is a closed task, open-ended or a combination of the two), the content of the information needed to be processed for each task, the skills required for their completion, the complexity of the tasks and relevance to the management of LoPHIEs as well as whether supporting material was provided and on what fashion knowledge was distributed.

Table 5: Task Classification

TASK CLASSIFICATION							
TASK		**TYPE OF TASK**	**CONTENT OF THE INFORMATION PROCESSED (based on)**	**SKILLS REQUIRED**	**COMPLEXITY**	**DIRECT RELEVANCE TO THE MANAG. OF LoPHIEs**	**SUPPORTING MATERIAL PROVIDED AND ACCESS**
1	Emergency Planning Activity – Case Study	Closed and Open-Ended	Social Cognitive Domains	Combination of: Coordination and Accuracy	Medium	Yes	Yes/Access allowed at any point during the completion of the task
2	Folk Physics Test (Part II)	Closed	Analytic (or Non-Social) Cognitive Domain	Accuracy	Low	No	No
3	Tsunami Disaster Scenario	Open-Ended	Social Cognitive Domain	Coordination	High	Yes	Yes/Access prohibited during the completion of the task

Performance is heavily influenced by the type of task at hand (Truninger et al., 2018). Open-Ended tasks usually have a range of appropriate responses/solutions and take longer to complete. Closed tasks, on the other hand, usually have one correct answer and can be completed quickly. Responders, based on the type of the task, reveal different thinking processes and levels of understanding (Way, 2013). Open tasks assess a range of knowledge and skills and provide information about problem-solving strategies and thinking. In addition, they offer the opportunity to demonstrate higher levels of understanding. In contrast, closed tasks evaluate a specific skill or procedure or one specific piece of knowledge. The information provided through a closed task, about the responders' thinking is limited. Also, closed tasks offer limited opportunities to demonstrate higher levels of understanding (Way, 2013). TASK 1 incorporated both closed and open-ended elements. TASK 2 contained only closed elements, and TASK 3 was designed incorporating only open-ended elements.

The content of the information needed to be processed for the completion of a task also affects performance (Jack et al., 2013; Friedman et al., 2015). Truninger et al. (2018), propose a taxonomy of tasks that considers the content of the information being processed. Task content, according to Jack et al. (2013), is based on two contrary cognitive domains: the social cognitive domain and the analytic (or non-social) cognitive domain. The first relates to tasks that involve interpersonal interaction and necessitate social information processing to be completed. The analytic (or non-social) cognitive domain, on the other hand, relates to tasks that involve reasoning about the mechanical or underlying properties of lifeless objects, and it is assumed to be most relevant for action control and focusing of attention. Therefore, while tasks based on the analytic (or non-social) cognitive domain, are concerned with arithmetic and abstract concepts and require nearly no social skills to be completed; tasks based on the social cognitive domain, require significantly more interpersonal interaction and social information processing for their completion. Boyatzis, Rochford and Jack (2014) provide an extensive review on tasks based on the two cognitive domains. TASKS 1 and 3 have been designed based on the social cognitive domain. TASK 2 was based on the analytic (or non-social) cognitive domain.

Taking into consideration both the type of each task and the information needed to be processed (whether based on the social or analytic cognitive domain), TASK 1 which incorporated both closed and open-ended elements, and was designed based on the social cognitive domain, required both coordination and analytic skills to be completed. TASK 2, which was a closed task, based on the analytic (or non-social) cognitive domain, required mainly only accuracy skills for its completion. In a similar manner, TASK 3, which incorporated only open-ended elements and was based on the social cognitive domain, required primarily only coordination skills for its completion.

The complexity of each task has been adjusted based on the type of the task (whether it is a closed, open-ended or a combination of the two), the content of the information needed to be processed (whether based on the social or analytic cognitive domain), the relevance to the management of LoPHIEs and on whether supporting material was provided or not and based on what fashion knowledge was distributed. Considering the above, the complexity of TASK 1 is set to medium, the complexity of TASK 2, to low and the complexity of TASK 3, to high. Even though TASK 1 requires a combination of skills to be completed (both coordination and accuracy skills), due to the fact it incorporated both closed and open-ended elements, as compared to TASK 3 that requires only coordination skills for its completion; the fashion in which knowledge (supporting material) was distributed for the completion of TASK 3, makes the task more complex and thus its complexity is assigned at a higher level of that of TASK 1.

4.6 CIMA Model - Second Cycle: Design Model Phase

This phase marks the initiation of the second development cycle of the CIMA Model (refer to Figure 11) in which the model is being redesigned, taking into account the findings of the initial analysis of the primary data collected, and an improved CIMA Model is presented.

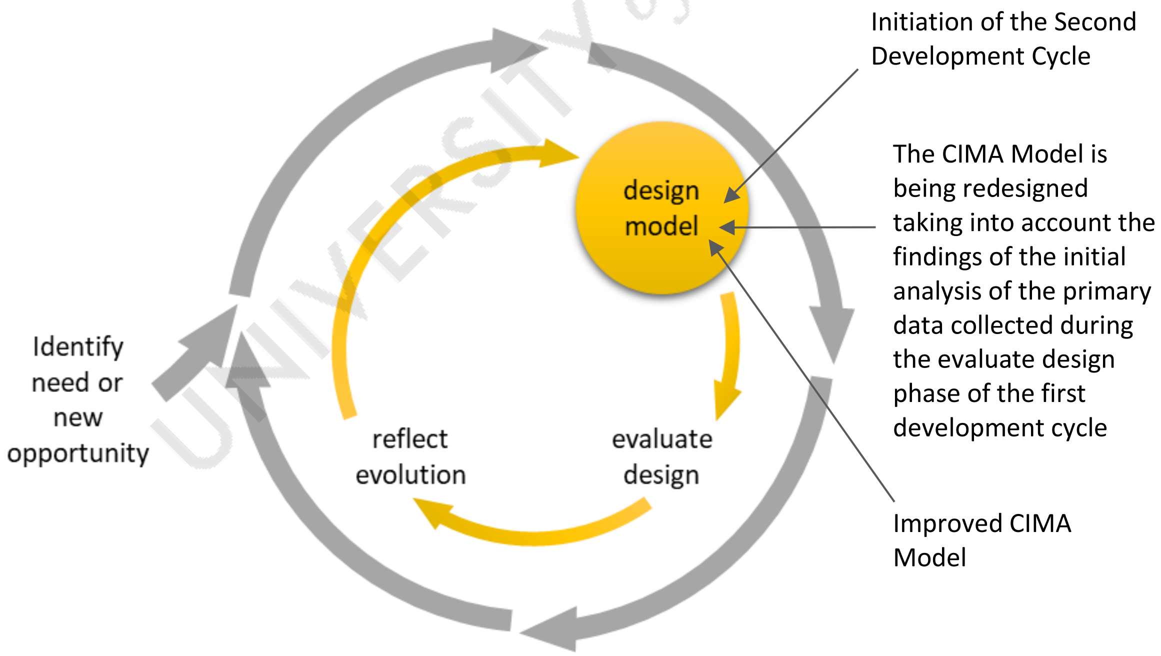


Figure 11: *Maturity Model Development Process: Cycle 2 – Phase 2 (adapted from Mettler, 2011)*

The initial analysis of the primary data collected during the 'evaluate design' phase of the first development cycle, revealed no indications demanding the modification of the scope of the proposed model. The first phase, therefore of the second development cycle 'define scope', is excluded, and the cycle begins with the second phase 'design model'.

4.6.1 CIMA Model – Improved Design

The main difference between the initial design of the CIMA model (refer to Section 4.3 of this Chapter, Sub-section 4.3.1) and the improved model designed, depicted in Figure 12, is that the initial design of the CIMA Model was build based on two dimensions: *Team Composition* and *Team Interaction.* The improved CIMA Model takes into account understanding dimensions of *Task Classification* and their impact on CI and performance.

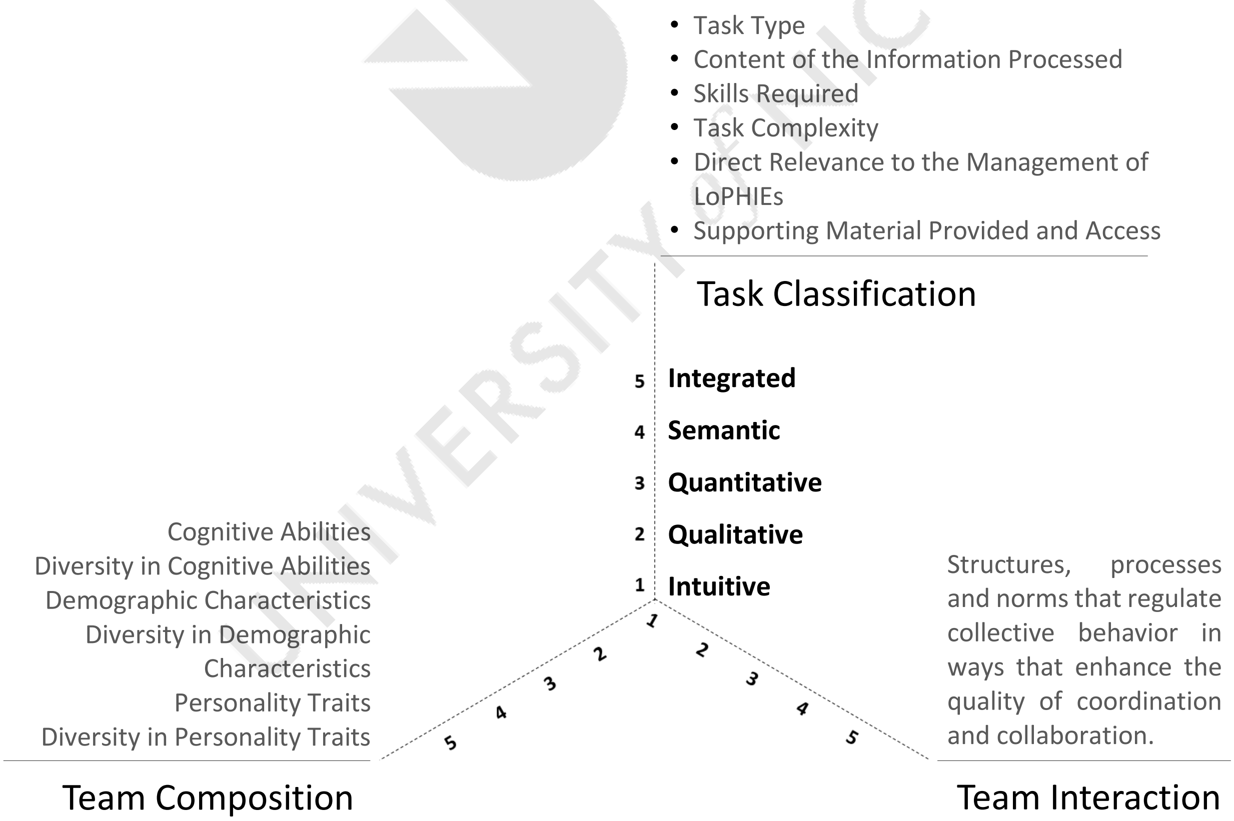


Figure 12: *CIMA Model – Improved Design*

The maturity of CI, as well as the performance of teams progress differently depending on different task characteristics – this has been evident from the initial analysis of the primary data collected (refer to Section 4.5 of this Chapter). As seen in Figure 12 (see page 120), the improved design of the CIMA Model builds on the initial design and incorporates three dimensions: 1. Team Composition, 2. Team Interaction and 3. Task Classification. The three dimensions mature in five levels, from an intuitive to an integrated stage.

The definitions developed for the maturity levels for each dimension have been derived based on secondary and primary data as well as expert opinion. The definitions of the maturity levels are shown below:

Maturity level 1: Intuitive

Team Composition:

Teams are formed with complete ignorance of how team composition dimensions influence performance. There is a lack of formal tools to measure dimensions of team composition (individual and collective intelligence as well as demographic characteristics in teams).

Team Interaction:

Team interaction is at a low level, with no presence of knowledge sharing. There is complete ignorance of how structures, processes, and norms regulate collective behavior in ways that enhance the quality of coordination and collaboration. Formal tools to measure team interaction levels are absent.

Task Classification:

There is complete ignorance of how specific characteristics of the situation at hand (Task Classification) and the way in which individual and collective task representations are developed in teams, influence the evolution and maturation of CI as well as Collective Performance. There is a lack of formal tools to measure the characteristics of the situation at hand.

Maturity level 2: Qualitative

Team Composition:

Team composition dimensions are intuitively assessed and analyzed. However, there is still a lack of formal tools to measure dimensions of team composition (individual and collective intelligence as well as demographic characteristics in teams).

Team Interaction:

Team interaction is at low – medium level, with limited knowledge sharing. The team interaction level is intuitively assessed, but formal tools to perform a comprehensive assessment are absent. Structures, processes, and norms that regulate collective behavior are intuitively being considered.

Task Classification:

The specific factors identified to positively influence the evolution and maturation of CI in teams as well as Collective Performance in relation to Task Classification are intuitively assessed and analyzed. However, there is still a lack of formal tools to measure these specific factors.

Maturity Level 3: Quantitative

Team Composition:

Plans are developed to assess and analyze team composition dimensions and assist in ways that positively influence performance. There is some awareness of diversity (in terms of personality traits, cognitive abilities, social category diversity, and demographic characteristics) and how it influences team performance. Some supporting tools to measure dimensions of team composition are in place, offering some reporting and metrics.

Team Interaction:

Team interaction is at a medium level, with improved knowledge sharing and interaction style. Some supporting tools to measure team interaction levels are in place, offering some reporting and metrics.

There is a limited understanding of how structures, processes, and norms regulate collective behavior in ways that enhance the quality of coordination and collaboration.

<u>Task Classification</u>:

There is a factual assessment and analysis of the specific factors related to Task Classification, with some awareness of their positive effects on the evolution and maturation of CI in teams as well as Collective Performance. Some tools to assess the characteristics of the situation at hand are in place, offering some reporting and metrics.

Maturity Level 4: Semantic

<u>Team Composition</u>:

Intuitive team modification based on team composition dimensions and awareness of diversity, with limited understanding of how these dimensions influence team performance. Supporting tools to measure dimensions of team composition are in place, offering advanced reporting and metrics.

<u>Team Interaction</u>:

Team interaction is at medium-high level, with extensive knowledge sharing. There is an improved understanding of the structures, processes, and norms that regulate collective behavior in ways that enhance the quality of coordination and collaboration. Supporting tools to measure team interaction are in place, offering advanced reporting and metrics.

<u>Task Classification</u>:

There is a good understanding of how specific factors related to Task Classification, positively influence CI and Collective Performance. Formal tools to measure the characteristics of the situation at hand, are in place, offering advanced reporting and metrics.

Maturity Level 5: Integrated

Team Composition:

There is informed team modification based on team composition dimensions and awareness of diversity, with a comprehensive understanding of how these dimensions influence team performance. Extensive supportive tools to measure dimensions of team composition are in place, offering measurable results.

Team Interaction:

Team interaction is at a high level, with broad knowledge sharing. There is a comprehensive understanding of how the structures, processes, and norms that regulate collective behavior in ways that enhance the quality of coordination and collaboration. Extensive supporting tools to measure team interaction levels are in place, offering measurable results.

Task Classification:

There is a comprehensive understanding of how specific characteristics of the situation at hand (Task Classification) and the way in which individual and collective task representations are developed in teams, influence the evolution and maturation of CI as well as Collective Performance. There is an extensive use of supportive tools to assess the characteristics of the situation at hand, offering measurable results.

Appendix X presents the evolution of the CIMA Model after the completion of the first development cycle.

4.7. CIMA Model - Second Cycle: Evaluate Design Phase

In this phase, a complete analysis of the data collected is conducted (refer to Figure 13, page 125). The statistical analysis was performed in R version 3.5.1 and it is fully reproducible: an R markdown document is available online, as denoted in Chapter Five, Section 5.3. The results of the analysis and discussion on the findings of the Thesis are presented in the following section of this Chapter.

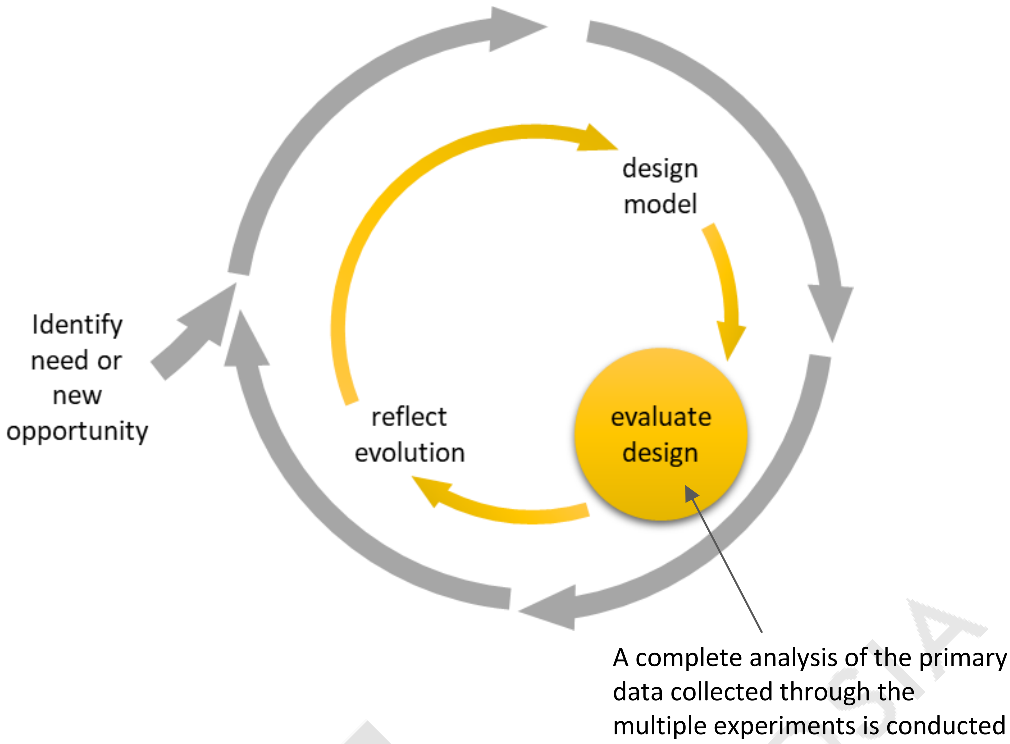


Figure 13: *Maturity Model Development Process: Cycle 2 – Phase 3 (adapted from Mettler, 2011)*

4.8 Research Findings and Discussion

The data collected through the 'evaluate design' phase of the first development cycle of the CIMA Model, with the conduction of multiple experiments, are analyzed in the following sub-sections. Information on the statistical tests and models used as well as on how the statistical analysis was conducted are provided below:

Associations between Variables and Team Performance

The Pearson correlation coefficient was utilized to explore the associations of teams' performance and Collective Intelligence with measurements in the three interlinked Experiments conducted (aggregated over team). The correlations were visually explored via scatterplots. Furthermore, a linear regression model was utilized to explore the multivariate effect of Experiment 1 measurements to the Total Task Score TTS of the teams, in Experiment 2.

Team Characteristics and Diversity

Measurements and demographic characteristics in Experiment 1 were aggregated over the team level using the mean value and the standard deviation (SD), forming the team composition characteristics. The mean value was used as the team characteristic and the standard deviation as the diversity in that characteristic. Associations of teams' performance with the diversity in the teams' characteristic was also explored via correlation analysis.

Total Task Scores and Collective Intelligence Calculations

Total Task Score TTS for teams was calculated as the average of Task 1, Task 2, and Task 3 scores in Experiment 2. The scores of the Tasks were first standardized due to their different possible range of values.

Collective Intelligence was calculated as the sum of the following standardized variables:

- The aggregated RME level of the team - The proportion of the female participants in the team - The team interaction level.

The standardization procedure subtracts the mean from the values, and the result is divided by the standard deviation. The standardization of the variables in the calculations of Total Task Score TTS and Collective Intelligence was performed since the range of the variables was different (e.g., RME is on the range of 1 to 36, while the proportion of females ranges from 0 to 1).

Distribution of the Tasks' Scores

The distribution of the tasks' scores was explored via boxplots and frequency histograms. The normality of the variables enabled the researcher to safely use parametric tests (i.e., t-tests for comparing the groups and Pearson correlation for associations between the scores and variables).

Comparison of Control and Experimental Groups

Differences between the Control and Experimental groups with regards to their performance (Task Scores) were explored via a t-test for independent samples and with the Cohen's d effect size difference index. While the t-test explores the generalizability of difference (statistical significance), the Cohen's d quantifies the observed difference. Cohen suggested that d ~ 0.2 be considered a 'small' effect size, 0.5 represents a 'medium' effect size and 0.8 (or greater) a 'large' effect size (Cohen, 2013).

4.8.1 Experiment 1 – Measuring Individual Intelligence

Experiment 1 explored Individual Intelligence, with the completion of three tests by all participants (N=100). The three tests were completed individually by participants and assessed their personality (Big Five Personality Test), their individual ability of spontaneously understanding the workings of the physical world (Folk Physics Test – Part I) and their ability to understand social causality (Reading the Mind in the Eyes Test - RME).

Table 6 presents the descriptive statistics of these measurements; the Big Five Personality Traits, the Folk Physics Test (Part I) score, and the RME score for the 100 participants.

Table 6: *Descriptive Statistics of Experiment 1 measurements (N=100)*

Variable	Mean	SD	Median	MIN	Max
Agreeableness	37.9	5.2	38	26	49
Conscientiousness	36.2	4.5	36	28	45
Emotional Stability	29.5	6.7	30	15	40
Extraversion	32.8	6.9	34	15	46
Intellect or Imagination	36.8	4.4	37	27	49
Folk Physics Test (Part I)	5.4	1.7	5	2	9
RME TOTAL	22.9	4.2	24	8	30

Figure 14 presents the distribution of the Big Five Personality Traits. It can be observed that the scores for each personality trait are fairly symmetrical around their mean level and do not exhibit noteworthy deviation. Figure 15 (see page 128) presents the distribution of the Reading the Mind in the Eyes test (RME) and Folk Physics Test (Part I) scores, where the distribution has a mild skewness to the left.

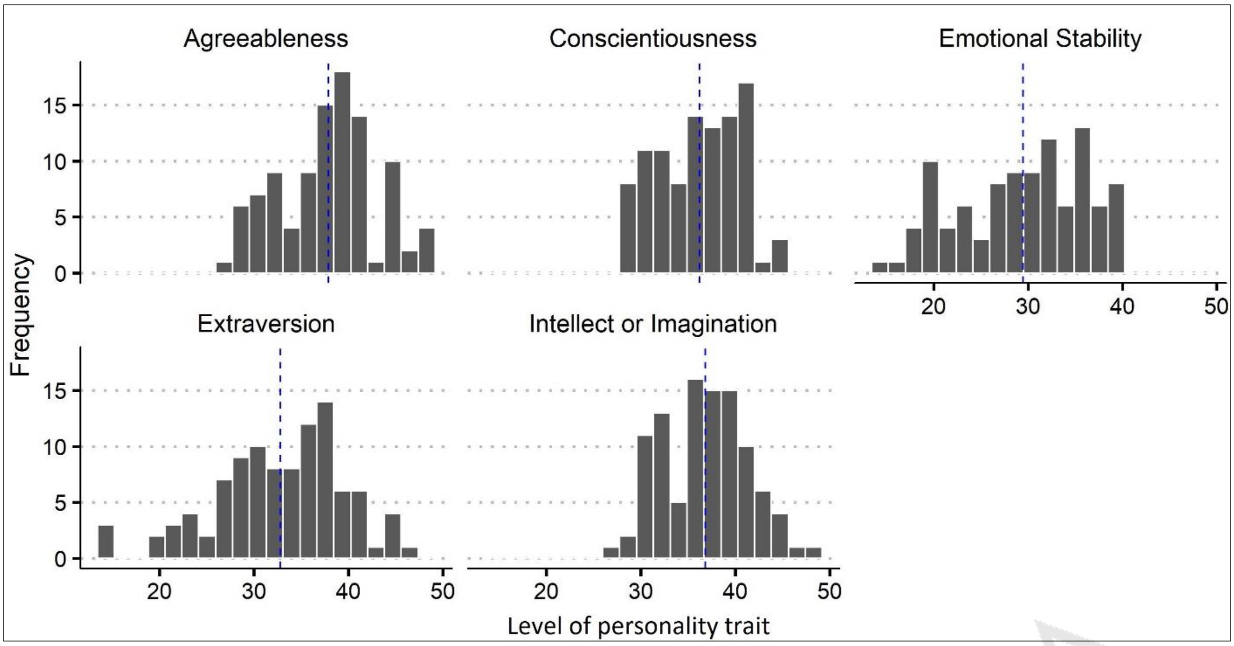


__Figure 14:__ Distribution of the "Big Five Personality" Traits in the Total Sample (N=100)

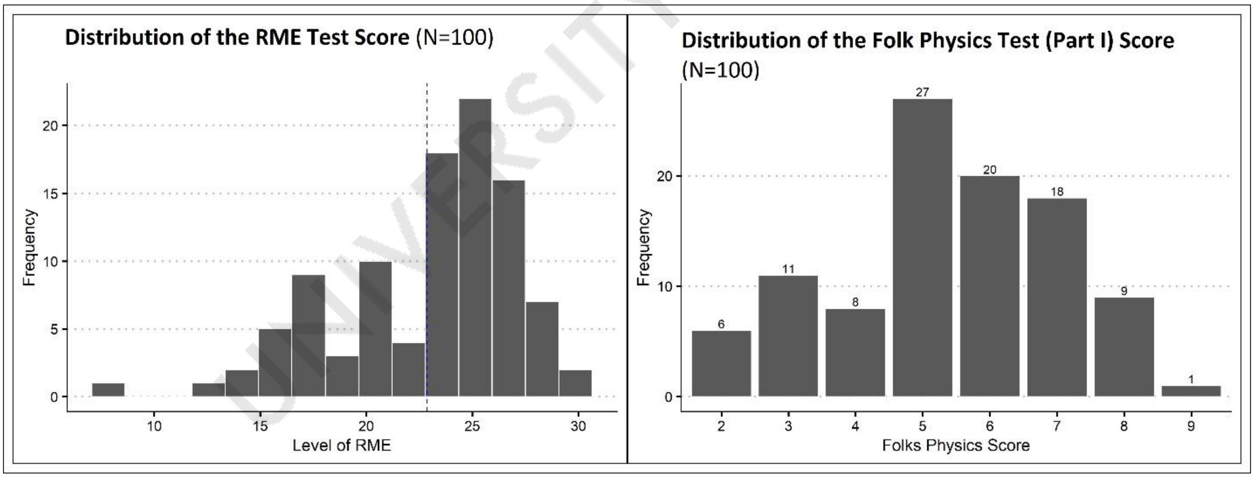


Figure 15: Distribution of RME and "Folk Physics" Test (Part I)

Correlation between Experiment 1 scales

Table 7 presents the correlation coefficients between Experiment 1 measurements. The analysis has shown that:

- Contrary to what has been expected, the participants' (N=100) ability of understanding social causality, as measured by the Reading the Mind in the Eyes Test RME has low to zero correlations ($r<0.10$) with the five primary dimensions of adult personality, as measured by the Big Five Personality Test (Extraversion: $r=0.043$, Agreeableness: $r=0.039$ Conscientiousness: $r=-0.104$, Emotional Stability: $r=0.089$, Intellect or Imagination: $r=-0.118$). **This finding, answers R.Q. 1.1** *Are personality traits positively correlated to social sensitivity?*
- Intellect or Imagination has a low and positive correlation with the Folk Physics Test (Part I) ($r = 0.23$, $p=0.023$), which measured participants' individual ability of spontaneously understanding the workings of the physical world.
- Agreeableness has a low and positive correlation with Conscientiousness ($r=0.28$, $p=0.01$)
- Extraversion has a low and positive correlation with Emotional Stability ($r=0.28$, $p=0.004$)

A visual inspection of the correlations is depicted in Figure 16 (see page 130).

Table 7: *Pearson correlations between Experiment 1 measurements*

Variable	RME TOTAL	Extraver.	Agreeabl.	Conscient.	Emot. Stabil.	Intel. or Imagin.	Folk Phys. Test (Part I)
Extraversion	0.043	NA					
Agreeableness	0.039	0.127	NA				
Conscientiousness	-0.104	-0.183	0.252	NA			
Emotional Stability	0.089	0.280	-0.053	0.102	NA		
Intellect or Imagination	-0.118	0.049	0.079	0.092	0.016	NA	
Folk Physics Test (Part I)	-0.110	-0.008	0.083	-0.091	-0.059	0.226	NA

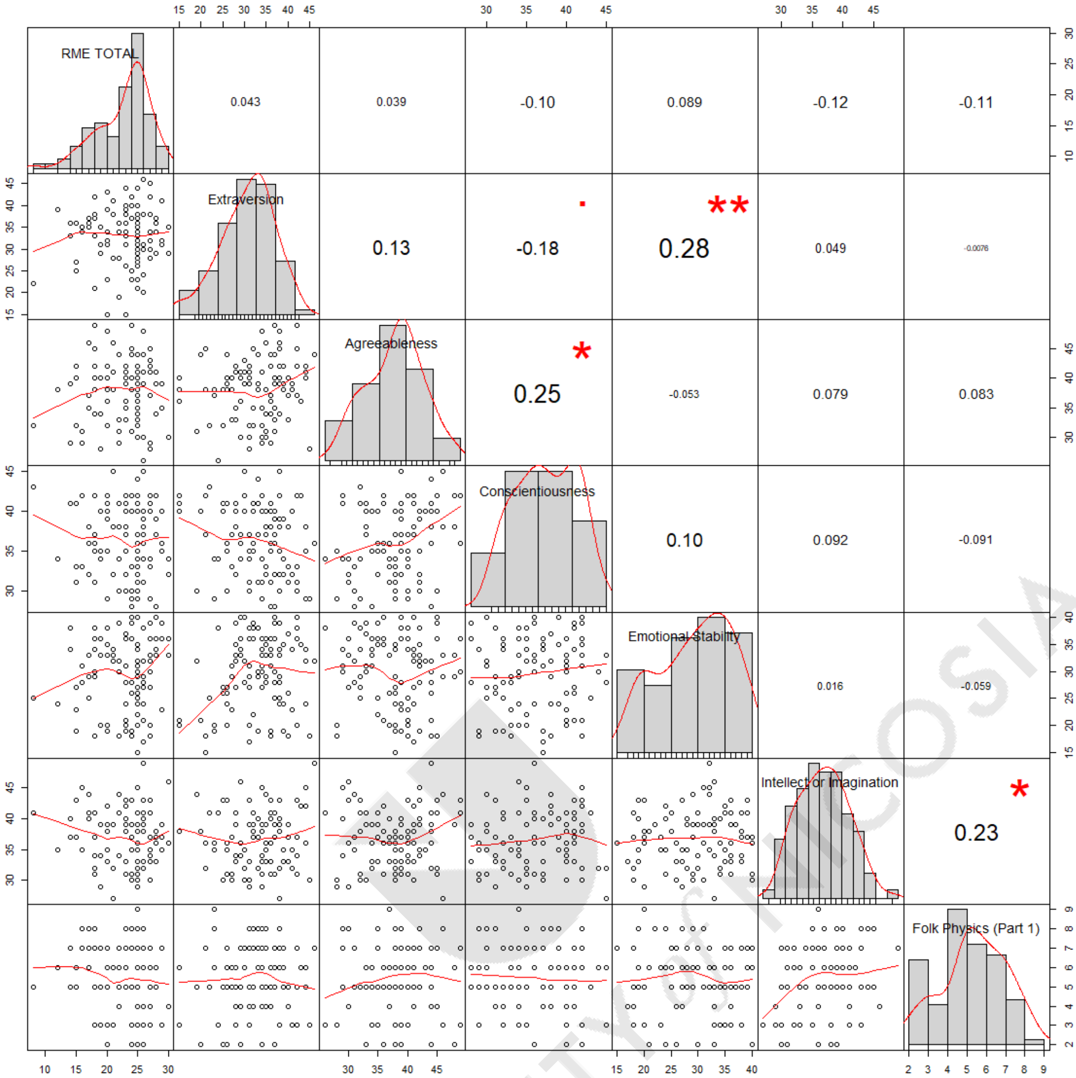


Figure 16: Matrix Scatterplot for the associations between Experiment 1 measurements

4.8.2 Experiment 2 – Measuring Collective Intelligence

Control Group vs. Experimental Group

Baseline check

Table 8 (see page 132) compares the Control and Experimental groups on measures assessed in Experiment 1 (personality traits, individual ability of spontaneously understanding the workings of the physical world, and ability of understanding social causality) and demographics.

The two groups have no significant differences in respect to personality traits (as measured with the Big Five Personality Test), participants' individual ability of spontaneously understanding the workings of the physical world (as measured with the Folk Physics Test – Part I) and ability of understanding social causality (as measured with the Reading the Mind in the Eyes Test RME). **This answers R.Q. 1.2** *Is there a statistical difference between each of the cognitive abilities (ability of understanding social causality and ability of spontaneously understanding the working of the physical world) and control or experimental mode participants?*

Nevertheless, there are differences in the demographics. The Control group's mean age of 36.6 (SD = 10.3) is higher than that of the Experimental group (28.9 SD = 7.9). Risk Management Relevance RMR in the Control group is also higher than that of the Experimental group - 48% High in Control Group vs. 10% in Experimental Group.

Overall, the Control group is composed of individuals with higher age and higher risk management relevance [expected since RMR is associated with job description]. Such composition was not designed methodologically but has instead resulted from the fact that experiment participants were allocated to the two groups (control and experimental), based on convenience.

Table 8: *Baseline Comparison - Control vs. Experimental groups*

	levels	Control Group (N= 50)	Experimental Group (N= 50)	Overall (N= 100)	p
Age group	18-34	26 (52.0)	43 (86.0)	69 (69.0)	0.001
	35-50	17 (34.0)	5 (10.0)	22 (22.0)	
	51-69	7 (14.0)	2 (4.0)	9 (9.0)	
Age	Mean (SD)	36.6 (10.3)	28.9 (7.9)	32.8 (9.9)	<0.001
Gender	Male	23 (46.0)	28 (56.0)	51 (51.0)	0.317
	Female	27 (54.0)	22 (44.0)	49 (49.0)	
Risk Manag. Relevance	Low Risk Manag. Relevant	1 (2.0)	34 (68.0)	35 (35.0)	<0.001
	Low - Medium Risk Manag. Relevant	12 (24.0)	5 (10.0)	17 (17.0)	
	Medium Risk Manag. Relevant	8 (16.0)	3 (6.0)	11 (11.0)	
	Medium - High Risk Manag. Relevant	5 (10.0)	3 (6.0)	8 (8.0)	
	High Risk Manag. Relevant	24 (48.0)	5 (10.0)	29 (29.0)	
Folk Physics Test (Part I)	Mean (SD)	5.3 (1.6)	5.5 (1.8)		0.496
RME TOTAL	Mean (SD)	22.2 (4.8)	23.5 (3.5)		0.134
Extraversion	Mean (SD)	32.8 (6.9)	32.8 (6.9)		0.631
Agreeableness	Mean (SD)	37.2 (5.2)	38.6 (5.2)		0.239
Conscientiousness	Mean (SD)	35.8 (4.4)	36.5 (4.6)		0.421
Emotional Stability	Mean (SD)	29.3 (6.6)	29.7 (6.9)		0.837
Intellect or Imagination	Mean (SD)	36.9 (4.3)	36.7 (4.7)	NA	0.673

Performance

Table 9 presents the mean performance measures across the Control and Experimental groups in Experiment 2. The experiment focused on measuring Collective Intelligence and involved the completion of three tasks.

Table 9: *Descriptive Statistics for Control and Experimental groups*

	Control	Experimental	Cohen's d	t value	p value
TASK 1 (Emergency Planning Activity)	4.8 (1.1)	4.2 (1.2)	0.55	2.749	0.007
TASK 2 (Folk Physics Test Part II)	4.2 (1.4)	6.1 (0.8)	-1.64	-8.215	0.000
TASK 3 (Tsunami Disaster Scenario)	60.3 (14.5)	59 (15.8)	0.09	0.428	0.669
Total Task Score (scaled)	-0.1 (0.7)	0.1 (0.6)	-0.35	-1.760	0.082

In TASK 1, the Control group (M=4.8, SD=1.1) scored higher than the Experimental group (M=4.2, SD=1.2) (t=2.7, p=0.007) with a moderate effect size difference (d=0.54). Considering the demographic characteristics of the two groups (Control and Experimental) as well as the characteristics of the specific task, this finding indicates that the higher age and the higher risk management relevance of the Control group participants had a positive effect and resulted in enhanced performance that surpassed the collective efforts of individuals of younger age and with lower risk management relevance (experimental group), as compared to the Control group.

In TASK 2, the Experimental group (M=6.1, SD=0.8) scored higher than the Control group (M=4.2, SD=1.4) (t=-8.2, p<0.001) with a high effect size difference (d=-8.2). The content of the specific task is indirectly related to the management of LoPHIEs. The task measures the ability of participants to spontaneously understand the workings of the physical world when addressing the task individually (control group) and collectively (experimental group). An ability needed for the successful management of LoPHIEs. Furthermore, TASK 2 was a closed task and was based on the analytic cognitive domain (refer to Table 5, Chapter Four, Section 4.5, page 117). It involved, therefore, reasoning about abstract concepts (mechanical or underlying properties of lifeless objects) and required solely analytic as well as accuracy skills and nearly no social competencies to be completed. In respect to this, the findings suggest that collective problem-solving has a positive effect on the ability of spontaneously understanding the workings of the physical world, enhances accuracy, and improves analytic skills.

In TASK 3, the Experimental group scored similarly to the Control group (t=0.3, p=0.669) (Cohen's d = 0.08), indicating that even though the Control group had a significant advantage over the Experimental group (individuals of higher age, with more expertise and higher risk management relevance), the Experimental group still managed to achieve similar scores in the task.

The above results concerning the performance of the two groups (Control and Experimental) in each of the three tasks consist one of the major managerial contributions of this Thesis. Within the bounds of the current study, what the findings discussed above indicate is that an organization involved in the management of LoPHIEs can take an informed decision whether to assign a team or an individual to handle an activity within the management process of an adverse event depending on the characteristics of the situation encountered and based on the demographic information of the responders. Table 5, presented in Section 4.5 (see page 117), classifies activities based on the type, the content of the information needed to be processed, the skills required for completion, the complexity, and relevance to the management of LoPHIEs as well as the fashion with which knowledge is distributed and encountered.

Two facts are believed to have had a significant impact on the performance of the control and experimental groups in the tasks asked to complete during the Experiment. The first has to do with the demographic characteristics of each group. As described in the previous sub-section of this Chapter, the Control group was composed of individuals with higher age and higher risk management relevance as compared to the Experimental group. Concerning this, the literature indicates that older and younger individuals behave differently from each other (Li, Low, and Makhija, 2017). A study conducted by Ali, Ng and Kulik (2014) provides evidence that older individuals tend to be more concerned in maintaining their status quo, while younger decision-makers may behave in a more conservative manner, trying to avoid risky decisions that can negatively and adversely affect their peers' perception of their skills. Gormley and Matsa (2016) provide further evidence that support the findings of Ali, Ng and Kulik (2014) and demonstrate that younger individuals are generally more risk-averse (for example, in investment - acquisition decisions) because of the possible unfavorable effect of their decisions on their future careers. In contrast, studies conducted by Li, Low and Makhija (2017) and Myers and Sadaghiani (2010) respectively, find that younger CEOs are likely to be more risk-seeking, for example taking braver investment decisions and establishing new business lines, as compared to older CEOs that are found to be more cautious and conservative when making decisions. These findings are also supported by Bertrand and Schoar (2003).

Furthermore, Berger, Kick, and Schaeck (2014) show that executive teams composed of younger individuals tend to increase portfolio risks. Collectively, the findings of the empirical studies mentioned above indicate that the behavior of older decision-makers is stable and can be characterized as cautious and conservative. The behavior of younger decision-makers, however, is characterized by a shift observed to be in some instances risk-averse and conservative and in some others, risk-seeking. In addition to the above mentioned, age is considered as a crucial proxy for experience (Talavera, Yin and Zhang, 2018) and as Hansen, Owan, and Pan (2013) note, it reflects differences in knowledge accumulation and maturity. In a similar manner, Risk Management Relevance may be regarded as an important proxy for knowledge accumulation, education, and functional background, experience, and training as well as expertise and information. The second fact believed to have had a significant impact on the performance of the Control and Experimental groups is concerned with the task classification (refer to Table 5, Chapter Four, Section 4.5, page 117). The type of the task, the skills required for its completion, the content of the information needed to be processed (whether based on the social or analytic cognitive domain) as well as its complexity and structure (whether supporting material was provided for its completion and how the knowledge was distributed and encountered in each case), may had an impact on the behavior and decision-making processes of the two groups (Control and Experimental) and consequently on the performance in each of the three tasks.

The comparative analysis below, in regards to the scores gained in each of the three tasks by the two groups (Control and Experimental), **answers R.Q. 1.3** *Is there a statistical difference between the Control and Experimental group, in relation to scores gained at the tasks?* The data analysis has shown that:

Overall, in the Total Task Score, the Experimental Group scored higher than the Control Group (t=-1.7, p=0.082) with a moderate effect size difference (d=-0.35). **This finding, answers R.Q. 1.4** *Does collective problem-solving lead to improved performance outcomes?* In addition, it supports the findings of previous studies that provide evidence that collective problem-solving leads to enhanced performance and improved solutions that no individual can achieve alone (e.g., Gulley and Lakhani, 2010; Jeppesen and Lakhani, 2010).

Figures 17 through 19 (see pages 137-139) show the distribution of scores for the Control group (boxplot) in comparison with the teams' scores (experimental group).

Task 1 - The median score for the control group is 5, while for the experimental group, only 2 teams scored higher than 5.

Task 2 - The median score for the control group is 4, and the third quartile (Q3) is 5, while all teams scored 5 or higher.

Task 3 - The distribution of teams' scores is similar to the Control's.

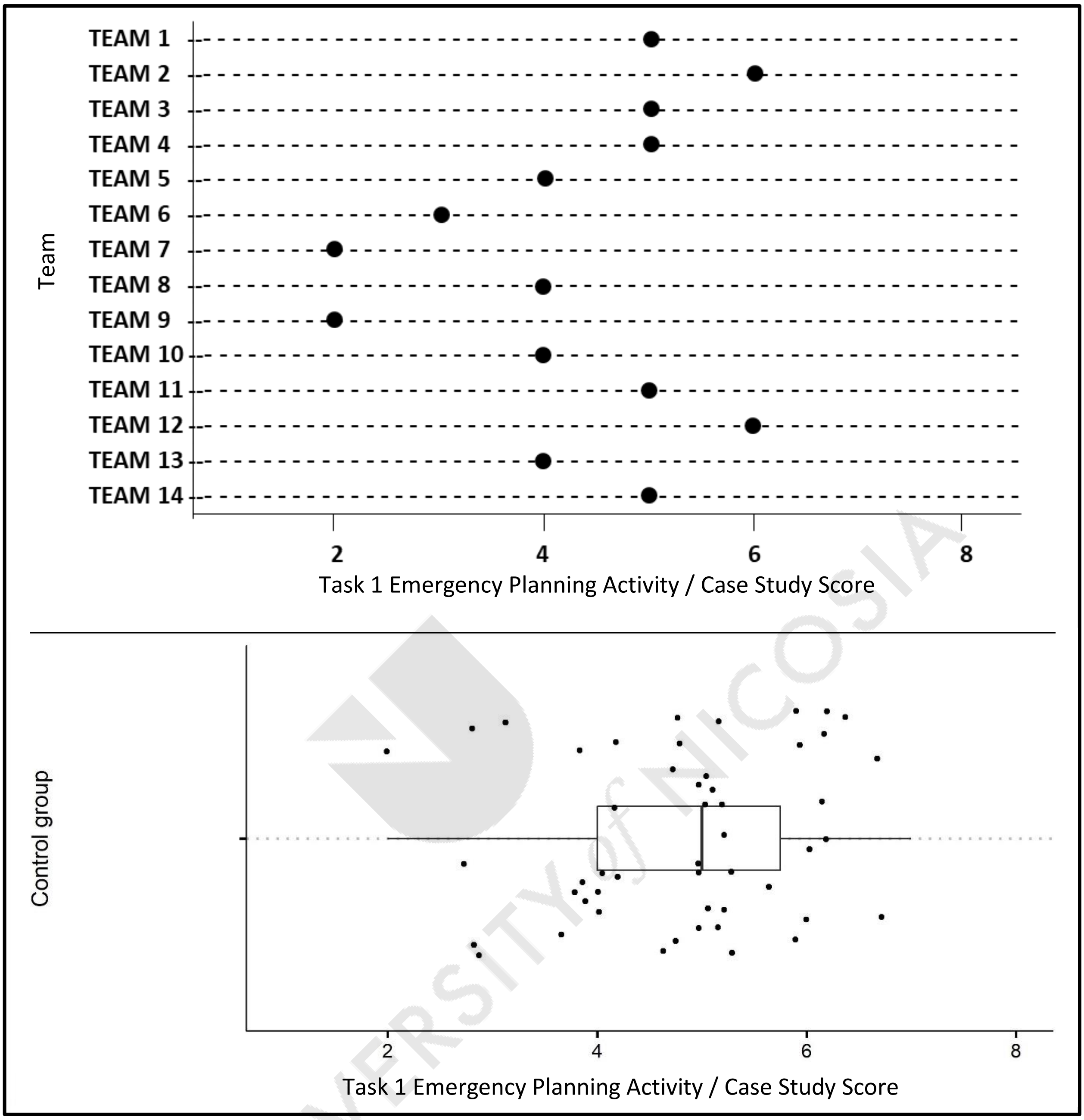


Figure 17: *Scores and Distribution of Control Group (Task 1)*

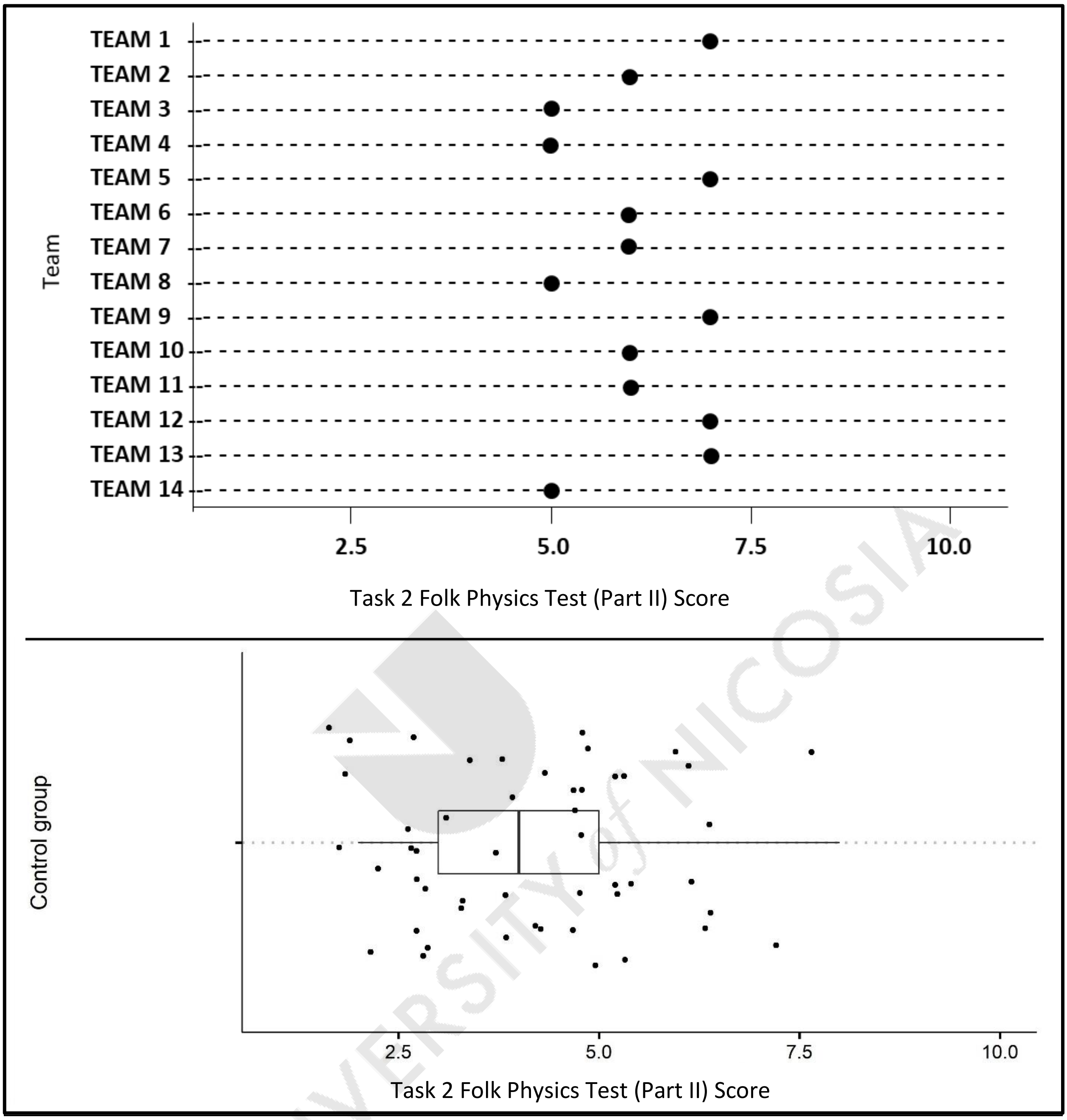


Figure 18: *Scores and Distribution of Control Group (Task 2)*

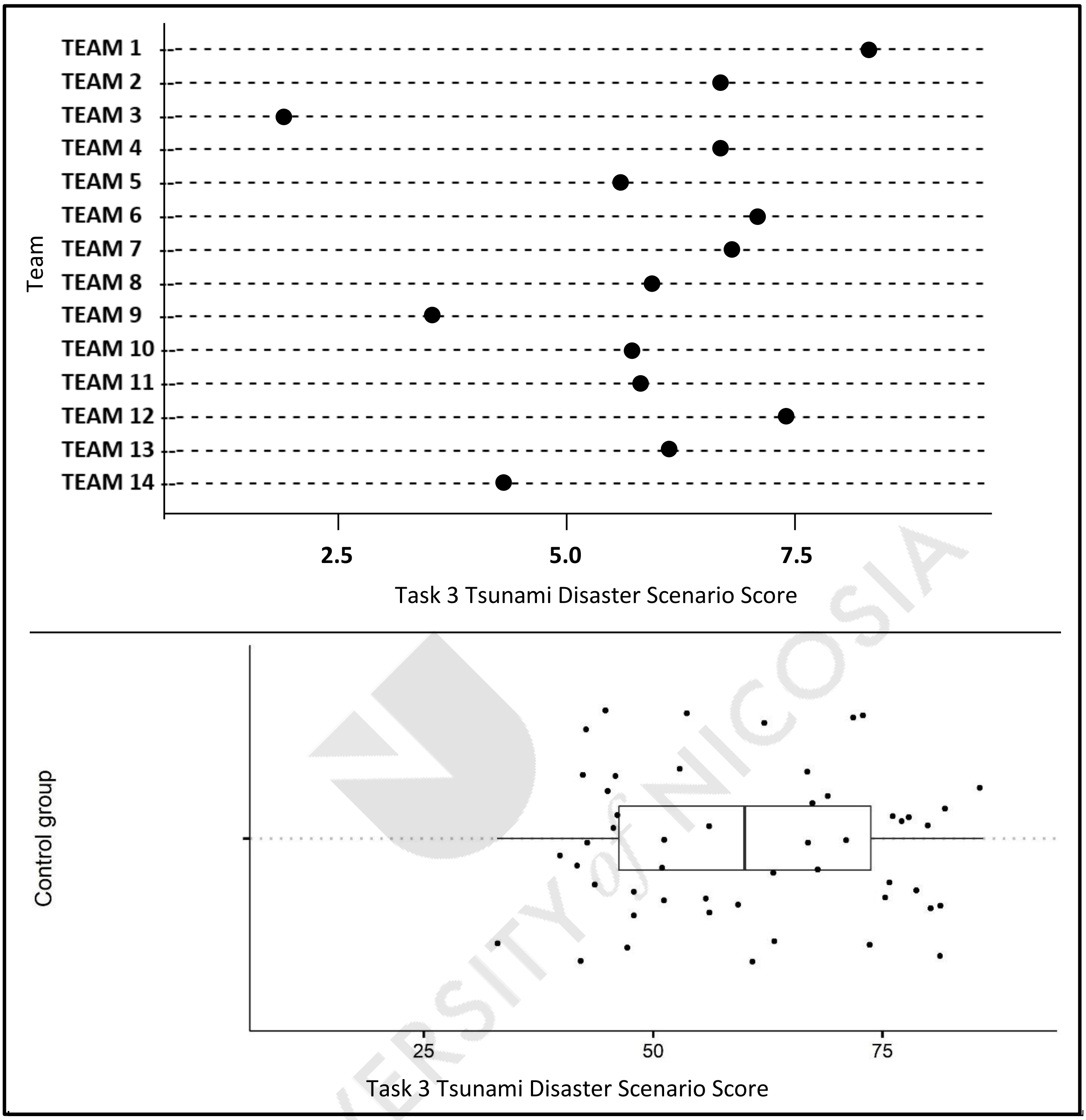


Figure 19: *Scores and Distribution of Control Group (Task 3)*

TEAMS

For Experiment 2, within the experimental group (N=50), fourteen (14) teams were formed.

Eight teams were composed of four individuals, and six teams were composed of three individuals. Six out of fourteen teams were male dominant, four teams were female dominant, and four were mixed-gender (equal number of male and female participants). The teams within the Experimental group were randomly formed.

- Experiment 1 measurements (Big Five Personality subscales, RME, and Folk Physics Test - Part I scores and Demographic characteristics) were aggregated over the team level.
- For Experiment 2, the descriptives are the teams' final scores.
- For Experiment 3, the descriptives are aggregated at the team level.
- Based on an extensive literature review, Collective Intelligence is a team characteristic significantly correlated with RME scores, female proportion, and the Team Interaction Level.

Teams' Descriptives

Table 10 presents statistics on the demographic characteristics by TEAM.

Table 10: *Teams' Demographic Composition*

Team	Female Proportion	Average Age	SD (Age)	Average Risk Manag. Relevance	Size
TEAM 1	0.50	27.75	3.86	1.00	4
TEAM 2	0.67	26.67	4.62	1.00	3
TEAM 3	0.33	25.67	0.58	1.00	3
TEAM 4	0.50	26.75	4.50	1.00	4
TEAM 5	0.25	30.00	4.08	1.00	4
TEAM 6	0.00	23.50	1.29	1.00	4
TEAM 7	0.75	22.75	0.96	1.00	4
TEAM 8	0.50	22.50	1.29	1.00	4
TEAM 9	0.50	23.50	1.29	1.00	4
TEAM 10	0.75	30.50	2.08	4.50	4
TEAM 11	0.33	32.00	3.00	4.33	3
TEAM 12	0.33	29.33	3.06	3.00	3
TEAM 13	0.67	50.00	5.20	2.00	3
TEAM 14	0.00	42.33	9.07	3.33	3

Associations with Total Task Score and Collective Intelligence

The associations of the Total Task Score and Collective Intelligence were explored in relation to the teams' demographic composition and Experiment 1 measurements.

Correlation (r) of Total Task Score and Collective Intelligence with Team Demographics

Table 11 presents the Pearson correlation coefficients of the *Total Task Score* (TTS) and *Collective Intelligence* (CI) with the teams' demographic composition.

Due to the small sample size (N=14), correlations are not expected to cross the statistically significant threshold ($p<0.05$); however, the correlations are presented in terms of their strength and direction (+ve, -ve).

The analysis has shown that the *Total Task Score* has a:

- Low and positive correlation with Age ($r=0.16$, $p=0.57$)
- Low and positive correlation with Risk Management Relevance ($r=0.14$, $p=0.62$)
- Low and positive correlation with Team Interaction ($r=0.20$, $p=0.49$)

Moreover, *Collective Intelligence* has a low and negative correlation with Age ($r=-0.15$, $p=0.61$) and a moderate positive correlation with Risk Management Relevance ($r=0.31$, $p=0.28$). **This finding, answers R.Q. 1.5** *Is there a relationship between the teams' demographic information (age and Risk Management Relevance) and CI?*

The high correlations of *Collective Intelligence* with the *Proportion of Women* and *Team Interaction* are due to the fact that these measurements are part of the *Collective Intelligence* calculations.

Table 11: *Pearson correlations of teams' demographics with TTS and CI*

Variable	Total Task Score - r	Collective Intelligence
Proportion of women	0.09	0.58
Average age	0.16	-0.15
Average Risk Management Relevance	0.14	0.31
Team Interaction	0.20	0.59

Correlation (r) of Total Task Score and Collective Intelligence with Experiment 1 Measurements

Table 12 presents the Pearson correlation coefficients of the Total Task Score (TTS) and Collective Intelligence (CI) with the aggregated level of the Big Five Personality Traits, RME score, and Folk Physics Test Part I measurements.

Note: Due to the small sample size (N=14), correlations are not expected to cross the statistically significant threshold (p<0.05).

Table 12: *Correlation (r) of TTS and CI with Experiment 1 measurements*

Variable	Total Task Score	Collective Intelligence
Collective Intelligence	0.40	NA
RME TOTAL	0.40	0.55
Extraversion	0.40	0.03
Agreeableness	0.44	0.27
Conscientiousness	-0.23	-0.23
Emotional Stability	0.08	0.01
Intellect or Imagination	0.20	0.05
Folk Physics (Part I)	0.19	0.31

Note: The high correlation of *Collective Intelligence* with the RME TOTAL SCORE is due to the fact that this measurement is part of the *Collective Intelligence* calculations.

The analysis has shown that there is a high strength of association between the Total Task Score and Collective Intelligence – the Total Task Score has a moderate and positive correlation with Collective Intelligence (r=0.40, p=0.16). This means that a higher level of Collective Intelligence is associated with higher Total Task Scores in Experiment 2. **This finding, answers R.Q. 1.6** *Does CI predict the performance of teams?* and supports the findings of previous studies that strongly suggest that CI predicts how well a team will perform on a wide range of different tasks (Engel et al., 2015; Woolley, Aggarwal and Malone, 2015 and Woolley et al., 2010). A visual inspection of the correlation can be seen in the scatterplot depicted in Figure 20 (see page 146).

Moreover, the analysis has shown that there is a high strength of association between the Total Task Score (= team performance outcomes) and RME Total and two of the primary dimensions of adult personality, Extraversion, and Agreeableness. These findings are discussed in detail below.

The Total Task Score has a:

- Moderate and positive correlation with the ability of understanding social causality/emotional intelligence - RME Total (r=0.40, p=0.16), as measured by the Reading the Mind in the Eyes Test. This indicates that higher levels of emotional intelligence in the team are associated with a higher level of performance. **This finding, answers R.Q. 1.7** *Is high social reasoning (RME scores) positively related to the overall team performance outcomes?* Drawing back to the literature presented in *Chapter Three*, concerning the design of Experiment 1 and the relevant materials and methods, the Reading the Mind in the Eyes Test RME specifically measures Theory of Mind – ToM, that appears to be the component of Emotional Intelligence EI with the most significant relevance to studies of collective intelligence (Baron-Cohen et al., 2001b). Considering the abovementioned, within the bounds of the current Thesis, what the correlation between the Total Task Score and the RME Total mainly implies is that ToM (as measured by the Reading the Mind in the Eyes RME test) and consequently EI, have a predictive power of over the performance outcomes of teams. This is in line with findings of several previous studies that investigated the relationship between ToM/EI and performance (e.g., Engel et al., 2014; Ferris, Witt and Hochwarter, 2001; Kidwell et al., 2011; Verbeke et al., 2008; O'Boyle et al., 2011; Joseph and Newman, 2010; Joseph et al., 2015; Côté and Miners, 2006; Lopes, 2016; Lopes et al., 2006; Guillén Ramo, Saris and Boyatzis, 2009; Boyatzis, Good and Massa, 2012; Boyatzis et al., 2015; Boyatzis, Rochford and Cavanagh, 2017; Camuffo, Gerli and Gubitta, 2012; Gil-Olarte Márquez, Palomera Martín and Brackett, 2006; Lam and Kirby, 2002).
- Moderate and positive correlation with Extraversion (r=0.40, p=0.16). This finding is consistent with the findings of studies conducted by De Fruyt and Mervielde (1999), Schneider (1999), and Tokar and Subich (1997), indicating that Extraversion predicts performance in various situations. In

addition, taking into consideration the fact that two out of the three tasks asked to be completed for the Experiment, were based on the social cognitive domain, the specific finding also supports the findings of several studies that reveal that Extraversion is a valid predictor of performance in tasks characterized by social interaction (e.g., Barrick and Mount, 1991; Bing and Lounsbury, 2000; Clark and Watson, 1991; Lowery and Krilowicz, 1994; Vinchur et al., 1998). However, all the studies mentioned above have been conducted in other contexts. The current study is the first to report results in regards to personality traits in correlation with CI. Therefore, additional studies that examine the relationship and dynamics between Extraversion and performance in the context of CI would unlock interesting directions for research.

- Moderate and positive correlation with Agreeableness (r=0.44, p=0.11). This result supports previous findings which suggest that Agreeableness predicts performance in situations where individuals work in teams (e.g., Awais Bhatti et al., 2014; Mount, Barrick, and Stewart; 1998) and especially for tasks that require high involvement with interpersonal skills (Tett, Jackson and Rothstein, 1991). In addition, this result is consistent with the findings of a study conducted by Costa, McCrae, and Dye (1991) which revealed that teams composed of highly agreeable individuals are able to promote a working environment free of conflict, focusing in this way on the efficient completion of tasks and therefore achieve enhanced performance outcomes.

Furthermore, the analysis has shown that the Total Task Score has a:

- Low and negative correlation with Conscientiousness (r=-0.23, p=0.43)
- Low and positive correlation with Intellect or Imagination (r=0.20, p=0.49)
- Low and positive correlation with the Folks Physics Test (Part 1) (r=0.19, p=0.52).

A visual inspection of the correlations can be seen in Figure 21 (see page 146).

Furthermore, the data analysis has shown that Collective Intelligence has a:

- Low and positive correlation with Agreeableness (r=0.27, p=0.35)

- Low and negative correlation with Conscientiousness (r=-0.23, p=0.44)

  <u>The above two findings, answer R.Q. 1.8</u> *Is there a relationship between personality traits and CI?* No significant correlations between CI and the other three primary dimensions of adult personality have been found.

- Moderate and positive correlation with the individual ability of spontaneously understanding the workings of the physical world, as measured by the Folk Physics Test – Part I (r=0.31, p=0.28). **<u>This finding, answers R.Q. 1.9</u>** *Is high Folk Physics scores positively related to CI?* and consists one of the major theoretical contributions of the current Thesis. Previous studies conducted in the field of CI have only focused on one of the two key neurocognitive adaptations of the human mind - Folk Psychology. To the best of the researcher's knowledge, this is the first study to investigate Folk Physics in the context of CI. As suggested, therefore, from the findings of the current Thesis and previous studies that have examined the relationship between Folk Psychology and CI, both Folk Psychology and Folk Physics appear to have independently a positive, noteworthy correlation with CI. Investigating the dynamics that govern the relationship between the two within the spectrum of the topic being explored by the current study and their collective, as well as independent impact on the emergence and success of CI, is a path worth exploring further.

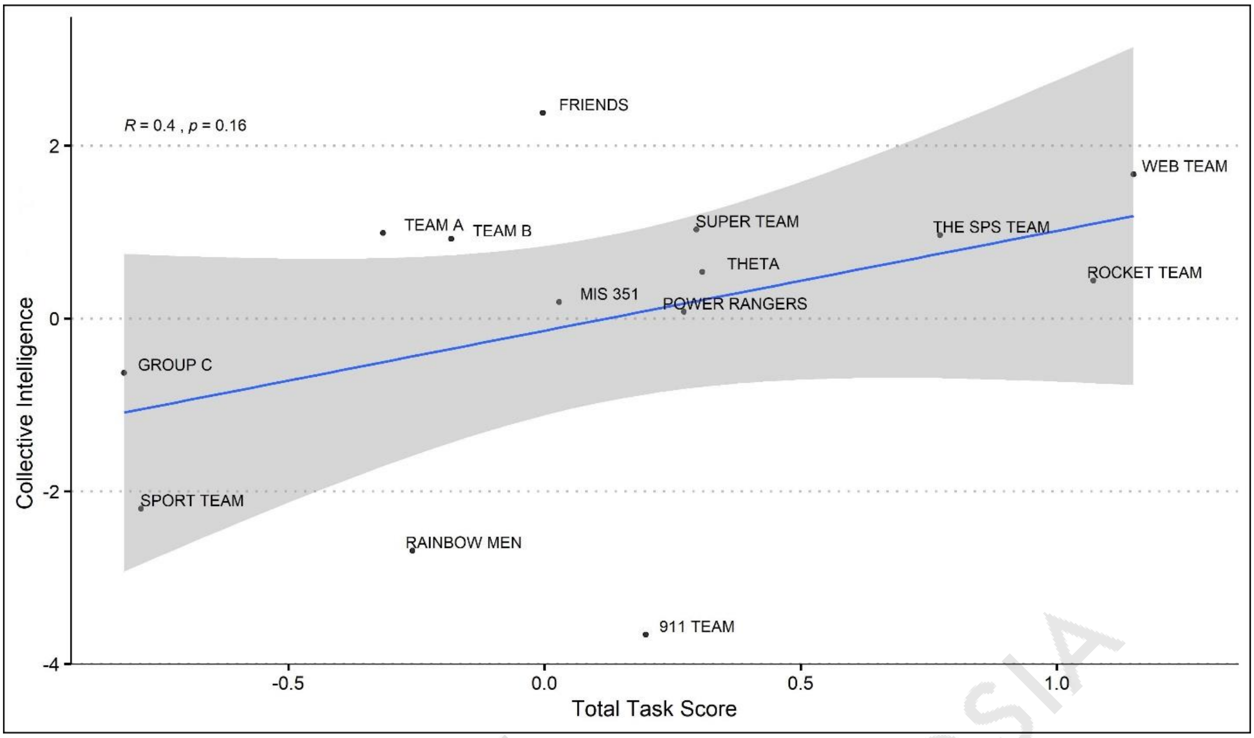


Figure 20: Association of TTS and CI

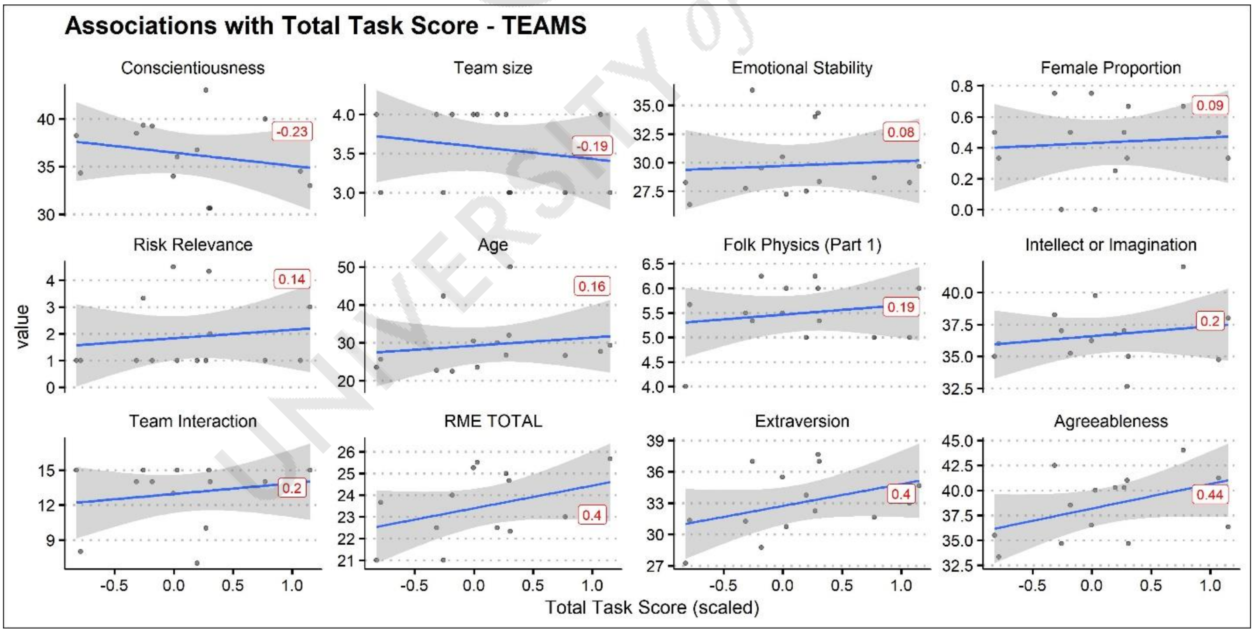


Figure 21: Collection of Associations between Measurements

Correlation (r) between Experiment 2 measurements (TASKS), Team Interaction and Collective Intelligence

Team Interaction

Within the bounds of the current study, the results discussed below suggest that two facts may have, collectively, a significant impact on Team Interaction. The first fact is related to the task classification (refer to Table 5, Chapter Four, Section 4.5, page 117). The type of the task, the skills required for its completion, the content of the information needed to be processed (whether based on the social or analytic cognitive domain) as well as its complexity and structure (whether supporting material was provided for its completion and how the knowledge was distributed and encountered in each case by the team), may had an impact on the behavior and decision-making processes of the teams and consequently on the Team Interaction in each of the three tasks. The second fact relates to the way in which individual and collective task representations were developed in the teams. As part of the decision-making process, team members form task representations that relate to both the perceived nature of the task at hand and to how the team is going to go about completing the task; in other words, a decision logic for the team processes (Poole, 1985; Poole and Doelger, 1986). Individuals form their own task representations that guide how they interact with other team members. In turn, team members' interaction enables the team to form collective task representations that guide the team's behavior. In relation to this, Brandon and Hollingshead (2004) explain that task representations may be incomplete at different points during the completion of a task and may change regularly as new information come to the surface.

The data analysis has shown that Team Interaction has a very low and negative correlation with TASK 1 ($r=-0.12$, $p=0.68$) and a low and positive correlation with TASK 2 (Folk Physics Test Part II) ($r=0.17$, $p=0.56$). It was also found that Team Interaction has a moderate and positive correlation with TASK 3 ($r=0.36$, $p=0.21$), indicating that higher scores in TASK 3 are associated with higher Team Interaction. Taking into consideration the specific characteristics of TASK 3, this finding is consistent with the findings of Littlepage et al. (2008), and Clark et al. (2000), who provide evidence indicating that team members' exchange of task-relevant information facilitates team performance. TASK 3 was open-ended and therefore on this ground, it is anticipated that as compared to TASK 1, which involved both closed and open-ended elements and TASK 2 which was a closed task, it encouraged teams to develop a comprehensive decision logic that influenced to a greater extent, primarily the way in which team members interacted with each other as a result of the individual task representations formed and, secondly, the way in which team member interaction formed collective task representations that guided the team's behavior. In other words, within the bounds of the current Thesis, what the results discussed above indicate is that the task classification and more specifically the task type (whether it is a closed, open-ended task or a combination of the two) has an impact on the procedures utilized by the team that may accordingly increase or decrease the depth of discussion (Henry, 1995; Hollingshead, 1996) and consequently lead to either more complete and efficient or inefficient use of team member knowledge. Moreover, the data analysis has shown that, overall, Team Interaction has a low and positive correlation with the Total Task Score ($r=0.20$, $p=0.48$).

Collective Intelligence

The data analysis revealed that Collective Intelligence is highly and positively correlated with TASK 3 ($r=0.56$, $p=0.034$). It is not correlated with TASK 1 ($r=0.04$, $p=0.90$) and has a very low correlation with TASK 2 ($r=0.12$, $p=0.68$). Jointly, the results of the current study support the findings of prior studies that provide evidence which strongly suggests that Collective Intelligence is positively correlated with performance on complex tasks (e.g., Engel et al. 2015; Engel et al., 2014; Woolley et al., 2010). TASK 3 was a high complexity task as compared to TASKS 1 and 2. In addition, as discussed earlier in this Section, the data analysis revealed that, overall, CI has a moderate and positive correlation with the Total Task Score ($r=0.40$, $p=0.16$). This finding confirms previous studies that provide evidence that CI is able to predict the performance of groups, lead to improved decision-making and increased performance beyond what can be achieved by individuals (e.g., Engel et al., 2015; Kerr and Hertel, 2011; Larson, 2010; Woolley, Aggarwal and Malone, 2015; Woolley et al., 2010).

<u>**The above findings, answer R.Q. 1.10**</u> *What is the relationship between the teams' performance (scores gained at the tasks and overall performance outcomes) and: (a) Team Interaction and (b) CI?*

Table 13: *Correlation (r) between Experiment 2 measurements, Team Interaction and CI*

Variable	Total Task Score	TASK 1 (Emergency Planning Activity)	TASK 2 (Folk Physics Part II)	TASK 3 (Tsunami Disaster Scenario)	Collective Intelligence	Team Interaction
TASK 1 (Emergency Planning Activity)	0.63	NA				
TASK 2 (Folk Physics)	0.43	-0.17	NA			
TASK 3 (Tsunami Disaster Scenario)	0.81	0.15	0.35	NA		
Collective Intelligence	0.40	0.04	0.12	0.56	NA	
Team Interaction	0.20	-0.12	0.17	0.36	0.59	NA

Diversity in Experiment 1 Measurements and Demographic Characteristics in Teams

It has been explored whether the diversity in the sample's demographic information and Experiment 1 measurements (composition of teams) are associated with the Total Task Score (indicative of the teams' overall performance outcomes) and Collective Intelligence. The diversity is measured with the standard deviation (SD) of the age and RMR with regards to the demographic composition and with the SD of the Big Five Personality Traits, RME, and Folk Physics scores in Experiment 1. Age is an important variable of team composition due to the fact it is a visible characteristic that can be taken into account for social categorization (Knippenberg and Schippers, 2007; Tajfel and Turner, 2004) and thus it is frequently considered as one dimension of social category diversity (e.g., Jehn, Northcraft and Neale, 1999; Pelled, Eisenhardt and Xin, 1999; Simons, Pelled and Smith, 1999). On the other hand, the Risk Management Relevance, the personality traits, the RME, and Folk Physics scores are distinct dimensions of cognitive diversity. **The findings presented below, answer:**

R.Q. 1.11 *Is the diversity in the teams' demographic information (age and Risk Management Relevance) correlated with: (a) the teams' performance outcomes and (b) CI?*

R.Q. 1.12 *Is the diversity in the teams' composition (examine each parameter individually) correlated with: (a) the teams' performance outcomes and (b) CI?*

Diversity in Age

The data analysis has shown that age diversity in teams has a moderate and negative correlation with Collective Intelligence (r=-0.33, p=0.26). This finding is consistent with Timmerman's (2000) findings that age diversity negatively affects Collective Intelligence. One possible explanation for this may be the fact that age diversity can induce a feeling of hierarchy between team members, hindering in this way the emergence of collective intelligence in the team (Harrison and Klein, 2007; Mayo et al., 2016). An additional explanation for the moderate and negative correlation between age diversity in teams and Collective Intelligence may be the fact that individuals of different ages are found to have different levels of comfort in working as a team as well as different attitudes towards and expectations of in-group communication (Myers and Sadaghiani, 2010). The data analysis has additionally revealed that age diversity in teams has a moderate and positive correlation with the Total Task Score (r=0.33, p=0.25), indicative of the overall performance outcome of the teams. Possible explanations for this finding may be given by Talavera, Yin, and Zhang (2018) and Hansen, Owan, and Pan (2013). Age, according to Talavera, Yin and Zhang (2018), is a critical proxy for experience, which might be reflected in team members' decision-making process. Similarly, Hansen, Owan, and Pan (2013) maintain that age heterogeneity in teams reflects differences in knowledge accumulation and in maturity, contributing to the team in various ways and being therefore responsible for the visible positive effect of age diversity on the overall team performance outcomes. The data analysis has further revealed that age diversity has a moderate and positive correlation with TASK 1 (r=0.47, p=0.087). Collectively, the results discussed above indicate that higher age diversity is associated with lower Collective Intelligence in the team but higher scores in TASK 1 and higher Total Task Score. Moreover, the data analysis revealed no correlation between age diversity in teams and TASK 2 (r=-0.05, p=0.87). Furthermore, it was found that age diversity has a weak and positive correlation with TASK 3 (r=0.11, p=0.71). It is apparent from the results uncovered that in regards to the correlation between age diversity in teams and the TASKS the effect of age diversity on performance is dependent on the different task characteristics (refer to Table 5, Chapter Four, Section 4.5, page 117).

Previous studies conducted in other contexts, examining the effect of age diversity on performance, in multiple team settings, report mixed results. For example, Arioglu (2019), Talavera, Yin and Zhang (2018), Ali, Ng, and Kulik, (2014), Waelchli and Zeller (2013), and Hagendorff and Keasey (2012) provide evidence that illustrate the negative impact of age diversity on performance. On the contrary, studies conducted by Nguyen and Noussair (2014), Mahadeo, Soobaroyen and Hanuman (2012), Kim and Lim (2010), Baer, Niessen-Ruenzi and Ruenzi (2007), Jackson, Joshi and Erhardt (2003) and Williams and O'Reilly (1998) reveal a positive relationship between age diversity in teams and performance. The mixed empirical evidence concerning the impact of age diversity in teams on performance have led several scholars to support the theoretical reasoning that based on the level of social category diversity in a team, the effect on performance may be different and that as soon as social categories (such as age) emerge, triggering dysfunctional group dynamics, it becomes problematic to employ informational resources to enhance decision quality in an effective manner. Consequently, the expected decision-making advantages of diversity, explained in detail in *Chapter Two, Literature Review,* become invalid or may even decline e.g., Baer, Niessen-Ruenzi and Ruenzi, 2007; Garcia-Meca et al., 2015; Jehn, Northcraft and Neale, 1999; Joshi, Liao and Jackson, 2006; Tajfel, 2010; Hewstone, Rubin and Willis, 2002; Ridgeway, 2009). Indeed, the above theoretical reasoning, along with evidence provided by Hansen, Owan and Pan (2013), suggesting that it is the older individuals that benefit more from age diversity in teams rather than younger individuals, may offer a substantial framework for understanding the findings uncovered from the data analysis of the current study in regards to the age diversity in teams. Future studies that investigate extensively the impact of different dimensions of social category diversity on team performance in relation to specific task characteristics within the spectrum of the topic being explored by the current study would be more revealing.

Diversity in Risk Management Relevance RMR

The diversity in Risk Management Relevance reflects differences in knowledge accumulation, education or functional background, experience, training, expertise, and information. In regards to the diversity in Risk Management Relevance within the teams, the data analysis revealed no correlation with Collective Intelligence (r=0.05, p=0.88). In addition, it can be seen from the data in Table 13 (see page 149) that the diversity in Risk Management Relevance in the teams has a moderate and positive correlation with TASK 1 (r=0.34, p=0.23) indicating that higher diversity in Risk Management Relevance is associated with higher scores in TASK 1. Furthermore, it was found that the diversity in Risk Management Relevance, has a weak and negative correlation with TASK 2 (r=-0.15, p=0.61), no correlation with TASK 3 (r=-0.09, p=0.77) and a weak and positive correlation with the Total Task Score (r=0.10, p=0.72). Within the bounds of the current study, the above-mentioned results in regards to the correlation between the diversity in Risk Management Relevance and the TASKS as well as the Total Task Score indicate that more research is needed to clarify the relationship between the diversity in Risk Management Relevance in the teams and collective performance based on task classification.

Diversity in the ability of understanding social causality (RME Total)

Lopes et al. (2004) found that emotional intelligence/social causality is remarkably relevant to tasks that require social interactions and group processes. These findings are also supported by Jordan and Troth (2004) and Druskat and Wolff (2001). It appears, however, that the diversity in the ability of understanding social causality works in reverse. Within the frame of this Thesis, the data analysis revealed that the diversity in the RME Total (indicative of the diversity in the ability of understanding social causality) in the teams, has a strong and negative correlation with TASK 1 (r=-0.60, p=0.024) and a moderate and positive correlation with TASK 2 (r=0.42, p=0.12), indicating that higher diversity in the RME scores in the team, is associated with lower scores in TASK 1 and higher scores in TASK 2. Additionally, it was found that RME Total has a weak and negative correlation with TASK 3 (r=-0.19, p=0.52). In other words, what these findings suggest is that the diversity in the ability of understanding social causality within a team leads to improved performance in closed tasks that are based on the analytic cognitive domain and involve reasoning about abstract concepts (mechanical or underlying properties of lifeless objects); and therefore, necessitate solely analytic and nearly no social skills to be completed. Whereas on the other hand, the diversity in the ability of understanding social causality in a team has a significant adverse effect on the team's performance in tasks that are combined in nature (incorporating also open-ended elements) and are based on the social cognitive domain and thus involve interpersonal interaction and necessitate social information processing to be completed (refer to Table 5, Chapter Four, Section 4.5, page 117). Further to the above interpretations, it is anticipated that the moderate and positive correlation between the diversity in the RME Total (indicative of the diversity in the ability of understanding social causality) and TASK 2, highlights a potential direct connection between the two critical neurocognitive adaptations of the human mind, Folk Psychology (as measured by the Reading the Mind in the Eyes Test RME) and Folk Physics (as measured by the Folk Physics Test). Higher diversity in the ability of understanding social causality in the team - RME Total, leads to higher collective ability of spontaneously understanding the workings of the physical world – TASK 2. Nonetheless, empirically investigating the issue further could be an important avenue for future research. Furthermore, the data analysis revealed a moderate and negative correlation between the diversity in the RME Total and the Total Task Score ($r=-0.33$, $p=0.24$) and a weak and positive correlation with Collective Intelligence ($r=0.13$, $p=0.66$). Collectively, the results discussed above, support Truninger's et al. (2018) remark that further studies are needed to examine how emotional intelligence/social causality may relate differently to performance depending on the type of task (Rode et al., 2007).

Diversity in Extraversion

The diversity in extraversion within the teams has a moderate and positive correlation with Collective Intelligence ($r=0.45$, $p=0.11$), the Total Task Score ($r=0.40$, $p=0.15$) and TASK 1 ($r=0.47$, $p=0.092$), indicating that higher diversity in extraversion is associated with higher Collective Intelligence in the team and higher scores in TASK 1 and higher Total Task Score. Several studies provide evidence that extraversion is positively associated with cooperative behavior (LePine and Van Dyne, 2001) and that it is a valid predictor of performance in tasks characterized by social interaction and require significant interpersonal communication skills to be completed (e.g., Barrick and Mount, 1991; Bing and Lounsbury, 2000; Clark and Watson, 1991; Lowery and Krilowicz, 1994; Rothmann and Coetzer, 2003; Vinchur et al., 1998). TASK 1 was designed based on the social cognitive domain as well as TASK 3, which was found to have a low and positive correlation with the diversity in extraversion within the teams (r=0.25, p=0.37). On the other hand, TASK 2, which was based on the analytic cognitive domain, was found to have a weak and negative correlation with the diversity in extraversion within the teams (r=-0.11, p=0.72). Based on the above, the moderate and positive correlation between the diversity in extraversion and the Total Task Score can be explained from the fact that two out of the three tasks were based on the social cognitive domain and only one task was based on the analytic cognitive domain – TASK 2. Collectively, the results discussed above indicate, firstly, that the diversity in extraversion does not appear to hinder or outweigh the positive effects of the specific personality trait and, secondly, that it is possible that in the presence of other task characteristics (other than the task being designed based on the social cognitive domain), the performance on tasks that involve interpersonal interaction and necessitate social information processing to be completed, is accordingly reduced or increased (refer to Table 5, Chapter Four, Section 4.5, page 117). Investigating the issue further would be valuable.

Diversity in Agreeableness

The data analysis has shown that diversity in agreeableness has a moderate and positive correlation with Collective Intelligence (r=0.49, p=0.07). In addition, it was found that it has a weak and positive correlation with TASK 3 (r=0.18, p=0.53) and a weak and negative correlation with TASK 1 (r=-0.19, p=0.52) and TASK 2 (r=-0.10, p=0.73). The data analysis revealed no correlation between the diversity in agreeableness within the teams and the Total Task Score (r=-0.03, p=0.93). LePine and Van Dyne (2001) found that agreeableness is positively related to cooperative behavior. In relation to this, an earlier study conducted by Costa, McCrae, and Dye (1991) reveals that agreeableness fosters teamwork, which in turn leads to improved performance. Teams composed by highly agreeable and cooperative individuals are able to promote a working environment free of conflict; focusing in this way on the efficient completion of tasks and therefore achieve enhanced overall performance outcomes (García-Gallego, Ibanez and Georgantzis, 2017; Ramalu, Wei and Rose, 2011; Salgado, 1997; Tett and Burnett, 2003; Tett, Jackson and Rothstein, 1991). Within the framework of the current Thesis, the findings of the data analysis suggest that while the diversity in agreeableness is associated with higher Collective Intelligence in the team, it outweighs the positive effects of the specific personality trait, since no visible correlation between performance (Total Task Score, TASKS 1, 2 and 3) and the diversity in agreeableness, is observed.

Diversity in Conscientiousness

Regarding diversity in conscientiousness, the data analysis has shown that it has no correlation with Collective Intelligence ($r=0.07$, $p=0.82$) and TASK 1 ($r=0.02$, $p=0.94$). However, a weak and negative correlation with the Total Task Score ($r=-0.18$, $p=0.54$) and TASK 2 ($r=-0.19$, $p=0.50$) is found. In addition, the data analysis revealed a low and negative correlation with TASK 3 ($r=-0.22$, $p=0.46$). Within the bounds of the current study, what the results mentioned above indicate is that diversity in conscientiousness within the teams appears to outweigh the positive effects of the specific personality trait since no visible correlation with performance (Total Task Score, TASKS 1, 2 and 3) is observed. Conscientiousness is manifested in achievement orientation (hardworking and persistent), dependability (responsible and careful), and orderliness (planful and organized) (Rothmann and Coetzer, 2003). Shaffer et al. (2006) maintain that individuals who are motivated to achieve conscientiousness devote more time to task completion. This task-oriented behavior often leads to effective work adjustment and task achievement. LePine and Van Dyne (2001) found that conscientiousness is positively related to cooperative behavior. Furthermore, Hurtz and Donovan (2000) found that among the big five factors, conscientiousness is highly correlated with job performance. Individuals with high conscientiousness are able to develop high-level job knowledge. Borman et al. (1991) and Hough et al. (1990) reveal a strong correlation between reliability (an aspect of conscientiousness) and job performance. Other researchers have also reported significant correlations between job performance and conscientiousness (e.g., Barrick and Mount, 1991; Barrick, Mount, and Strauss, 1993; Frink and Ferris, 1999; Ones and Viswesvaran, 1997; Sackett and Wanek, 1996). It appears, therefore that within the bounds of the current study, homogeneity in conscientiousness instead of heterogeneity would be more beneficial for the teams.

Diversity in Emotional Stability

Emotional stability is indicative of the ability to remain balanced and stable under stressful conditions and reflects the overall adjustment level and emotional resilience to situations of pressure (Rothmann and Coetzer, 2003). Shaffer et al. (2006) support this view and note that emotionally stable individuals are more likely to deal with unpleasant situations and handle problems more effectively. The data analysis has shown that diversity in emotional stability has a moderate and negative correlation with the Total Task Score ($r=-0.32$, $p=0.26$) and TASK 1 ($r=-0.46$, $p=0.10$). In addition, no correlation between diversity in emotional stability and Collective Intelligence ($r=-0.02$, $p=0.96$) was found. Furthermore, the data analysis revealed a weak and negative correlation between the diversity in emotional stability and TASK 3 ($r=-0.14$, $p=0.62$) and a weak and positive correlation with TASK 2 ($r=0.12$, $p=0.69$). Within the frame of the current Thesis, the results indicate that higher diversity in emotional stability in the teams is associated with tendencies found to interfere with attention to tasks and reduce performance, a phenomenon observed also in situations where scores in the specific personality trait of emotional stability, are low (De Raad and Schouwenburg, 1996; Nye, Orel, and Kochergina, 2013; Zhao et al., 2011).

Diversity in Intellect or Imagination

Within the Big Five Model, intellect or imagination, also referred to as openness to experience (or openness, in short) is a broad and multifaceted construct that measures the variability as well as the extensiveness and depth in a person's imagination and desire for experiences (Buss, 1991; Williamson, 2018). In the context of the current study, the data analysis has shown that the diversity in intellect or imagination has a moderate and positive correlation with TASK 3 ($r=0.30$, $p=0.29$). In addition, the data analysis revealed no correlation between the diversity in intellect or imagination in the teams and TASKS 1 ($r=-0.06$, $p=0.84$) and 2 ($r=0.07$, $p=0.83$). The above findings of the current study are associated with the findings of Mohan and Mulla (2013), who provide significant evidence in regards to the relation between the personality trait of intellect or imagination and task complexity. The results of their study indicate that openness to experience is positively correlated with high complexity tasks. Furthermore, the above findings of the current study, associate with previous studies that suggest that individuals who score high on openness, perform better in unfamiliar environments and are more attentive to multiple influences when making decisions (e.g., Bing and Lounsbury, 2000; de Jong, van der Velde and Jansen, 2001; McElroy and Dowd, 2007; Mohan and Mulla, 2013). A study conducted by Hodson, Hogg and MacInnis (2009) revealed that uncertainty-oriented individuals are highly open to experience. This may link both to a mental aspect of needing to know and an emotional aspect of finding joy in new experiences. Both, as Heinström (2010) notes, relate to a positive stance towards information seeking. Openness reflects an overall interest to explore, whereas uncertainty orientation triggers vigorous information seeking, especially under unclear situations. It is evident, therefore, from the results of the current study that the findings of the above-mentioned empirical studies also apply in the presence of diverse levels of intellect or imagination in a team (refer to Table 5, Chapter Four, Section 4.5, page 117). As compared to TASKS 1 and 2, TASK 3 was a high complexity task. The fact that it was an open-ended task, as well as its structure (the way in which the supporting material was distributed for its completion and how the knowledge was encountered by the teams) have played a significant role in conveying an environment unfamiliar to the experiment participants. Moreover, the data analysis has shown that the diversity in intellect or imagination in the teams, has a weak and positive correlation with Collective Intelligence ($r=0.19$, $p=0.51$). Furthermore, it was found that it has a weak and positive correlation with the Total Task Score ($r=0.17$, $p=0.56$). Collectively, the findings of the current study discussed above are associated with the findings of Bing and Lounsbury (2000). The specific personality trait, according to Bing and Lounsbury (2000), is highly context-dependent. It is found to have a positive impact on performance under specific conditions and within particular criteria, even though no evidence was found that it positively affects the overall performance outcomes.

Diversity in the individual ability of spontaneously understanding the workings of the physical world (Folk Physics Test Part I)

Within the bounds of the current Thesis, the data analysis revealed that the diversity in the individual ability of spontaneously understanding the workings of the physical world – as measured by the Folk Physics Test Part I, has no correlation with Collective Intelligence ($r=0.00$, $p=0.99$). In addition, the data analysis revealed that the diversity in the individual ability of spontaneously understanding the workings of the physical world has a weak and negative correlation with the Total Task Score (r=-0.17, p=0.56) and TASK 3 (r=-0.13, p=0.66), a weak and positive correlation with TASK 2 (r=0.12, p=0.67) and low and negative correlation with TASK 1 (r=-0.22, p=0.44). Due to the fact the current study is the first, to the best of the researcher's knowledge, to incorporate Folk Physics in the context of CI, additional experimental research is needed to better understand the dynamics of the relationship between Folk Physics and CI and its impact on collective performance in relation to specific task characteristics.

Table 14: Correlation between the variation (SD) of Experiment 1 measurements with Task Scores and CI

Variable	Collective Intelligence	Total Task Score	TASK 1 (Emergency Planning Activity)	TASK 2 (Folk Physics)	TASK 3 (Tsunami Disaster Scenario)
Age	-0.33	0.33	0.47	-0.05	0.11
Risk Management Relevance	0.05	0.10	0.34	-0.15	-0.09
RME TOTAL	0.13	-0.33	-0.60	0.43	-0.19
Extraversion	0.45	0.40	0.47	-0.11	0.26
Agreeableness	0.49	-0.03	-0.19	-0.10	0.18
Conscientiousness	0.07	-0.18	0.02	-0.19	-0.22
Emotional Stability	-0.02	-0.32	-0.46	0.12	-0.14
Intellect or Imagination	0.19	0.17	-0.06	0.07	0.30
Folk Physics Test (Part I)	0.00	-0.17	-0.22	0.12	-0.13

Cognitive diversity is the component of collective intelligence, affecting the most the quality of collective problem-solving (Hong and Page, 2001 and 2004; Page, 2008). As seen, however, from the results of the current study, only two dimensions of cognitive diversity examined appear to have a positive effect on Collective Intelligence, the diversity in Extraversion, and the diversity in Agreeableness. As seen earlier (refer to *Correlation (r) of Total Task Score and Collective Intelligence with Experiment 1 Measurements*), Collective Intelligence has no correlation with Extraversion (r=0.03, p=0.92) and a low and positive correlation with Agreeableness (r=0.27, p=0.35), the diversity though in these two personality traits appears to have a moderate and positive effect on the emergence and success of CI in the teams. Nonetheless, the lack of visible correlation between CI and the diversity in RMR, RME and Folk Physics scores as well as the other personality traits respectively, could be due to the moderation occurring by other cognitive diversity dimensions and their variation in the teams or due to a number of external conditions and constraints that may had an effect.

The empirical literature concerning the effects of team diversity on performance, in various contexts, is extensive (e.g., Baer et al., 2008; Gibson and Vermeulen, 2003; Glover and Kim, 2019; Groysberg, Polzer and Elfenbein, 2011; Hambrick, Cho, and Chen, 1996; Hoogendoorn, Oosterbeek, and Van Praag, 2013; Jackson, Joshi and Erhardt, 2003; Milliken and Martins, 1996; Murtha, Challagalla and Kohli, 2011; Pelled, Eisenhardt and Xin, 1999; Reiter-Palmon, Wigert and de Vreede, 2012). Despite however the plethora of studies, it is still inconclusive and controversial whether diversity has a positive or negative impact on team performance (e.g., Harrison and Shaffer, 2005; Jehn, Northcraft and Neale, 1999; Kochan et al., 2003; Siciliano, 1996). In fact, it is commonly agreed within diversity research, that the effects of group diversity on performance can be both negative and positive (Bell et al., 2011; Cox, 2005; Milliken and Martins, 1996). Positive outcomes are, in most instances, associated with improved decision-making processes resulting from value-added information access and analysis, while adverse outcomes are usually associated with dysfunctional group dynamics (Schwab et al., 2016). For example, diversity in teams has been found to relate to both defective outcomes, such as increased conflict incidents (Putnam, 2007) and lower productivity in some cases (Hamilton, Nickerson and Owan, 2012; Hjort, 2014) as well as functional outcomes, such as increased information sharing (McLeod, Lobel and Cox, 1996), more careful information processing (Phillips, Liljenquist and Neale, 2008), creative problem-solving (Kurtzberg, 2005; Parayitam and Papenhausen, 2016) and increased productivity (Freeman and Huang, 2015; Lazear, 1999).

The mixed direct results have led scholars to theorize that, to some extent, the impact of team diversity on performance may vary across contexts (Watson, Kumar and Michaelsen, 1993). In addition, one promising stance argues that the nature of the underlying task is critical in understanding the divergent effects of diversity (Ingersoll, Malesky, and Saiegh, 2014) and that its impact on team performance can depend on the task design and characteristics (Ancona and Caldwell, 1992; Baer, Niessen-Ruenzi and Ruenzi, 2007; Pelled, Eisenhardt and Xin, 1997). The empirical findings of the abovementioned studies as well as the extensive literature review conducted on diversity, provided in *Chapter Two*, as well as the findings of the current study in regards to the diversity in teams, explored in this section, have led the researcher to associate with the above assumptions. In addition, the researcher maintains that overall, the findings of the current Thesis concerning team diversity, confirm the notion that teamwork output is the result of multiple mechanisms that may interact; and that diversity in skills, knowledge and demographic characteristics, including personality traits, as well as the characteristics of the task at hand, affect team performance through multiple channels. Thus, future research could focus on the development of a methodological standardization in regards to how studies on diversity are conducted. Such a methodological standardization can offer reproducible and comparable results.

4.8.3 Experiment 3 – Measuring the Construct of Transactive Memory Systems TMS

Experiment 3 focused on measuring the construct of the Transactive Memory System developed in the teams during Experiment 2 and therefore focused solely on the Experimental Group - only individuals who worked in teams at Experiment 2 have participated in Experiment 3. Drawing back to the previous Chapter and the design of the Experiments conducted, Transactive Memory Systems have three components (Akgün et al., 2005; Kanawattanachai and Yoo, 2007; Lewis, 2004): (1) Specialization, (2) Credibility and (3) Coordination. Within the bounds of this thesis, two facts are believed to have played an essential role in the way in which the transactive memory systems were developed in the teams. The first fact is concerned with the demographic characteristics of the Experimental Group. As seen in the previous section of this Chapter, overall, the Experimental Group was formed by individuals with lower age and lower Risk Management Relevance, as compared to the Control Group. As examined earlier, age is considered as a crucial proxy for experience, which might be reflected in team members' decision-making process (Talavera, Yin and Zhang, 2018). While age heterogeneity in teams is believed to reflect differences in knowledge accumulation and maturity (Hansen, Owan and Pan, 2013). Similarly, Risk Management Relevance is regarded as an important proxy for knowledge accumulation, education, and functional background, experience, and training as well as expertise and information. The second fact believed to have played a significant role in the way in which transactive memory systems were developed in the teams and possibly had an impact on all three components of TMS as well as on team performance, is concerned with the composition of the teams. Several studies examining the impact of team composition on the development of TMS and team performance reveal mixed results. For instance, Wegner (1986) maintains that the transactive memory developed in teams who share close relations is more effective. Littlepage, Robison, and Reddington (1997) support Wegner's (1986) argument by providing evidence illustrating that teams who had previously worked with the same team members on a closely related task are in a better position to identify member expertise and that this facilitates group performance. Furthermore, in relation to Wegner's (1986) argument, Akgün et al. (2005) further suggested that familiarity and communication between team members ought to have a positive effect on TMS and, therefore, on performance; however, their data do not validate this argument. An earlier study conducted by Austin (2003) revealed a positive correlation between team performance and TMS not only in continuing and experienced teams but also in single project teams. Within the context of this thesis, the teams were formed as single project teams, for the purposes of the experiments. Even though team members were familiar with each other, they had not previously worked as a team, and therefore, their understanding of the memory storage and expertise of each team member was rather narrow.

Brandon and Hollingshead (2004) note that in transactive memory theory, notions of expertise are rather wide-ranging. Wegner (1995) describes a variety of ways that directories to others' knowledge are developed. Attributions of expertise usually originate from assumptions based on surface characteristics, for example, gender, age, ethnicity, clothes, possessions, etc. These basic information concerning social categorization, serve as Wegner, Erber, and Raymond (1991) note, through stereotyping in order to inform in regards to possible areas of knowledge, in the sense that one would expect different areas of memory storage from a man for example, than from a woman or from an older individual than from an individual of younger age (Ross and Holmberg, 1988). Inferences could also be made from expertise based on roles or an obvious indication of proficiency, such as an academic degree. In addition, team members may also be assigned areas of expertise based on duration, primacy, or most recent exposure to information, for instance, a team member being the last to mention a topic. Expertise based on assignments, for example, a team member is assigned to a specific task or voluntarily taking responsibility, is an additional source of expertise attributions. In view of the foregoing, Brandon and Hollingshead (2004, p. 636-37) note, ′′Basically, any domain of knowledge that can be labeled and associated with a group member qualifies that group member as an expert on that topic.′′ Wegner, Erber, and Raymond (1991) argue that these default settings enable humans to form an initial estimation of the memory items available even from a stranger. Expertise judgments based only on stereotypes, however, can be problematic. The development of an advanced transactive memory structure requires going beyond the defaults (Hollingshead and Fraidin, 2003). The development of transactive memory in teams involves the communication and updating of information each team member has about the areas of other team members' knowledge. In addition to the above and taking into account the ways in which directories to others' knowledge are developed, it is noteworthy to mention that in the current study, due to the fact the teams were formed as single-project teams just for the purposes of the experiments, they did not start out with any sort of group mind since they had no shared system for knowledge storage and access. Without such a system in place, memory performance among team members has dependent primarily on the combination processes through which individuals' retrievals were assembled into a group retrieval (e.g., Clark, Stephenson and Rutter, 1986; Hartwick, Sheppard and Davis, 1982; Hinsz, 1990; Stasser, Taylor and Hanna, 1989; Stephenson, Wagner and Brandstatter, 1983) and essentially, each team member cultivated the other team members as an external memory aid (Engestrom et al., 1990; Harris, 1978; Norman, 2002).

Descriptives

Table 15 presents the descriptive statistics of the TMS components and TMS total scale, and Figure 22 presents the distribution of scores. The subscale scores look normally distributed and around their mean score.

Table 15: *Descriptive Statistics of TMS Components and TMS Total Scale*

Scale	Mean	SD	Median	MIN	Max
TMS Coordination [avg]	3.9	0.7	4.0	2.4	5.0
TMS Credibility [avg]	3.8	0.6	3.8	1.8	4.8
TMS Specialisation [avg]	3.2	0.7	3.2	2.0	4.8
TMS TOTAL	10.9	1.4	10.8	8.0	13.8

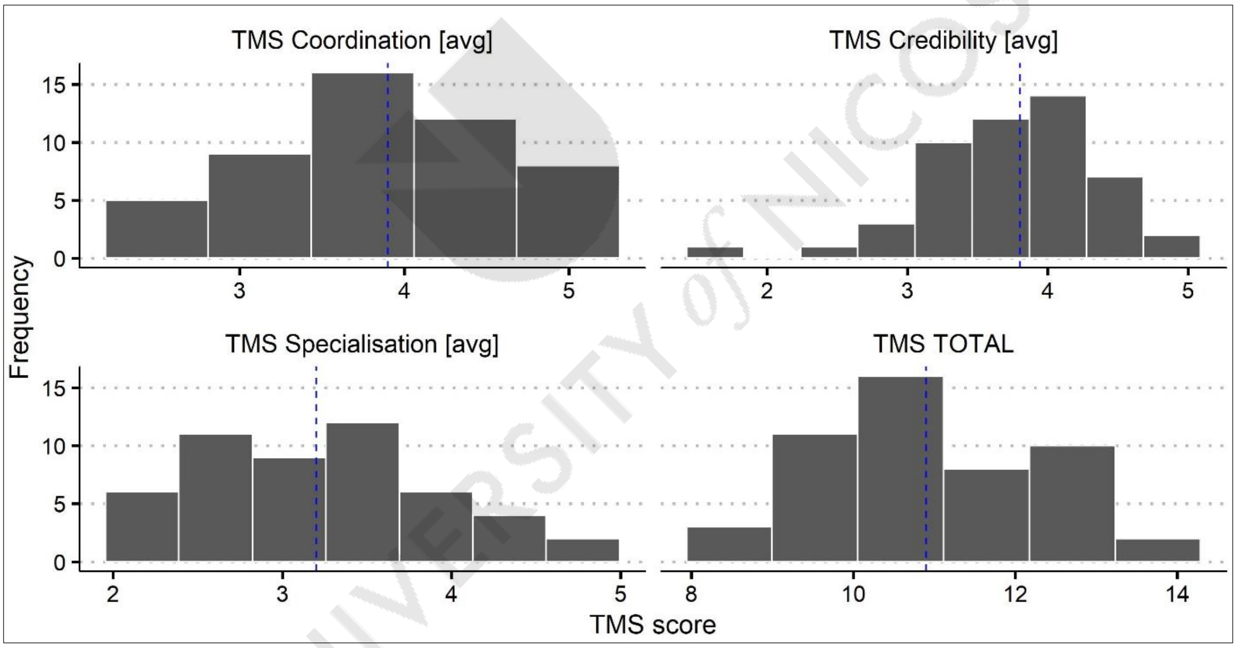


Figure 22: *Distribution of the TMS Components and TMS Total Scale (N=50)*

Correlation (r) of TMS with TASK SCORES, Collective Intelligence, and Team Interaction

Table 16 (see page 171) presents the Pearson correlation coefficients of the TMS scores (TMS components and Total TMS) with the scores gained at each of the three tasks, Total Task Score, Collective Intelligence, and Team Interaction. <u>**The analysis and findings presented below, answer R.Q. 1.13**</u> *What is the* *relationship between the TMS developed in the teams and: (a) the scores gained at the tasks (b) the teams' overall performance outcomes (c) CI and (d) Team Interaction (examine each TMS component individually and collectively)?*

A plethora of transactive memory definitions generally comprise two viewpoints, closely linked to the dimension of Specialization. The first is the mixture of personal knowledge; the second is the awareness of which member knows what within a team (Wegner, 1986). Specialization refers to the differentiated structure of team member knowledge (Lewis, 2004). Taking into account the ways in which directories to others' knowledge are developed, explained earlier, individuals in the current Thesis, are viewed as being linked to knowledge as a result of their personal expertise, but mostly through the circumstantial responsibility for knowledge that occurred on the basis of how the knowledge has been encountered by the teams (Wegner, 1986). In regards to the dimension of Specialization, the data analysis has shown that it has a moderate and positive correlation with Collective Intelligence ($r=0.31$, $p=0.29$), indicating that higher Specialization in the team is associated with higher CI. In addition, the data analysis has shown that specialization has a low and negative correlation with TASK 2 ($r=-0.24$, $p=0.41$), indicating that within the context of the current study, specialization does not seem to improve the collective ability of spontaneously understanding the workings of the physical world. Furthermore, specialization was found to have a low and positive correlation with TASK 3 ($r=0.20$, $p=0.48$) and no correlation with TASK 1 ($r=0.08$, $p=0.80$). It is a fact that none of the participants in the experiments had specialized knowledge in managing LoPHIEs. Some of the participants had high Risk Management Relevance indicative of some understanding of the basics in regards to handling LoPHIEs, something that could provide an advantage for the completion of Tasks 1 and 3. However, the majority of those participants, as explained in the previous section of this Chapter, were included in the Control Group. The issue concerning expertise relevant to managing LoPHIEs was mediated by the fact that for the completion of Tasks 1 and 3, participants were provided with supporting material that could be of assistance and establish the appropriate mode of thinking for the completion of the tasks. On the basis of this, it can be argued that transactive memory was developed because individuals in the teams accepted responsibility for knowledge. However, in relation to the results uncovered concerning TASKS 1 and 3, one possible explanation could be that Specialization cannot guarantee that those team members who possess needed knowledge will actually satisfy the demand for that knowledge or related information. Specialization in teams necessitates substantial planning among team members since attention should be given not only to who knows what, but also to who is responsible for what (Brandon and Hollingshead, 2004). Huang, Liu, and Zhong (2013) explain that the phenomenon of being incapable to satisfy the demand for needed knowledge or related information usually takes place when team members come from different professional backgrounds or do not have the necessary skills to recognize exactly which knowledge or relevant information is needed. In addition, as Huang, Liu and Zhong (2013) further explain, the phenomenon may also take place in situations where team members are incapable of communicating knowledge in an explicit and easy to understand manner or do not want to share some part of their knowledge. The situation may be worsened in cases that the knowledge is itself complex or tacit and hard to interpret in a simple and explicit format. The supporting material provided for TASK 1 was available for participants to access at any point during the completion of the task. On the contrary, the supporting material provided for the completion of TASK 3 was available to the participants before beginning to work on the task and had to be memorized since participants were prohibited from taking any sort of notes on the information provided and were not allowed access during the completion of the task. It is possible, therefore, that the way in which the supporting material was distributed in each case, for the completion of the two tasks, as well as the fact that it exposed participants to new information and was possibly perceived as hard to interpret in a simple and explicit fashion, may have had an effect on the dimension of Specialization. Nevertheless, additional research that focuses on transactive memory is required to validate this interpretation and offer a better understanding of the dynamics between circumstantial responsibility for knowledge that occurs on the basis of how the knowledge has been encountered by the team and the ability of team members to satisfy the demand for needed knowledge.

In regards to Credibility, the data analysis has shown that it has a low and negative correlation with Collective Intelligence ($r=-0.23$, $p=0.44$) and a low and positive correlation with TASK 3 ($r=0.27$, $p=0.35$).

Furthermore, it has a weak and negative correlation with TASK 1 (r=-0.13, p=0.66) and a weak and positive correlation with TASK 2 (r=0.13, p=0.65). Credibility is concerned with team members' beliefs about the accuracy and reliability of other team members' knowledge (Akgün et al., 2005; Kanawattanachai and Yoo, 2007; Lewis, 2004). Ko, Kirsch, and King (2005) note that Credibility can enhance the efficiency of the knowledge transfer process and have a positive impact on the overall team performance. One possible explanation for the trivial results of the current Thesis in regards to the dimension of Credibility could be the lack of trust in the knowledge sharer, which according to Huang, Liu and Zhong (2013) is one of the main reasons that although team members may be willing to share information, not all shared knowledge and information is actually being used. In relation to this, Holste and Fields (2005) maintain that cognition-based trust has a considerable effect on knowledge transfer and can influence an individual as to whether a piece of information or knowledge is credible and worth being used. Huang, Liu and Zhong (2013, p. 191) provide a comprehensive description of the phenomenon by stating that ''Simply assigning [individuals] with different types of expertise into a single team is unlikely to produce the desired results unless they can develop mutual credibility and coordinate their tasks effectively. To achieve such outcomes, they will need to feel comfortable in their work context – and comfortable to exchange knowledge with their team members''. Within the bounds of the current study, the lack of trust in the knowledge sharer might have resulted due to the fact that the tasks were unfamiliar to all team members as well as due to the fact that the supporting material provided for the completion of TASKS 1 and 3, exposed participants to new information; a situation that in turn might have led to inability to communicate knowledge in an explicit and easy to understand manner. The phenomenon might have escalated in the case that the supporting material provided as well as the tasks, were perceived as complex (Huang, Liu, and Zhong, 2013).

The dimension of Coordination is concerned with the efficient and orchestrated knowledge processing (Akgün et al., 2005; Kanawattanachai and Yoo, 2007; Lewis, 2004). Huang, Liu, and Zhong (2013) maintain that in order for a team to achieve enhanced knowledge coordination, team members should not only know how to find the knowledge needed, but must also have an understanding of how tasks are divided, as well as how sub-tasks are correlated and allocated to different team members (Cannon-Bowers and Salas, 2001; Huang, Liu, and Zhong, 2013; Kanawattanachai and Yoo, 2007). Indeed, several studies support the view that the quality of team performance, depends vastly on the task-knowledge coordination among team members, including whether the team is in position to identify and utilize effectively the skills and knowledge possessed by its members (e.g., Brandon and Hollingshead, 2004; Hollingshead, 1998a; Littlepage, Robison and Reddington, 1997; Stasser, Stewart and Wittenbaum, 1995). In this respect, a longitudinal study conducted by Kanawattanachai and Yoo (2007) revealed that task-knowledge coordination is a key construct that influences team performance because it can mediate the impact of the other two TMS dimensions (Specialization and Credibility). The data analysis has shown that the dimension of Coordination, within the context of this Thesis, has a weak and negative correlation with Collective Intelligence ($r=-0.16$, $p=0.58$) and a weak and positive correlation with TASK 2 ($r=0.10$, $p=0.72$). In addition, it was found that Coordination has a moderate and negative correlation with TASK 1 ($r=-0.30$, $p=0.29$) and a moderate and positive correlation with TASK 3 ($r=0.35$, $p=0.22$). The findings concerning the correlation of the dimension of Coordination with TASKS 3 and 2 support the findings of earlier studies conducted by Wegner (1987) and Thompson (1967) who provide evidence that transactive memory is more likely to prosper and be more beneficial when teams perform complex tasks that require high-level coordination for their completion, and less useful when teams perform simple tasks that require low-level coordination among team members. This is due to the fact complex tasks enable teams to employ member expertise more effectively to achieve higher levels of performance (Baumann and Bonner, 2004; Libby, Trotman, and Zimmer, 1987). One possible explanation for this is that task structure can encourage cognitive interdependence, which is less likely to evolve when a group task is simple and most likely to evolve when the group task is complex and necessitates high-level coordination among team members (Levine and Moreland, 2014; Moreland, 1999; Thompson, 1967; Wegner, 1987). Simply put, it is highly possible that the way in which the supporting material was distributed for the completion of TASK 3 (the fact that the participants were not allowed access to it during the completion of the task and the fact that it had to be memorized since taking notes on the information provided was prohibited), as well as the high complexity of the task itself and in general its structure, might have encouraged cognitive interdependence causing transactive memory to flourish in the teams. On the contrary, this was not the case for TASK 2. The task was of low complexity, and no supporting material was provided for its completion. Within the bounds of the current study, the results yield in regards to this specific TMS dimension, indicate that TASKS 2 and 3 respond to the principle - higher task complexity is associated with higher coordination. Assuming that this principle is correct, one possible explanation for the moderate and negative correlation of the dimension of Coordination and TASK 1, which is of medium complexity, could be traced to the fact that the task was of combined nature in terms of task type (closed and open-ended) and skills required for completion (both accuracy and coordination), as compared to the other two tasks that were singular in nature (refer to Table 5, Chapter Four, Section 4.5, page 117). Investigating the issue further would be valuable firstly in order to determine whether the nature of the task, either combined or singular in terms of type and skills required for completion can impact the dimension of Coordination; and secondly, to gain new insights on the relationship between the dimension of Coordination and team performance based on task classification. An additional explanation for the moderate and negative correlation between Coordination and TASK 1 could relate to task complexity level perception. By examining the results concerning the correlation between the dimension of Coordination and TASK 2, it is evident that participants perceived TASK 2 as more complex than TASK 1, possibly because no supporting material was provided for its completion. Whereas for the completion of TASK 1, participants were not only provided with supporting material, but they were also allowed access to it at any point during the completion of the task, something that it is likely to have made the participants perceive the task as less complex than it actually was.

The data analysis has shown that the Total TMS score has a moderate and positive correlation with TASK 3 ($r=0.37$, $p=0.19$). In addition, it was found that it has a low and negative correlation with TASK 1 ($r=-0.16$, $p=0.58$) and no correlation with TASK 2 ($r=-0.01$, $p=0.97$). Within the bounds of the current study, these findings reinforce the above-analyzed reasoning in regards to task complexity and further support the findings of the studies conducted by Wegner (1987) and Thompson (1967); that transactive memory is more likely to prosper and be more beneficial when teams perform complex tasks that require high-level coordination for their completion. However, Wegner's (1987) and Thompson's (1967) studies have been conducted in other contexts. To the best of the researcher's knowledge, the current study is the first to verify the positive correlation between transactive memory and high complex tasks within the context of managing LoPHIEs with the use of CI. In addition, the findings concerning the relationship between Total TMS score and the TASKS, provide further evidence that task structure can encourage cognitive interdependence, causing transactive memory to flourish in the teams. Nevertheless, investigating the issue further is needed to understand better, primarily the relationship between TMS and team performance based on task classification; and secondly, the dynamics that underlay the relationship between task structure, cognitive interdependence, and TMS. The data analysis has further shown that the Total TMS score has a weak and positive correlation with Total Task Score ($r=0.13$, $p=0.66$), indicating that in the context of this Thesis, TMS as one single construct does not appear to facilitate team performance. Moreover, within the bounds of the current study, the data analysis has shown that the Total TMS score has no correlation with Collective Intelligence ($r=-0.02$, $p=0.94$). This finding is contrary to the researcher's expectations, since the comprehensive literature review conducted individually on the two, points to the conclusion that both share common factors that are significantly correlated with their emergence in teams. The lack of a visible correlation between CI and TMS could be, therefore, due to the moderation occurring by a number of external conditions and constraints. Furthermore, it is essential to recall here that, to the best of the researcher's knowledge, the current study is the first to examine transactive memory in correlation with Collective Intelligence. Therefore, future studies that investigate the dynamics between the two are needed to explore further their relationship.

The research on the role of team interaction and communication in the use of shared knowledge is inconsistent. While numerous studies present evidence that interaction and communication between team members play a significant role in the development and efficient use of transactive memory (e.g., Hollingshead and Brandon, 2003; Lewis, 2004; Liang, Moreland, and Argote, 1995; Palazzolo et al., 2006; Rulke and Rau, 2000; Yoo and Kanawattanachai, 2001), several other studies, as Littlepage et al. (2008, p.

225) note, support that ''Although communication can enhance the effectiveness of utilization of an existing transactive memory system (Hollingshead, 1998b; Palazzolo, 2005), it does not appear to be essential.'' For instance, a study conducted by Lewis (2004) with student consulting teams, revealed a positive correlation between face-to-face communication and the development as well as the refinement of transactive memory. On the contrary, other studies examining teams encoding new information, illustrate that the distribution of responsibility within a team can also be accomplished without explicit communication, in a way that team performance is increased (Hollingshead, 2000, 2001; Wegner, Erber, and Raymond, 1991). Similarly, studies of tacit coordination indicate that, without communication, teams can use their expectations about member expertise to coordinate task allocation in a manner that facilitates performance (Wittenbaum, Stasser, and Merry, 1996; Wittenbaum, Vaughan and Stasser, 1998). Three communication processes are key to the development of transactive memory: 1. Directory updating, which involves discovering the types of information that other team members know (Hollingshead and Brandon, 2003; Moreland and Myaskovsky, 2000; Palazzolo, 2005), 2. Communication to distribute information within the team, which involves transferring information to members who are considered as experts in a specific field or have accepted the responsibility for holding a specific type of information and 3. Communication to retrieve information which involves obtaining needed information from members who have been considered as experts in a specific field or have accepted the responsibility for holding a specific type of information (Hollingshead, 1998b; Palazzolo, 2005; Wegner, 1995). For the purposes of the experiments conducted for the current study, a team interaction and communication scale of 1-5 has been developed as well as observational techniques have been employed to monitor the overall communication process that has taken place within the teams. Within the framework of this Thesis, Team Interaction has been found to have a low and positive correlation with Specialization ($r=0.23$, $p=0.44$). In addition, the data analysis has shown that Team Interaction has a moderate and negative correlation with Credibility ($r=-0.34$, $p=0.24$), indicating that the higher the communication and interaction between team members, the less accurate, reliable and credible the knowledge shared within the team, becomes. Furthermore, no correlation between Team Interaction and Coordination ($r=-0.06$,

p=0.84) was found. Moreover, within the bounds of the current study, the data analysis has shown that as one single construct, TMS (Total TMS) has no correlation with Team Interaction (r=-0.05, p=0.86). Despite the results of this Thesis in regards to the correlation between Team Interaction and the different TMS dimensions as well as Total TMS score, the significance and positive effect of communication on team performance is well documented in the literature. Communication and interaction between team members is critical for the development and efficient use of transactive memory (e.g., Hollingshead and Brandon, 2003; Lewis, 2004; Palazzolo et al., 2006; Yoo and Kanawattanachai, 2001). What the results of this Thesis in regards to the above-discussed findings evidently suggest, is that the issue is subject to further investigation. Furthermore, the absence during conducting Experiment 2 of tools to monitor each communication process separately in the teams appears as a limitation for the current study. Thus, future studies of similar nature should consider ways of recording each communication process that takes place within a team, while in action (1. directory updating, 2. communication to distribute information within the team and 3. communication to retrieve information) separately, rather than treating them as one single construct.

Table 16: *Correlation (r) of TMS SCORES with TASK SCORES, CI, and Team Interaction*

Variable	Total Task Score	Collective Intelligence	TASK 1 (Emergency Planning Activity)	TASK 2 (Folk Physics Test Part II)	TASK 3 (Tsunami Disaster Scenario)	Team Interaction
Specialization	0.10	0.31	0.08	-0.24	0.20	0.23
Credibility	0.13	-0.23	-0.13	0.13	0.27	-0.34
Coordination	0.07	-0.16	-0.30	0.10	0.35	-0.06
Total TMS	0.13	-0.02	-0.16	-0.01	0.37	-0.05

Results on Experiment 1, Experiment 2 and Experiment 3 by Team, are provided in Appendix XI

4.8.4 Additional Research Findings

Multivariate Model

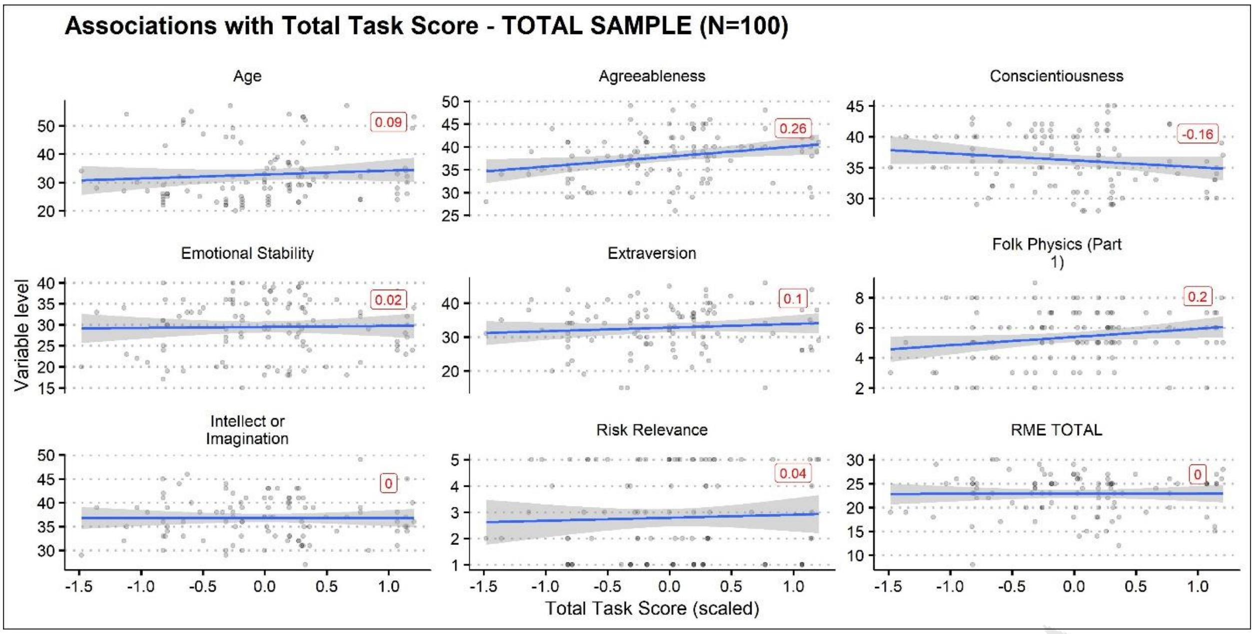
Correlations (r) of Total Task Score with Experiment 1 measures and Demographics

Considering the full sample (N=100) of participants, the variables used to assess individual intelligence in Experiment 1, including demographic characteristics, were explored in association with the Total Task Score (TTS) obtained in Experiment 2. The TTS of participants that were assigned to teams for the conduction of Experiment 2 inherited their team's TTS.

Table 17 (see page 173) presents the Pearson correlation r values with TTS, and Figure 23 (see page 174) presents the scatterplots between the variables and the TTS as a visual inspection of the associations. Regarding the demographic characteristics, it has been observed that Age (r=0.09) and Risk Management Relevance (r=0.04) are not associated with the TTS. In addition, with regards to the five primary dimensions of adult personality, it was found that Agreeableness has a low and positive correlation with TTS (r=0.26, p=0.008) and Conscientiousness (r=-0.16, p=0.12) has a low and negative correlation with TTS. No other personality traits seem to be associated with the TTS. It was also revealed that the ability to spontaneously understand the workings of the physical world, as measured by the Folk Physics Test (Part I) (r=0.20, p=0.042), has a low and positive correlation with TTS. Lastly, it is important to note that RME Total (r=0) is also not correlated with the TTS. Within the bounds of the current Thesis, considering the total sample (N=100) of participants, what this finding indicates is that ToM (as measured by the Reading the Mind in the Eyes RME test) and consequently EI, do not have a predictive power of over individual performance. This is contrary to the findings of previous studies. The relationship between EI and performance in various contexts is well documented. Meta-analyses conducted by O'Boyle et al. (2011) and Joseph and Newman (2010) respectively, suggest that emotional intelligence positively affects several aspects of workplace performance, including company rank and pay increases (Lopes et al., 2006) and supervisor ratings (Côté and Miners, 2006). In particular, emotional and social competencies have been shown to positively affect sales leadership performance (Boyatzis, Good and Massa, 2012), management (Guillén Ramo, Saris and Boyatzis, 2009; Boyatzis, Good and Massa, 2012), entrepreneurship performance (Camuffo, Gerli and Gubitta, 2012) and engineers' effectiveness and engagement (Boyatzis, Rochford and Cavanagh, 2017). In regards to the effect of EI on academic performance, Gil-Olarte Márquez, Palomera Martín and Brackett (2006) and Lam and Kirby (2002) illustrate that EI explains achievement in high school and undergraduate programs. To the best of the researcher's knowledge, only the study conducted by Petrides, Frederickson and Furnham (2004), examining the impact of EI on academic performance, suggests that there is no relation or a non-significant one between EI and performance. Nevertheless, the empirical studies mentioned above have been conducted in other contexts than the one being examined by the current Thesis. It should be reminded at this point that the predictive power of ToM (as measured by the RME test) and consequently EI, over the performance outcomes of teams, has been verified in Section 4.8.2, TEAMS of this Chapter.

Table 17: *Correlation (r) of TTS with Experiment 1 Measurements*

Variable	Total Task Score - r
Age	0.09
Risk Management Relevance	0.04
RME TOTAL	0.00
Extraversion	0.10
Agreeableness	0.26
Conscientiousness	-0.16
Emotional Stability	0.02
Intellect or Imagination	0.00
Folk Physics Test (Part I)	0.20



[red labels on plots indicate -r- the correlation coefficient between the variable and TTS]

Figure 23: *Associations of Total Task with Demographics and Experiment 1 Measurements*

To adjust for the multivariate effect of the variables to the TTS, a multiple linear regression model was fitted. TTS as the dependent variable and Experiment 1 measures with demographic characteristics as the independent variables. The model additionally adjusts whether the individuals participated in Experiment 2 individually or as a member of a team.

The model explains 7.95% (Adh. R2), (p=0.093) of the variation of the Total task Score.

Belonging in a team is associated with a higher Total Task Score as compared to working individually (b=0.34, p=0.066). This finding reinforces the findings of the comparative analysis conducted between the Control and Experimental group, and further supports the answer to R.Q. 1.4 *Does collective problem-solving lead to improved performance outcomes?* (refer to Section 4.8.2, Control Group Vs. Experiment Group).

Agreeableness is positively associated with TTS (b=0.034, p=0.012), meaning that increased Agreeableness of the individual is associated with increased TTS.

Conscientiousness is negatively associated with TSS (b=-0.031, p=0.053), meaning that increased Conscientiousness of the individual is associated with reduced TTS.

Model assumptions for normality, linearity, multicollinearity, heteroscedasticity, and influential points were validated (see Appendix XII).

Table 18: *Linear Regression Results of Total Task Score on Experiment 1 variables*

term	estimate	std.error	statistic	p.value
(Intercept)	-0.711	1.016	-0.700	0.486
Experimental (Vs. Control)	0.340	0.182	1.863	0.066
age	0.006	0.008	0.778	0.439
Female (vs Male)	-0.151	0.144	-1.046	0.298
Risk Manag. Relevance (vs Low Risk Manag. Relevance)				
Low - Medium Risk Manag. Relevant	0.098	0.241	0.405	0.687
Medium Risk Manag. Relevant	0.176	0.285	0.617	0.539
Medium - High Risk Manag. Relevant	0.100	0.276	0.361	0.719
High Risk Manag. Relevant	0.245	0.247	0.993	0.324
rme_total	-0.003	0.016	-0.182	0.856
b5_ex	-0.005	0.010	-0.518	0.606
b5_ag	0.035	0.013	2.678	0.009
b5_co	-0.028	0.016	-1.790	0.077
b5_em_st	0.004	0.010	0.387	0.699
b5_in_or_im	-0.002	0.015	-0.153	0.879
folk_ph_part_i	0.036	0.041	0.881	0.381

Model for Predicting Team Interaction

Through the data analysis process, the question of whether Team Interaction can be predicted has emerged, and a draft model was developed with Team Interaction as the dependent variable and the five primary dimensions of adult personality and RME scores as the independent variables. Because the sample size is quite low (N=14 groups) and a general rule of thumb for regression analysis is 100 observations [https://stats.stackexchange.com/questions/10079/rules-of-thumb-for-minimum-sample-size-for-multiple-regression], the analysis is merely exploratory, with no intention of making inferences about the association of the personality traits and RME scores with the Team Interaction Level.

What has been attempted, therefore, is simply an estimation of how much variation of the Team Interaction Level can be explained by the personality traits and RME factors – that is, the (adjusted) R^2. The analysis has shown that the personality traits and RME scales explain the 32% (Adj R2) of the variation of the Team Interaction Level.

Developing the model further by investigating and incorporating more factors that have been or may not have been explored by the current Thesis would be an important direction for future research. Previous studies have shown that the total amount of communication that takes place within groups, is one of the three factors significantly correlated with CI; and that CI is found to be predicted by how equally communication is distributed among group members (e.g., Engel et al., 2014; Kim et al., 2015; Woolley et al., 2010). The development, therefore, of a model that predicts Team Interaction, at its maximum, would offer new insights into the dynamics of collective problem-solving.

Table 19: *Multiple Regression analysis for the Team Interaction Level on the five primary dimensions of adult personality and RME (N=14)*

term	estimate	std.error	statistic	p.value
(Intercept)	37,59564	19,13106	1,965163	0,084977
rme_total	-0,67355	0,448359	-1,50225	0,171433
b5_ex	-1,24769	0,448154	-2,78406	0,023775
b5_co	-1,29296	0,413845	-3,12425	0,014138
b5_em_st	1,391983	0,434643	3,202591	0,012563
b5_in_or_im	1,035416	0,410619	2,521596	0,03572

4.9 CIMA Model - Second Cycle: Reflect Evolution Phase

In this section, the findings of the Thesis are applied onto the improved CIMA Model, and the resilience of the model against the results of the data analyzed is being considered (refer to Figure 24).

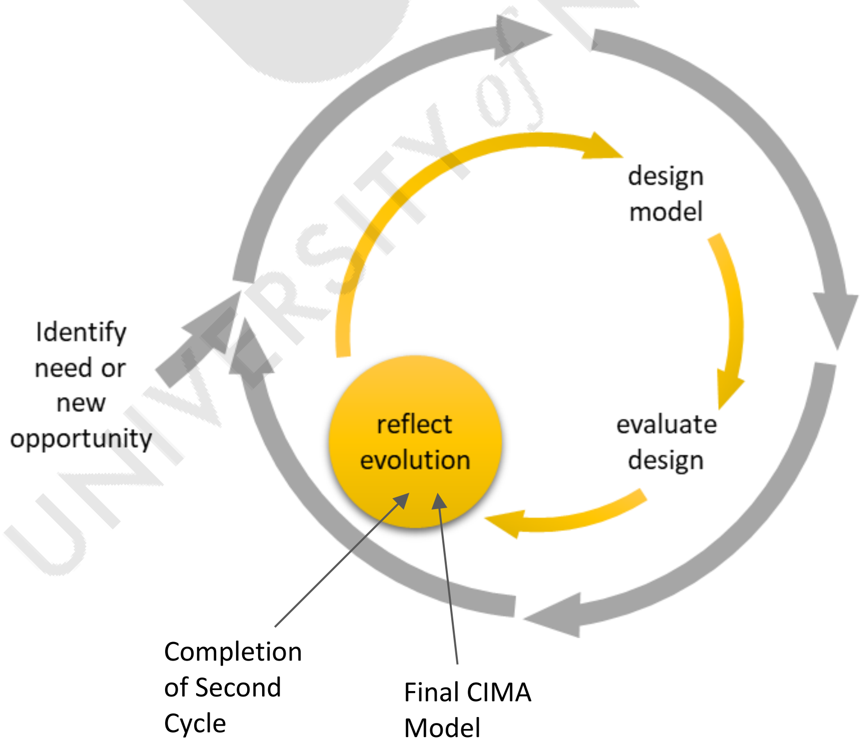


Figure 24: *Maturity Model Development Process: Cycle 2 – Phase 4 (adapted from Mettler, 2011)*

Drawing back to Table 3 (refer to Section 4.2, page 103), decisions related to the ‘reflect evolution’ phase are of particular importance because after the application of the CIMA Model design and its evaluation, the understanding of the maturity of the phenomenon under study is enhanced and therefore the model needs to be refaced. The initial analysis of the primary data collected through the three interlinked experiments that has taken place during the first cycle of the development process for the proposed model, has resulted to an improved CIMA Model that incorporated an additional dimension, that of Task Classification. After conducting the full analysis of the primary data collected, during the ‘evaluate design’ phase of the second development cycle, several changes in regards to the form and function of the CIMA model are necessary, in order to integrate in full, the maturity of the phenomenon under study.

There are two main differences between the initial and improved CIMA Model designs, and the final model developed. These differences are, first, the final CIMA Model developed, contrary to the initial and improved model designs, focuses on specific factors. This has caused the model to evolve from being abstract (initial and improved CIMA Model) to concrete and tangible (final CIMA Model) and allowed the inclusion of precise tools to measure the maturity levels of these specific factors, as well as the consideration of methods to improve their maturation through five maturity levels. Second, the final CIMA Model takes into consideration Transactive Memory System (TMS) dimensions. These have not been incorporated in the initial CIMA Model since the concept of transactive memory has not been examined previously in relation to CI, and no actual indications were found in the literature in regards to their relation. In addition, the initial analysis of the primary data collected did not provide clear data necessitating the inclusion of the dimension of TMS in the improved model.

4.9.1 CIMA Model – Final Design

The complete analysis of the primary data collected during the ‘evaluate design’ phase of the second development cycle has shown that there is a high strength of association between the overall team performance outcomes and Collective Intelligence – the Total Task Score has a moderate and positive correlation with Collective Intelligence (r=0.40, p=0.16). This means that a higher level of Collective Intelligence in a team is associated with higher performance (Total Task Scores). The specific factors incorporated in the final CI Maturity Assessment (CIMA) Model (depicted in Figure 24, page 177), have either a direct positive impact on CI or on Collective Performance.

The four dimensions based on which the final CIMA model is developed, following the factors placed on the model depicted in Figure 24 (see page 177), in counter-clockwise direction, are: 1. Team Composition, 2. Transactive Memory System (TMS), 3. Team Interaction, and 4. Task Classification. Eight factors incorporated into the final CIMA model relate to the dimension of *Team Composition* and correspond to five categories. These categories are: 1. Cognitive abilities (includes: the ability of understanding social causality, as measured by the Reading the Mind in the Eyes RME test and the ability of spontaneously understanding the workings of the physical world – understanding physical causality, as measured by the Folk Physics test), 2. Demographic characteristics (includes: Risk Management Relevance - RMR), 3. Diversity in demographic characteristics (includes: diversity in age), 4. Personality traits (includes: the primary dimensions of adult personality, Agreeableness and Extraversion, as measured by the Big Five Personality Test), and 5. Diversity in personality traits (includes: the diversity in Agreeableness and the diversity in Extraversion). A clearly visible change between the initial and improved Vs. the final maturity model design is that the diversity in cognitive abilities, a category in relation to Team Composition, that has been incorporated in the initial and improved maturity model designs, has been excluded from the final model developed. In regards to the diversity in the ability of understanding social causality (as measured by the Reading the Mind in the Eyes RME test), the data analysis revealed a moderate and negative correlation with the Total Task Score (r=-0.33, p=0.24) and a weak and positive correlation with Collective Intelligence (r=0.13, p=0.66). On the other hand, in regards to the diversity in the ability of spontaneously understanding the workings of the physical world – understanding physical causality (as measured by the Folk Physics test), the data analysis revealed no correlation with Collective Intelligence (r=0.00, p=0.99) and a weak and negative correlation with the Total Task Score (r=-0.17, p=0.56). The above findings led to the exclusion of factors related to the diversity in cognitive abilities, from the final maturity model developed.

In regards to the dimension of Transactive Memory System (TMS), only Specialization has been incorporated in the final CIMA model. This is because the other two TMS components, have been found to have weak to low negative correlations with CI (Credibility: -0.23, Coordination: -0.16) and weak to zero correlations with Collective Performance (Credibility: 0.13, Coordination: 0.07). On the other hand, concerning Specialization, the data analysis has shown that it has a moderate and positive correlation with Collective Intelligence ($r=0.31$, $p=0.29$), indicating that higher Specialization in the team is associated with higher CI.

Table 20 (see page 183) has been derived based on the complete analysis of the data collected during the 'evaluate design' phase of the first development cycle of the proposed model, and presents more closely the factors incorporated in the final maturity model, comparatively in relation to their effect on CI and Collective Performance. The factors included in the Table relate to the dimensions of *Team Composition* and *Transactive Memory System (TMS)* and are divided into two categories: 1. Factors that have a primary influence on CI and Collective Performance, and 2. Factors that have a secondary influence on CI and Collective Performance. As shown in the table, both CI and Collective Performance are positively influenced by five primary factors.

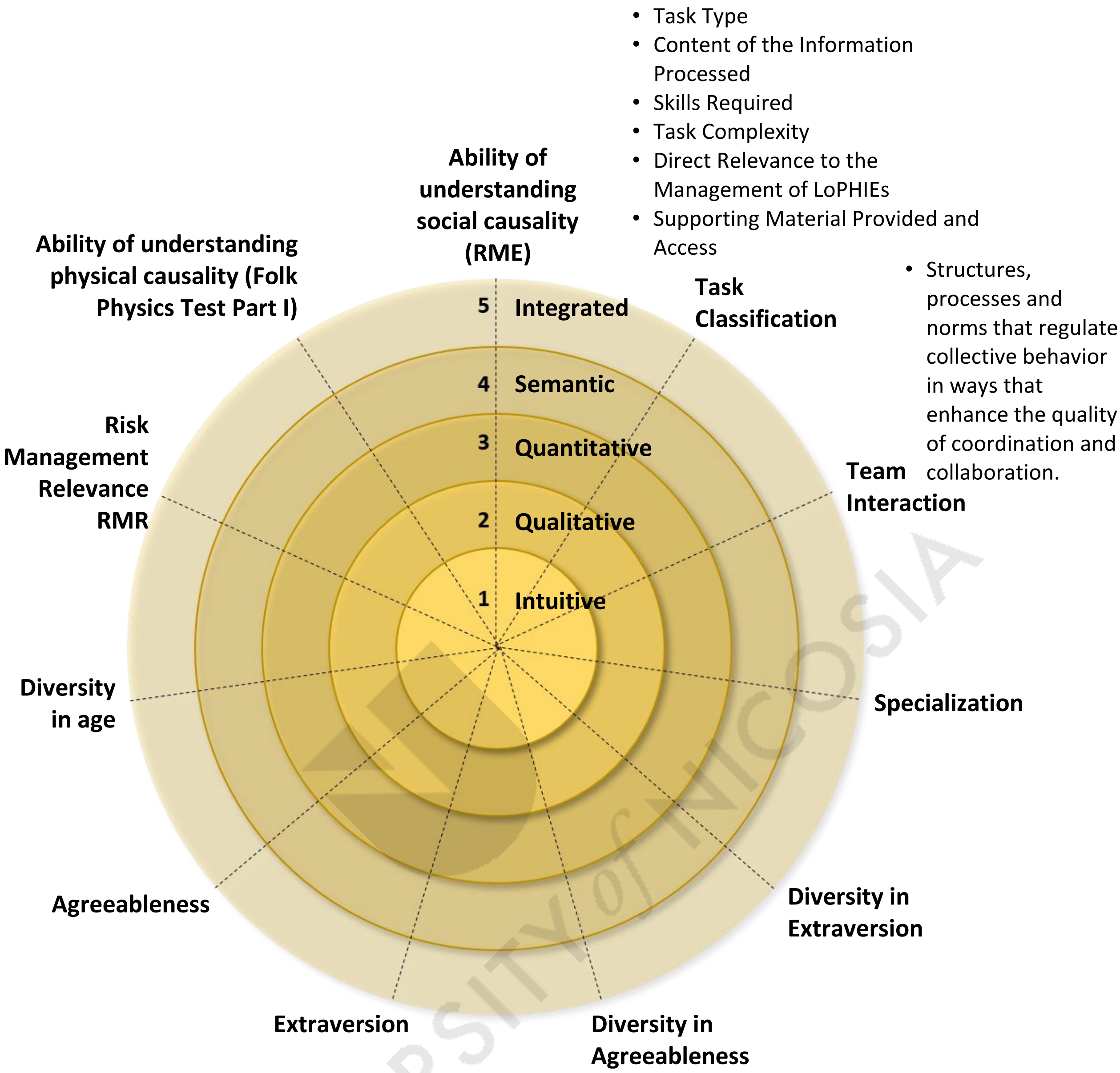


Figure 25: *CIMA Model – Final Design*

The five primary factors identified to drive the evolution and maturation of CI in teams, in regards to the management of LoPHIEs, as shown in Table 20 are: 1. The ability of understanding physical causality - Folk Physics test (part I). 2. Risk Management Relevance (RMR), 3. The diversity in Extraversion within team members. 4. The diversity in Agreeableness in the team and 5. Specialization (TMS component). The data analysis has shown that these factors have a moderate and positive correlation with Collective Intelligence (Ability of understanding physical causality - Folk Physics test Part I: r=0.31, Risk Management Relevance

RMR: r=0.31, Diversity in Extraversion: r=0.45, Diversity in Agreeableness: r=0.49, Specialization: r=0.31). On the other hand, the five primary factors identified to positively influence Collective Performance in relation to the management of LoPHIEs, are: 1. The ability of understanding social causality – RME, 2. The diversity in age between team members, 3. Extraversion, 4. Agreeableness and 5. The diversity in Extraversion within team members. The data analysis has shown that these factors have a moderate and positive correlation with Collective Performance (Ability of understanding social causality – RME: r=0.40, Diversity in age: r=0.33, Extraversion: r=0.40, Agreeableness: r=0.44, Diversity in Extraversion: r=0.40). The diversity in Extraversion within team members is the only consistent primary factor identified to influence both CI and Collective Performance positively. This finding is subject to further research in order to better understand the dynamics of the relationship between the diversity in Extraversion and CI as well as Collective Performance in relation to the management of LoPHIEs.

The two secondary factors identified to drive the evolution and maturation of CI in teams, in regards to the management of LoPHIEs, Extraversion and Agreeableness, as shown in Table 20 (see page 183), are found within the five primary factors positively influencing Collective Performance; and vice versa, the four secondary factors identified to positively influence Collective Performance are included within in the primary factors positively influencing the maturation of CI in teams. These secondary factors are: 1. Ability of understanding physical causality - Folk Physics test (part I), 2. Risk Management Relevance RMR, 3. Diversity in Agreeableness and 4. Specialization.

Table 20: *Factors Influencing the Maturation of CI and Collective Performance*

Collective Intelligence (CI)		Collective Performance	
PRIMARY FACTORS		**PRIMARY FACTORS**	
Cognitive Abilities	Ability of understanding physical causality - Folk Physics test (part I)	**Cognitive Abilities**	Ability of understanding social causality - RME
Demographic Characteristics	Risk Management Relevance RMR	**Diversity in Demographic Characteristics**	Diversity in Age
Diversity in Personality Traits	Diversity in Extraversion Diversity in Agreeableness	**Personality Traits**	Extraversion Agreeableness
TMS Dimensions	Specialization	**Diversity in Personality Traits**	Diversity in Extraversion
SECONDARY FACTORS		**SECONDARY FACTORS**	
Personality Traits	Extraversion Agreeableness	**Cognitive Abilities**	Ability of understanding physical causality - Folk Physics test (part I)
		Demographic Characteristics	Risk Management Relevance RMR
		Diversity in Personality Traits	Diversity in Agreeableness
		TMS Dimensions	Specialization

The impact of the dimensions of *Team Interaction* and *Task Classification* on CI and Collective Performance is more widespread in relation to the other two dimensions incorporated in the final CIMA model and their related factors. Within the bounds of the current study, the results uncovered from the data analysis suggest that Team Interaction is significantly influenced by the characteristics of the situation at hand (Task Classification) and the way in which individual and collective task representations are developed in a team (refer to Table 5, Chapter Four, Section 4.5, page 117). The type of the task at hand, the skills required for its completion, the content of the information needed to be processed (whether based on the social or analytic cognitive domain) as well as its complexity and structure (whether supporting material was provided for its completion and how the knowledge was distributed and encountered in each case by the team), have an impact on the behavior and decision-making processes of the team and consequently on Team Interaction. More specifically the type of the task (whether it is a closed, open-ended task or a combination of the two) has an impact on the procedures utilized by the team that may accordingly increase or decrease the depth of discussion (Henry, 1995; Hollingshead, 1996) and consequently lead to either more complete and efficient or inefficient use of team member knowledge, leading to enhanced or decreased team performance.

Drawing back to Figure 25 (see page 181), the final CIMA Model developed, incorporates eleven factors that mature in five levels, from an intuitive to an integrated stage. The definitions developed for the maturity levels for each factor incorporated in the final CIMA Model have been derived based on primary and secondary data as well as on expert opinion. The definitions of the maturity levels are shown in Table 21 (see page 185).

Based on the literature reviewed in Chapter Two (refer to Section 2.4), maturity assessment models disclose existing maturity levels and identify the essential corresponding actions and measures for improvement. In relation to the proposed maturity model, the tools that can be used to measure the maturity levels of the specific factors identified to positively influence the evolution and maturation of CI in teams as well as Collective Performance, in relation to the dimension of *Team Composition* are: 1. The Reading the Mind in the Eyes test RME to measure the ability of understanding social causality (a copy of the full test can be found in Appendix IV), 2. The Folk Physics Test developed and validated by Baron-Cohen et al. (2001b) to measure the ability of understanding physical causality – ability of spontaneously understanding the workings of the physical world (a copy of the full test can be found in Appendix V), 3. The Big Five Personality Test, to measure the personality traits of Agreeableness and Extraversion, as well as to assess the diversity of these two traits within the team (a copy of the full test can be found in Appendix VI), 4. Demographic records and registers to document experience, background, training, expertise, and education, can provide the means to measure levels of relevance to risk management (RMR) and assess the diversity in age within a team.

Table 21: *CIMA Model – Maturity Levels Definitions*

TEAM COMPOSITION Factors identified to positively influence the evolution and maturation of CI in teams and Collective Performance: **1. Ability of understanding social causality (as measured by the Reading the Mind in the Eyes RME test), 2. Ability of understanding physical causality – ability of spontaneously understanding the workings of the physical world (as measured by the Folk Physics test), 3. Risk Management Relevance RMR, 4. Diversity in age, 5. Agreeableness, 6. Extraversion, 7. Diversity in Agreeableness, 8. Diversity in Extraversion**				
Maturity Level 1: Intuitive	**Maturity Level 2: Qualitative**	**Maturity Level 3: Quantitative**	**Maturity Level 4: Semantic**	**Maturity Level 5: Integrated**
• Teams are formed with complete ignorance of how specific factors related to Team Composition, positively influence the evolution and maturation of CI in teams as well as Collective Performance. • There is a lack of formal tools to measure these factors in the teams.	• The specific factors related to Team Composition identified to positively influence the evolution and maturation of CI in teams as well as Collective Performance are intuitively assessed and analyzed. • There is still a lack of formal tools to measure these specific factors.	• There is a factual assessment and analysis of the specific factors identified to positively influence the evolution and maturation of CI in teams as well as Collective Performance, with some awareness of their positive effects. • Some tools to measure these specific factors are in place, offering some reporting and metrics.	• Intuitive team modification takes place based on specific factors related to Team Composition. • There is a good understanding of how these specific factors positively influence CI and Collective Performance. • Formal tools to measure these specific factors are in place, offering advanced reporting and metrics.	• There is informed team modification based on specific factors related to Team Composition. • There is a comprehensive understanding of how these specific factors positively influence CI and Collective Performance. • There is extensive use of supportive tools to measure the specific factors of Team Composition, offering measurable results.
TRANSACTIVE MEMORY SYSTEM (TMS) Factors identified to positively influence the evolution and maturation of CI in teams and Collective Performance: **1. Specialization**				
Maturity Level 1: Intuitive	**Maturity Level 2: Qualitative**	**Maturity Level 3: Quantitative**	**Maturity Level 4: Semantic**	**Maturity Level 5: Integrated**
• There is complete ignorance of how transactive memory, as a collective mechanism, forms the style in which teams encode, store and retrieve information. • Teams are formed with ignorance of how Specialization may positively influence the evolution and maturation of CI in teams as well as Collective Performance. • It is generally considered that the performance of each team member relies solely on their own knowledge. • There is a lack of formal tools to measure the transactive memory system developed in teams.	• The specific TMS component of Specialization is intuitively assessed and analyzed. • It is generally considered that the performance of each team member relies solely on their own knowledge. • There is still a lack of formal tools to measure the component of Specialization in the teams.	• There is a factual assessment and analysis of Specialization, with some awareness of how this specific TMS component, positively influences CI and Collective Performance. • The idea that the performance of each team member may not depend solely on their own knowledge, but also the knowledge of others in their team, is being considered. • Some tools to measure Specialization in the teams are in place, offering some reporting and metrics.	• Intuitive team modification takes place based on the specific TMS component of Specialization. • There is a good understanding of how this specific TMS component positively influences CI and Collective Performance. • There is a good understanding of the fact that the performance of each team member relies on the collective knowledge of the team. • Formal tools to measure Specialization in teams, are in place, offering advanced reporting and metrics.	• There is informed team modification based on the specific TMS component of Specialization. • There is a comprehensive understanding of how this specific TMS component positively influence CI and Collective Performance. • There is a comprehensive understanding of the fact that the performance of each team member relies on the collective knowledge of the team. • There is extensive use of supportive tools to measure Specialization in the teams, offering measurable results.
TEAM INTERACTION **Structures, processes, and norms that regulate collective behavior in ways that enhance the quality of coordination and collaboration**				
Maturity Level 1:	**Maturity Level 2: Qualitative**	**Maturity Level 3: Quantitative**	**Maturity Level 4: Semantic**	**Maturity Level 5: Integrated**
• Team Interaction is at a low level, with no presence of knowledge sharing. • There is complete ignorance of how structures, processes, and norms regulate collective behavior in ways that enhance the quality of coordination and collaboration. • There is ignorance of the fact that Team Interaction is influenced by the characteristics of the situation at hand (Task Classification) and the way in which individual and collective task representations are developed in teams. • Formal tools to measure Team Interaction level are absent.	• Team Interaction is at a low-medium level, with limited knowledge sharing. • Structures, processes, and norms that regulate collective behavior are intuitively being considered. • The Team Interaction level is intuitively assessed and analyzed, but formal tools to perform a comprehensive assessment are absent.	• Team Interaction is at a medium level, with improved knowledge sharing and communication style. • Some supportive tools to measure Team Interaction levels are in place, offering some reporting and metrics. • There is a factual assessment and analysis of the structures, processes, and norms that regulate collective behavior, with some awareness of their effect on the quality of coordination and collaboration.	• Team Interaction is at a medium-high level, with extensive knowledge sharing. • There is an improved understanding of the structures, processes and norms that regulate collective behavior, and their positive effect on the quality of coordination and collaboration. • Formal tools to measure Team Interaction are in place, offering advanced reporting and metrics.	• Team Interaction is at a high level, with broad knowledge sharing. • There is a comprehensive understanding of how structures, processes, and norms regulate collective behavior in ways that enhance the quality of coordination and collaboration. • There is extensive use of tools to measure Team Interaction level, offering measurable results.
TASK CLASSIFICATION Factors identified to positively influence the evolution and maturation of CI in teams and Collective Performance: **1. Task Type (Closed, Open-ended, combination of both), 2. Content of the Information Processed (based on the social or analytic/non-social cognitive domain), 3. Skills Required for the completion of the task (accuracy, coordination, combination of both), 4. Task Complexity (low, medium, high), 5. Direct Relevance to the Management of LoPHIEs, 6. Supporting Material Provided and Access**				
Maturity Level 1:	**Maturity Level 2: Qualitative**	**Maturity Level 3: Quantitative**	**Maturity Level 4: Semantic**	**Maturity Level 5: Integrated**
• There is complete ignorance of how specific characteristics of the situation at hand (Task Classification) and the way in which individual and collective task representations are developed in teams, influence the evolution and maturation of CI as well as Collective Performance. • There is a lack of formal tools to measure the characteristics of the situation at hand.	• The specific factors identified to positively influence the evolution and maturation of CI in teams as well as Collective Performance in relation to Task Classification are intuitively assessed and analyzed. • There is still a lack of formal tools to measure these specific factors.	• There is a factual assessment and analysis of the specific factors related to Task Classification, with some awareness of their positive effects on the evolution and maturation of CI in teams as well as Collective Performance. • Some tools to assess the characteristics of the situation at hand are in place, offering some reporting and metrics.	• There is a good understanding of how specific factors related to Task Classification, positively influence CI and Collective Performance. • Formal tools to measure the characteristics of the situation at hand, are in place, offering advanced reporting and metrics.	• There is a comprehensive understanding of how specific characteristics of the situation at hand (Task Classification) and the way in which individual and collective task representations are developed in teams, influence the evolution and maturation of CI as well as Collective Performance. • There is an extensive use of supportive tools to assess the characteristics of the situation at hand, offering measurable results.

In regards to the dimension of *Transactive Memory System (TMS)*, a TMS scale, developed by Lewis (2003), can be used to measure the specific TMS component of Specialization (the TMS measurement model can be found in Appendix IX). The dimension of *Team Interaction* can be assessed using the team interaction and communication scale of 1-5 that has been developed and used in the 'evaluate design' phase of the first development cycle of the proposed maturity model, during the conduction of Experiment 2. The team interaction and communication scale developed, is a tool that can be used to monitor the overall communication process that takes place within teams while in action and necessitates the use of observational techniques. Alternatively, the same scale can be distributed to team members for completion in case monitoring a team while in action is not possible. Such an evaluation, however, will be based on the perceptions of team members. To further strengthen the assessment of the maturity levels of this specific dimension, the team interaction and communication scale can be used in combination with either the use of special-purpose devices or with the conduction of a team members perception-based survey, including a questionnaire aimed to measure personal characteristics of team interaction and communication. Such a questionnaire can be found in Appendix XIII.

Lastly, for measuring the maturity levels of the dimension of *Task Classification*, a situation awareness register, as shown in Appendix XIV, has been developed. The register has derived based on the findings of the analysis of the data collected during the 'evaluate design' phase of the first development cycle, and expert opinion. The register is an instrument that offers a way to assess the awareness of the situation at hand based on specific characteristics, incorporated in the final CIMA Model, in relation to the dimension of Task Classification. Taking into consideration the findings of the analysis of the primary data collected, that suggest that team interaction is significantly influenced by the characteristics of the situation at hand as well as by the way in which task representations are developed, the register aims to measure collective task representations. As discussed, in the previous section of this Chapter (refer to Sub-section 4.5.2), task representations relate to both the perceived nature of the task at hand and to how the team is going to go about completing the task (Poole, 1985; Poole and Doelger, 1986). Individuals form their own task representations that guide how they interact with other team members. In turn, team members' interaction enables the team to form collective task representations that guide the team's behavior. Due to the fact task representations may be incomplete at different points during the completion of a task and may change regularly as new information come to the surface (Brandon and Hollingshead, 2004), the register is to be refined regularly throughout the management of the situation.

The maturation of the specific factors incorporated in the final CIMA model, through the five levels, takes place with gradual understanding of their effect on CI and Collective Performance. The improvement from an intuitive to an integrated stage may result through this understanding but also through team modification. Some activities that aim to train and enhance particular skills may also be considered to improve the specific factors incorporated in the final CIMA model. For instance, a study conducted by Kidd and Castano (2013) suggests that Theory of Mind (ToM) abilities as measured by RME or otherwise can be, at least temporarily, improved by reading literary fiction. The systematic investigation of the specific factors incorporated in the final CIMA model in relation to activities that could offer training and improve particular skills is an interesting avenue for future research. A promising research perspective is the development of training procedures aiming to improve particular skills related to the factors incorporated into the final CIMA model by adopting the *Understanding by Design* UbD approach. The specific approach, according to (Bowen, 2017), relies on ''backward design'' and could be used also for the development of assessments to measure performance improvement on the specific factors identified to positively influence the evolution and maturation of CI in teams and Collective Performance. A Backward Design template with descriptions can be found in Appendix XV.

4.10 Summary and Conclusions

The Chapter detailed the complete process followed for the development of the CIMA Model. Two development cycles have been performed to arrive to the final CIMA Model. This has gradually increased the expressive power of the model. The CIMA Model has derived by adopting a combination of theory-driven and practitioner-based design process. The Chapter, in addition, provided an analysis of the data gathered through the three interlinked experiments that have taken place during the ‘evaluate design’ phase of the first development cycle. Throughout the Chapter, the specific research questions of this Thesis have been answered. Furthermore, several paths for future research have been highlighted.

The Chapter has been initially concerned with the first development cycle in which an initial design of the CIMA Model is proposed. The form and function of the initial design have been discussed. The initial design has resulted from the systematic literature review conducted and expert opinion and was built based on two dimensions: Team Composition and Team Interaction. Both dimensions mature in five levels, from an intuitive to an integrated stage. During the first development cycle of the proposed maturity model, an initial analysis of the primary data collected through the three interlinked experiments has been performed. The initial analysis of the primary data has led to the identification of additional factors that play a significant role in the maturation of CI in teams. These factors are related to Task Classification. In addition, the initial analysis of the data collected and the identification of the additional factors related to the maturation of CI in teams, have created the need to examine the tasks included in the second experiment in relation to additional task taxonomies. Furthermore, have led to the initiation of the second iteration of the development cycle.

After the completion of the first development cycle, the Chapter proceeds to examine the second development cycle in which an improved design of the CIMA Model is presented. The improved design of the CIMA Model builds on the initial design and by taking into account, the results of the initial analysis of the primary data incorporates three dimensions: 1. Team Composition, 2. Team Interaction and 3. Task Classification. The three dimensions progressively mature in five levels, from an intuitive to an integrated stage. The improved design has derived based on secondary and primary data as well as expert opinion. Furthermore, during the second development cycle, a complete analysis of the primary data has been conducted. The primary data analysis begins with an examination of the data gathered in the first experiment, in which the individual intelligence of the participants was measured. Three tests have been distributed to the participants, in order to assess their personality (Big Five Personality Test), their ability to understand social causality (Reading the Mind in the Eyes Test - RME) and their ability of spontaneously understanding the workings of the physical world (Folk Physics Test – Part I). The correlations between these measures have been examined. The data analysis has shown that there are no significant correlations between Experiment 1 measurements. A notable result, contrary to what has been expected, is that the participants' (N=100) ability of understanding social causality, has low to zero correlations (r<0.10) with the five primary dimensions of adult personality. This finding answered R.Q. 1.1. After the analysis of the data concerning the first experiment, the focus shifted on the analysis of the data collected through the second experiment, in which Collective Intelligence was measured. With the analysis of the data related to the second experiment, specific research questions R. Q. 1.2 - 1.12, have been answered. The experiment involved the completion of three tasks. The data analysis showed that overall, as compared to the Experimental group, the Control group was composed of individuals with higher age and higher risk management relevance. Such composition was not designed methodologically but has instead resulted from the fact that experiment participants were allocated to the two groups (Control and Experimental), based on convenience. Furthermore, the performance of each group (Control and Experimental) on each of the three tasks has been examined thoroughly and a comparative analysis has been provided. The analysis of the data indicates that the demographic characteristics of each group and the task classification have in general, a significant impact on the performance of the two groups in each of the three tasks. Task classification refers to the type of the task, the skills required for its completion, the content of the information needed to be processed as well as its complexity and structure. The examination of the mean performance measures across the Control and Experimental groups, in Experiment 2, uncovered that overall, in the Total Task Score (average of Task 1, Task 2 and Task 3 scores), the Experimental group scored higher than the Control Group. This finding supports the findings of previous studies that provide evidence that collective problem-solving leads to enhanced performance and improved solutions that no individual can achieve alone. In addition, the results concerning the performance of the two groups (Control and Experimental) in each of the three tasks have let to one of the major managerial contributions of this Thesis. Within the bounds of the current study, what the findings of the comparative analysis indicate, is that an organization involved in the management of LoPHIEs can take an informed decision whether to assign a team or an individual to handle an activity within the management process of an adverse event, depending on the characteristics of the situation encountered and based on the demographic information of the responders. The Experimental group has been examined in detail and statistics on the demographic characteristics by team have been provided. In addition, associations of the Total Task Score (average of the Task 1, Task 2 and Task 3 scores) and Collective Intelligence have been explored in relation to the teams' demographic composition and Experiment 1 measurements (participants' personality traits, individual ability of spontaneously understanding the workings of the physical world and ability of understanding social causality). Concerning the demographic composition of the teams, the data analysis revealed a moderate and positive correlation between CI and Risk Management Relevance. Furthermore, the analysis conducted confirmed the findings of previous studies that CI is able to predict the performance of groups. It was found that a higher level of CI in the team is associated with higher Total Task Scores. It was also uncovered that there is a high strength of association between the Total Task Score and the ability of understanding social causality/emotional intelligence and two of the primary dimensions of adult personality, Extraversion, and Agreeableness. The most striking result to emerge from the analysis of the data collected during the second Experiment is that CI has a moderate and positive correlation with the individual ability of spontaneously understanding the workings of the physical world, as measured by the Folk Physics Test – Part I. In regards to this, the comparative analysis conducted between the Control and Experimental group provided substantial evidence that collective problem-solving positively affects the ability of spontaneously understanding the workings of the physical world, enhances accuracy, and improves analytic skills. The findings in relation to Folk Physics consist one of the major theoretical contributions of the current Thesis. Previous studies conducted in the field of CI have only focused on one of the two key neurocognitive adaptations of the human mind - Folk Psychology. This is the first study to investigate Folk Physics in the context of CI. The performance of the teams in each of the three tasks, in relation to Team Interaction and Collective Intelligence, has also been explored, and correlations have been highlighted. A notable result revealed is that CI is highly and positively correlated with TASK 3. This finding supports the findings of prior studies that provide evidence that strongly suggest that CI is positively correlated with performance on complex tasks. TASK 3 was a high complexity task as compared to TASKS 1 and 2. It has been further revealed that Team Interaction has also a moderate and positive correlation with TASK 3, indicating that higher scores in TASK 3 are associated with higher Team Interaction. Discussion on the two facts believed to have had collectively, a significant impact on Team Interaction, has been provided (1. task classification and 2. the way in which individual and collective task representations were developed in the teams). Moreover, it has been explored whether the diversity in the sample's demographic information and Experiment 1 measurements (composition of teams) are associated with the Total Task Score (indicative of the overall performance outcome of the teams) and Collective Intelligence. The findings of the current Thesis concerning team diversity and its impact on performance, confirm the notion that teamwork output is the result of multiple mechanisms that may interact, and that diversity in skills, knowledge and demographic characteristics, including personality traits, as well as the characteristics of the task at hand, affect team performance through multiple channels. The researcher stressed the fact that despite the plethora of studies in various contexts, it is still inconclusive and controversial whether diversity has a positive or negative impact on team performance. In addition, reflection on raising suggestions from various scholars, that the impact of diversity on team performance can depend on the task design and characteristics and that the nature of the underlying task, is critical in understanding the divergent effects of diversity, is provided. The researcher highlighted the need for the development of a methodological standardization in regards to how studies on diversity are conducted. Such a methodological standardization can offer reproducible and comparable results. In a similar manner, the data collected in the third experiment, which measured the construct of Transactive Memory System TMS developed in the teams, has been examined. The current study is the first to examine transactive memory in correlation with Collective Intelligence. With the analysis of the data related to the third experiment, the specific research question R.Q. 1.13, has been answered. Descriptive statistics on the TMS components (Coordination, Credibility, and Specialisation) and TMS Total Scale for the 50 Experimental group participants, have been provided. In addition, correlations between TMS and task scores, Collective Intelligence, and Team Interaction were explored. The analysis of the data indicates that the demographic characteristics of the Experimental Group and the composition of the teams played a significant role in the way in which transactive memory systems were developed in the teams and possibly had an impact on all three components of TMS as well as on team performance. The researcher explained that in the current study, transactive memory was developed in the teams as a result of the individuals' personal expertise and through circumstantial responsibility for knowledge that occurred on the basis of how the knowledge has been encountered by the teams. Memory performance among team members has dependent primarily on the combination processes through which individuals' retrievals were assembled into a group retrieval, and essentially, each team member cultivated the other team members as an external memory aid. A notable finding emerged from the data analysis, is that higher Specialization in the team is associated with higher CI. In regards to Credibility, no significant correlations between the tasks scores, CI, and Team Interaction have been observed. In respect to the dimension of Coordination the findings in relation to the tasks scores, collectively support the findings of earlier studies that transactive memory is more likely to prosper and be more beneficial when teams perform complex tasks that require high-level coordination for their completion; and less useful when teams perform simple tasks that require low-level coordination among team members. The current study is the first to verify the positive correlation between transactive memory and high complexity tasks, within the context of managing LoPHIEs with the use of CI. In respect to the Total TMS score, the data analysis has shown that it has a weak and positive correlation with the Total Task Score, indicating that in the context of this Thesis, TMS as one single construct does not appear to facilitate team performance. In addition, the findings concerning the relationship between Total TMS score and the TASKS, provide further evidence that task structure can encourage cognitive interdependence, causing transactive memory to flourish in the teams. Additional research findings have been provided considering the full sample (N=100) of participants. The measures in Experiment 1, including demographic characteristics, have been explored in association with the Total Task Score (TTS) obtained in Experiment 2. It was found that the RME Total (r=0) is not correlated with the TTS. Within the bounds of the current Thesis, what this finding indicates is that ToM (as measured by the Reading the Mind in the Eyes RME test) and consequently EI, do not have a predictive power of over individual performance. This finding is contrary to the findings of previous studies. It was further revealed that in regards to the five primary dimensions of adult personality, Agreeableness has a low and positive correlation with TTS and Conscientiousness has a low and negative correlation with TTS. A multiple linear regression model, fitted to regulate the multivariate effect of the variables (demographic characteristics and Experiment 1 measures) to the Total Task Score, has been presented. The Total Task Score was treated in the model as the dependent variable and Experiment 1 measures with demographic characteristics, as the independent variables. Whether the individuals participated in Experiment 2 as a member of a team or individually was also adjusted. The model explains 7.95% (Adh. R2), (p=0.093) of the variation of the Total task Score. It was found that belonging in a team is associated with a higher Total Task Score as compared to working individually. This finding reinforces the findings of the comparative analysis conducted between the Control and Experimental groups. In regards to the five primary dimensions of adult personality, the model revealed that increased Agreeableness of the individual is associated with increased TTS, and increased Conscientiousness of the individual is associated with reduced TTS. Furthermore, a draft model for predicting Team Interaction has been presented. Team Interaction is treated in the model as the dependent variable and the five primary dimensions of adult personality and RME scores as the independent variables. The model was developed merely for exploratory purposes, with an attempt to simply provide an estimation of how much variation of the Team Interaction Level can be explained by the personality traits and RME factors – that is, the (adjusted) R^2. The analysis has shown that the personality traits and RME scales explain the 32% (Adj R2) of the variation of the Team Interaction Level. The researcher has highlighted literature that illustrates the significance of Team Interaction in the study of CI and noted the importance of developing the model further.

Lastly, the Chapter has been concerned with the final phase of the second development cycle of the CIMA Model. At this phase, the findings of the Thesis have been applied onto the improved CIMA Model, and the resilience of the model against the results of the data analyzed has been considered. A final design of the CIMA Model, in which the maturity of the phenomenon under study, is fully integrated, has been presented and its form and function have been discussed. The final proposed model focuses on specific factors that have been identified to positively influence the evolution and maturation of CI in teams, as well as Collective Performance. Specifically, the model incorporates eleven factors that mature in five levels, from an intuitive to an integrated stage. Definitions for the maturity levels for each factor incorporated in the final design of the CIMA Model have been provided, and reference to precise tools for measuring the maturity levels of these specific factors is made. In addition, methods for improving their maturation through the five maturity levels, are considered.

Chapter 5 Conclusions and Directions for Future Research

5.1 Introduction

The current Chapter integrates the discussion and findings from the previous chapters into a general conclusion. It examines the extent to which the research objectives have been achieved, followed by an outline of the main findings. It discusses the main contributions of the current study as well as its limitations. Finally, the Chapter outlines directions for future research.

5.2 Examining Research Objectives

This section seeks to identify the extent to which the objectives of this Thesis have been met.

The present study was initialized with the intent to answer one main research question - *What are the significant factors that need to be included in a CI maturity assessment model examining the preparedness of teams for managing LoPHIEs?* In addressing the main Research Question of the current study, four Research Objectives were proposed.

The first research objective (R.O. 1) was to *identify indicators related to the management of LoPHIEs*. This objective was fully achieved with the collection of secondary data through systematic literature review. The second objective of this Thesis (R.O. 2) was to *explore indicators related to the management of LoPHIEs in the presence of CI-supported decision making*. This specific objective was partially achieved through secondary data collection. The systematic literature review conducted in meeting R.O. 1 and R.O. 2 allowed to generate specific research questions in relation to the main research question. These specific questions generated, incorporated indicators and factors identified through the systematic literature review and helped outline the complex relationships and forces occurring within teams and affect CI and Collective Performance, in relation to the management of LoPHIEs.

The secondary data collected in relation to R.O. 1 and R.O. 2 provided the foundation for the design of the proposed Collective Intelligence Maturity Assessment (CIMA) Model, leading to the partial completion of R.O. 3. The third objective of this Thesis (R.O. 3), was to *design and develop a CI maturity assessment* *model*. Secondary data collection through systematic literature review as well as expert opinion have contributed in meeting this specific research objective. Specifically, expert opinion was acquired at different stages of the study as the research progressed towards the design and development of a CI maturity assessment model, by specialists in the field. Expert opinion provided support in narrowing the research focus, drafting the CI Maturity Assessment (CIMA) Model, and designing the multiple experiments for the evaluation of the model. The design of the CIMA Model developed for assessing teams' CI maturity levels in dealing with LoPHIEs, has been verified and validated with the implementation of an experimental research strategy. This has satisfied the fourth objective of the current Thesis (R.O. 4) which was to *validate how the proposed CI maturity assessment model can be applied to assess teams' maturity levels in dealing with LoPHIEs*. More specifically, three interconnected experiments were conducted, each with a different focus but all contributing in answering the main research question and specific questions of this study. The multiple experiments conducted, allowed the collection of primary data that enabled to fully meet the requirements of achieving R.O. 2, R.Q. 3 and R.O. 4.

5.3 Main Findings

This Section outlines the main findings of this Thesis with reference to the specific research questions, regenerated in relation to the main research question, set out in the introductory Chapter. The data analysis is fully reproducible as an R markdown document, available online in the following links, also found in Appendix XVI:

https://www.dropbox.com/sh/ruruo3bw2a8dlwn/AACZexvkzpPEM7HVp48vF9NSa?dl=0

https://1drv.ms/u/s!AgN7OfT5QYvahx20PZd7hw8s_4E2?e=WV8R8q

R.Q. 1.1 Are personality traits positively correlated to social sensitivity (RME scores)?

Contrary to what has been expected, the findings of this research show that the ability of understanding social causality, as measured by the Reading the Mind in the Eyes Test RME has low to zero correlations ($r<0.10$) with the five primary dimensions of adult personality, as measured by the Big Five Personality

Test (Extraversion: r=0.043, Agreeableness: r=0.039 Conscientiousness: r=-0.104, Emotional Stability: r=0.089, Intellect or Imagination: r=-0.118).

R.Q. 1.2 Is there a statistical difference between each of the cognitive abilities (ability of understanding social causality and ability of spontaneously understanding the working of the physical world) and control or experimental mode participants?

The planned intervention made in the context of the current Thesis and in relation to the three interlinked experiments was the emergence of CI that can only be achieved through the interaction between a number of individuals. CI emerged in the Experimental group, where the participants were split randomly into teams, for the second Experiment. In regards to R.Q. 1.2, the empirical results obtained in this research show that there are no significant differences between each of the cognitive abilities, in the presence or absence of CI - No significant differences were found in respect to the ability of understanding social causality (as measured with the Reading the Mind in the Eyes Test RME) and the ability of spontaneously understanding the workings of the physical world (as measured with the Folk Physics Test – Part I) between the Control and Experimental groups.

R.Q. 1.3 Is there a statistical difference between the Control and Experimental group, in relation to scores gained at each of the tasks?

The findings of the present research indicate that the performance of the Control and Experimental group in the tasks asked to complete during the second Experiment is significantly influenced by two factors. The first factor has to do with the demographic characteristics of each group (Control and Experimental). Differences in the demographic characteristics between the two groups have been observed. Overall, the Control group was composed of individuals with higher age and higher Risk Management Relevance RMR. Concerning this, the literature reviewed indicates that older and younger individuals behave differently from each other (e.g., Ali, Ng, and Kulik, 2014; Berger, Kick and Schaeck, 2014; Bertrand and Schoar, 2003; Gormley and Matsa, 2016; Myers and Sadaghiani, 2010; Li, Low and Makhija, 2017). In addition, age is considered as a crucial proxy for experience (Talavera, Yin and Zhang, 2018) and it reflects differences in knowledge accumulation and maturity (Hansen, Owan, and Pan, 2013). In a similar manner, Risk Management Relevance may be regarded as an important proxy for knowledge accumulation, education, and functional background, experience, and training as well as expertise and information.

The second factor identified, relates to the task classification (refer to Table 5, Chapter Four, Section 4.5, page 117). The empirical results obtained in this research, indicate that specific characteristics of the task at hand (the type, the skills required for its completion, the content of the information needed to be processed, its complexity and structure) influence significantly the behavior and decision-making processes of individuals (Control group) and teams (Experimental group) and consequently the performance outcomes.

Specifically, in TASK 1, the Control group ($M=4.8$, $SD=1.1$) scored higher than the Experimental group ($M=4.2$, $SD=1.2$) ($t=2.7$, $p=0.007$) with a moderate effect size difference ($d=0.54$). In TASK 2, the Experimental group ($M=6.1$, $SD=0.8$) scored higher than the Control group ($M=4.2$, $SD=1.4$) ($t=-8.2$, $p<0.001$) with a high effect size difference ($d=-8.2$). In TASK 3, the Experimental group scored similarly to the Control group ($t=0.3$, $p=0.669$) (Cohen's $d = 0.08$).

R.Q. 1.4 Does collective problem-solving lead to improved performance outcomes?

The empirical results obtained in this research show that, overall, in the Total Task Score, the Experimental Group scored higher than the Control Group ($t=-1.7$, $p=0.082$) with a moderate effect size difference ($d=-0.35$). In addition, the results obtained indicate that belonging in a team is associated with a higher Total Task Score as compared to working individually ($b=0.34$, $p=0.066$). The findings of the present study support the findings of previous studies that provide evidence that collective problem-solving leads to enhanced performance and improved solutions that no individual can achieve alone (e.g., Gulley and Lakhani, 2010; Jeppesen and Lakhani, 2010).

R.Q. 1.5 Is there a relationship between the teams' demographic information (age and Risk Management Relevance) and CI?

According to the findings of this research, CI has a low and negative correlation with Age (r=-0.15, p=0.61) and a moderate positive correlation with Risk Management Relevance RMR (r=0.31, p=0.28). Risk Management Relevance RMR is one of the factors incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model.

R.Q. 1.6 Does CI predict the performance of teams?

The findings of the present study show that there is a high strength of association between the overall team performance outcomes and Collective Intelligence – the Total Task Score has a moderate and positive correlation with Collective Intelligence (r=0.40, p=0.16). This indicates that a higher level of Collective Intelligence is associated with higher Collective Performance. This finding confirms previous studies that provide evidence that CI is able to predict the performance of groups and increased performance beyond what can be achieved by individuals (e.g., Engel et al., 2015; Kerr and Hertel, 2011; Larson, 2010; Woolley, Aggarwal and Malone, 2015; Woolley et al., 2010).

R.Q. 1.7 Is high social reasoning (RME scores) positively correlated with the overall team performance outcomes?

The empirical findings obtained in the present study show that the overall team performance outcomes (Total Task Score) have a moderate and positive correlation with the ability of understanding social causality/Emotional Intelligence (EI) - RME Total (r=0.40, p=0.16). This indicates that higher levels of EI in the team are associated with a higher level of performance. Specifically, the current research suggests that *Theory of Mind* ToM (as measured by the Reading the Mind in the Eyes RME test) and, consequently EI, have a predictive power of over the performance outcomes of teams. The findings of this research, are in line with the findings of numerous previously conducted studies that investigate the relationship between ToM/EI and performance (e.g., Engel et al., 2014; Ferris, Witt and Hochwarter, 2001; Kidwell et al., 2011; Verbeke et al., 2008; O'Boyle et al., 2011; Joseph and Newman, 2010; Joseph et al., 2015; Côté and Miners, 2006; Lopes, 2016; Lopes et al., 2006; Guillén Ramo, Saris and Boyatzis, 2009; Boyatzis, Good and Massa, 2012; Boyatzis et al., 2015; Boyatzis, Rochford and Cavanagh, 2017; Camuffo, Gerli and

Gubitta, 2012; Gil-Olarte Márquez, Palomera Martín and Brackett, 2006; Lam and Kirby, 2002). The ability of understanding social causality is one of the factors incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model.

R.Q. 1.8 Is there a relationship between personality traits and CI?

The present study produced results that show that CI has a low and positive correlation with Agreeableness (r=0.27, p=0.35) and a low and negative correlation with Conscientiousness (r=-0.23, p=0.44). The results of this study did not show significant correlations between CI and the other three primary dimensions of adult personality (Extraversion, Emotional Stability, Intellect, or Imagination). On the other hand, the empirical findings of this study, place Agreeableness and Extraversion within the five primary factors identified to positively influence Collective Performance in relation to the management of LoPHIEs (Agreeableness: r=0.44, Extraversion: r=0.40). For this reason, the two specific personality traits have been incorporated into the proposed Collective Intelligence Maturity Assessment (CIMA) Model.

R.Q. 1.9 Is high Folk Physics scores positively related to CI?

The empirical results obtained in this research show that CI has a moderate and positive correlation with the ability of spontaneously understanding the workings of the physical world – ability of understanding physical causality, as measured by the Folk Physics Test – Part I (r=0.31, p=0.28). The ability of understanding physical causality is one of the factors incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model.

R.Q. 1.10 What is the relationship between the teams' performance (scores gained at the tasks and overall performance outcomes) and: (a) Team Interaction and (b) CI?

Within the bounds of the current study, the results obtained suggest that Team Interaction is significantly influenced by two factors. The first factor is concerned with the task classification (refer to Table 5, Chapter Four, Section 4.5, page 117). The type of the task, the skills required for its completion, the content of the information needed to be processed (whether based on the social or analytic cognitive domain) as well as its complexity and structure (whether supporting material is provided for its completion and how the knowledge is distributed and encountered by the team), have an impact on the behavior and decision-making processes of the teams and consequently on the Team Interaction, affecting in this way the performance. The second factor is concerned with the way in which individual and collective task representations are developed in teams. Task representations relate to both the perceived nature of the task at hand and to how the team is going to go about completing the task (Poole, 1985; Poole and Doelger, 1986). Individuals form their own task representations that guide how they interact with other team members. In turn, team members' interaction enables the team to form collective task representations that guide the team's behavior (Brandon and Hollingshead, 2004).

Specifically, the present study found that Team Interaction has a very low and negative correlation with TASK 1 ($r=-0.12$, $p=0.68$) and a low and positive correlation with TASK 2 (Folk Physics Test Part II) ($r=0.17$, $p=0.56$). It was also found that Team Interaction has a moderate and positive correlation with TASK 3 ($r=0.36$, $p= 0.21$). Taking into consideration the specific characteristics of TASK 3, this finding is consistent with the findings of Littlepage et al. (2008), and Clark et al. (2000), who provide evidence indicating that team members' exchange of task-relevant information facilitates team performance. Within the bounds of the current Thesis, the empirical results obtained indicate, that task classification and more specifically the type of the task (whether it is a closed, open-ended task or a combination of the two) has an impact on the procedures utilized by the team that may accordingly increase or decrease the depth of discussion (Henry, 1995; Hollingshead, 1996) and consequently lead to either more complete and efficient or inefficient use of team member knowledge.

Regarding Collective Intelligence, the results of this study support the findings of prior studies that provide evidence that Collective Intelligence is positively correlated with performance on complex tasks (e.g., Engel et al. 2015; Engel et al., 2014; Woolley et al., 2010). In addition, as discussed earlier (refer to R.Q. 1.6), the empirical findings of the present study reveal that there is a high strength of association between the overall team performance outcomes and Collective Intelligence – the Total Task Score has a moderate and positive correlation with Collective Intelligence (r=0.40, p=0.16). This finding confirms previous studies that provide evidence that CI is able to predict the performance of groups, lead to improved decision-making and increased performance beyond what can be achieved by individuals (e.g., Engel et al., 2015; Kerr and Hertel, 2011; Larson, 2010; Woolley, Aggarwal and Malone, 2015; Woolley et al., 2010).

R.Q. 1.11 Is the diversity in the teams' demographic information (age and Risk Management Relevance) correlated with: (a) the teams' performance outcomes and (b) CI?

Age is an important variable of team composition due to the fact it is a visible characteristic that can be taken into account for social categorization (Knippenberg and Schippers, 2007; Tajfel and Turner, 2004) and thus it is frequently considered as one dimension of social category diversity (e.g., Jehn, Northcraft and Neale, 1999; Pelled, Eisenhardt and Xin, 1999; Simons, Pelled and Smith, 1999). On the other hand, Risk Management Relevance is a distinct dimension of cognitive diversity.

The findings of the present study show that age diversity in teams has a moderate and negative correlation with Collective Intelligence (r=-0.33, p=0.26). This finding is consistent with the findings of studies conducted by Mayo et al. (2016), Harrison and Klein (2007), and Timmerman (2000), respectively, indicating that age diversity negatively affects Collective Intelligence. The present study has additionally revealed that age diversity in teams has a moderate and positive correlation with Collective Performance - Total Task Score (r=0.33, p=0.25). Collectively, the empirical results obtained in this research indicate that higher age diversity is associated with lower Collective Intelligence in the team but higher Collective Performance. Specifically, this research has shown that the effect of age diversity on performance is dependent on different task characteristics (refer to Table 5, Chapter Four, Section 4.5, page 117). The diversity in age is one of the factors incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model.

The diversity in Risk Management Relevance RMR reflects differences in knowledge accumulation, education or functional background, experience, training, expertise, and information. According to the findings of this research, the diversity in Risk Management Relevance within teams has no correlation with Collective Intelligence (r=0.05, p=0.88). Furthermore, the study found that Risk Management Relevance has a weak and positive correlation with the teams' overall performance outcomes - Total Task Score (r=0.10, p=0.72).

R.Q. 1.12 Is the diversity in the teams' composition (examine each parameter individually) correlated with: (a) the teams' performance outcomes and (b) CI?

The abilities of understanding social and physical causality (as measured by the RME and Folk Physics tests respectively) and the personality traits (as measured by the Big Five Personality Test) are distinct dimensions of cognitive diversity.

The findings of the present study show that the effect of the diversity in the ability of understanding social causality on Collective Performance is dependent on different task characteristics (refer to Table 5, Chapter Four, Section 4.5, page 117). Specifically, it was found that it has a moderate and negative correlation with the teams' performance outcomes - Total Task Score (r=-0.33, p=0.24). At the same time, the findings of this study show that the diversity in the ability of understanding social causality has a weak and positive correlation with Collective Intelligence (r=0.13, p=0.66).

With regard to the diversity in the individual ability of spontaneously understanding the workings of the physical world – ability of understanding physical causality, the results obtained in this research did not reveal a correlation with Collective Intelligence (r=0.00, p=0.99). Moreover, the present study revealed that the diversity in the individual ability of spontaneously understanding the workings of the physical world has a weak and negative correlation with the teams' performance outcomes - Total Task Score (r=-0.17, p=0.56) Due to the fact the current study is the first, to the best of the researcher's knowledge, to incorporate Folk Physics in the context of CI, additional experimental research is needed to better understand the dynamics of the relationship between Folk Physics and CI and its impact on collective performance in relation to specific task characteristics.

Concerning the diversity in extraversion within the team, the empirical findings of this research, show that it has a moderate and positive correlation with Collective Intelligence (r=0.45, p=0.11) and the teams' performance outcomes - Total Task Score (r=0.40, p=0.15), indicating that higher diversity in extraversion is associated with higher Collective Intelligence in the team and higher Collective Performance. The diversity in Extraversion within team members is the only consistent primary factor, identified to influence both CI and Collective Performance positively. The diversity in Extraversion is one of the factors incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model.

Within the bounds of the current study, the results obtained show that diversity in agreeableness has a moderate and positive correlation with Collective Intelligence (r=0.49, p=0.07). For this reason, the diversity in agreeableness is incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model. The results of this research did not reveal a correlation between the diversity in agreeableness within the teams and the teams' performance outcomes - Total Task Score (r=-0.03, p=0.93).

The findings of this research show that diversity in emotional stability has a moderate and negative correlation with the teams' performance outcomes - Total Task Score (r=-0.32, p=0.26). In addition, no correlation between diversity in emotional stability and Collective Intelligence (r=-0.02, p=0.96) was found.

Regarding the remaining two primary dimensions of adult personality, no significant correlations have been found between the diversity in conscientiousness and Collective Intelligence (r=0.07, p=0.82) and the teams' performance outcomes - Total Task Score (r=-0.18, p=0.54). Furthermore, the empirical results of the present study did not show significant correlations between Intellect or Imagination and Collective Intelligence (r=0.19, p=0.51) and the teams' performance outcomes - Total Task Score (r=0.17, p=0.56).

The results obtained in the current Thesis in regards to team diversity (refer to R.Q.s 1.11 and 1.12), confirm the notion that teamwork output is the result of multiple mechanisms that may interact; and that diversity in skills, knowledge and demographic characteristics, including personality traits, as well as the characteristics of the task at hand, affect team performance through multiple channels.

R.Q. 1.13 What is the relationship between the TMS developed in the teams and: (a) the scores gained at the tasks (b) the teams' overall performance outcomes (c) CI and (d) Team Interaction (examine each TMS component individually and collectively)?

As seen in previous Chapters, Transactive Memory Systems have three components (Akgün et al., 2005; Kanawattanachai and Yoo, 2007; Lewis, 2004): (1) Specialization, (2) Credibility and (3) Coordination. The empirical evidence obtained in this research show that the component of Specialization has a moderate and positive correlation with Collective Intelligence (r=0.31, p=0.29), indicating that higher Specialization in the team is associated with higher CI. The TMS component of Specialization has been incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model. In addition, the findings of this study showed that Specialization has insignificant correlations with the score gained at the tasks included in the second Experiment (TASK 1: r=0.08, TASK 2: r=-0.24, TASK 3: r=0.20). Within the framework of this Thesis, Team Interaction has been found to have a low and positive correlation with Specialization (r=0.23, p=0.44).

Regarding Credibility, the findings of this study show that it has a low and negative correlation with Collective Intelligence (r=-0.23, p=0.44). The current study, additionally found that Credibility has insignificant correlations with the score gained at the tasks included in the second Experiment (TASK 1: r=-0.13, TASK 2: r=0.13, TASK 3: r=0.27). Furthermore, the results of the present study show that Team Interaction has a moderate and negative correlation with Credibility (r=-0.34, p=0.24), indicating that the higher the communication and interaction between team members, the less accurate, reliable and credible the knowledge shared within the team, becomes.

Concerning the dimension of Coordination, the findings of the present study show that it has a weak and negative correlation with Collective Intelligence (r=-0.16, p=0.58). In addition, it was found that Coordination has a moderate and negative correlation with TASK 1 (r=-0.30, p=0.29), a weak and positive correlation with TASK 2 (r=0.10, p=0.72) and a moderate and positive correlation with TASK 3 (r=0.35, p=0.22). The findings concerning the correlation of the dimension of Coordination with TASKS 3 and 2 support the findings of earlier studies conducted by Wegner (1987) and Thompson (1967) who provide evidence that transactive memory is more likely to prosper and be more beneficial when teams perform complex tasks that require high-level coordination for their completion, and less useful when teams perform simple tasks that require low-level coordination among team members. The present study additionally revealed no correlation between Team Interaction and Coordination (r=-0.06, p=0.84) was found.

The empirical results of the present research show that as one single construct, TMS (Total TMS) has a moderate and positive correlation with TASK 3 (r=0.37, p=0.19). The correlation with the other two tasks is insignificant (TASK 1: r=-0.16, TASK 2: r=-0.01). Within the bounds of the current study, these findings reinforce the reasoning that transactive memory is more likely to prosper and be more beneficial when teams perform complex tasks that require high-level coordination for their completion and further support the findings of the studies conducted by Wegner (1987) and Thompson (1967). In addition, the findings of the present study provide further evidence that task structure can encourage cognitive interdependence, causing transactive memory to flourish in the teams. The empirical results obtained in this research additionally shown that the Total TMS score has a weak and positive correlation with the teams' overall performance outcomes - Total Task Score (r=0.13, p=0.66), indicating that in the context of this Thesis, TMS as one single construct does not facilitate team performance. Moreover, within the bounds of the current study, the findings of this research show that the Total TMS score has no correlation with Collective Intelligence (r=-0.02, p=0.94). This finding is contrary to the researcher's expectations, since the comprehensive literature review conducted individually on the two, points to the conclusion that both share common factors that are significantly correlated with their emergence in teams. Moreover, within the bounds of the current study, the findings indicate that as one single construct, TMS (Total TMS) has no correlation with Team Interaction (r=-0.05, p=0.86).

5.4 Main Research Contribution and Limitations

This research adds substantially to the growing body of literature on the management of Low Probability High Impact Events (LoPHIEs) and decision making under uncertainty, Collective Intelligence, and the concepts of maturity assessment and transactive memory and will undoubtedly serve as a base for future studies. However, as with any study that represents an initial attempt to investigate a novel topic, a number of limitations need to be noted in regards to the present study. This Section examines the main contributions and limitations of this research in the following two Sub-section.

5.4.1 Main Contributions

This research has made several theoretical, managerial, and systemic contributions. The first theoretical contribution of this study relates to the emphasis placed in considering Collective Intelligence (CI) as a systemic dimension that can provide organizations with a methodological assessment of their maturity levels in dealing with Low Probability High Impact Events (LoPHIEs). Even though both the domain of LoPHIEs and the domain of CI, study independently a mature phenomenon, this is the first time, to the best of the researcher's knowledge, that both are studied jointly in an attempt to provide a more efficient solution to the problem under investigation.

The second theoretical contribution made by this research relates to the attention drawn to the relation between Collective Intelligence and Transactive Memory Systems. To the best of the researcher's knowledge, the current study is the first to examine Transactive Memory Systems in relation to Collective Intelligence. Additionally, the present study is the first to verify a positive correlation between transactive memory and high complexity tasks, within the context of managing LoPHIEs with the use of CI. This consists the third main theoretical contribution made by this research.

The current research has established a relationship between Collective Intelligence and the ability of spontaneously understanding the workings of the physical world – ability of understanding physical causality, as measured by the Folk Physics Test. To the best of the researcher's knowledge, this is the first study to investigate Folk Physics in the context of CI. This consists the fourth main theoretical contribution of this research. The empirical results obtained show that Collective Intelligence has a moderate and positive correlation with the ability of spontaneously understanding the workings of the physical world – ability of understanding physical causality, as measured by the Folk Physics Test – Part I ($r=0.31$, $p=0.28$).

The current study is also the first, based on the researcher's knowledge, to report results in regards to personality traits in correlation with Collective Intelligence, especially within the context of managing LoPHIEs. Even though previous studies conducted in the field of Collective Intelligence involved measuring the personality of the participants engaged, they fail to draw associations and identify correlations. This consists the fifth theoretical contribution of the present study.

Moreover, the current research adds to managerial knowledge by providing organizations involved in the management of LoPHIEs, with insight valuable in taking an informed decision whether to assign a team or an individual to handle an activity within the management process of an adverse event, depending on the characteristics of the situation encountered and based on the demographic information of the responders. The task taxonomies reviewed in this Thesis, are valuable tools with practical applications and present an innovative platform for further academic research, with managerial implications.

Finally, the Collective Intelligence Maturity Assessment (CIMA) Model developed and proposed in this Thesis, consists the main systemic contribution. The findings of the present study give the reader valuable insight into a number of key issues related to the evolution and maturation of CI in teams as well as Collective Performance and provide a novel perception of the complex nature of the examined research subject. This research has identified some of the ideal characteristics a team must possess for the successful and sustainable management of LoPHIEs. These characteristics are incorporated in the proposed Collective Intelligence Maturity Assessment (CIMA) Model. In addition, the distinction made between the primary and secondary factors influencing the maturation of CI in teams and Collective Performance may be useful in both professional and academic contexts.

A number of other contributions peripheral to the main research contributions have also emerged and are identified in the corresponding sections.

5.4.2 Limitations

There are two main limitations that need to be considered in regards to this Thesis. The first main limitation of the present study relates to the communication processes that are key to the development of transactive memory. These communication processes, as seen in previous chapters, are: 1. Directory updating, which involves discovering the types of information that other team members know (Hollingshead and Brandon, 2003; Moreland and Myaskovsky, 2000; Palazzolo, 2005); 2. Communication to distribute information within the team, which involves transferring information to members who are considered as experts in a specific field or have accepted the responsibility for holding a specific type of information; and 3. Communication to retrieve information which involves obtaining needed information from members who have been considered as experts in a specific field or have accepted the responsibility for holding a specific type of information (Hollingshead, 1998b; Palazzolo, 2005; Wegner, 1995). For the purposes of the experiments conducted for the current study, a team interaction and communication scale of 1-5 has been developed as well as observational techniques have been employed to monitor the overall communication process that has taken place within the teams. The absence, however, during the conduction of the second Experiment, of tools to monitor each communication process separately in the teams, appears as a limitation for the current study. The use of tools to record and evaluate separately each communication process within teams, while in action, rather than treating them as one single construct, could have offered additional profound knowledge in relation to how individuals and teams encode, store and retrieve information within the spectrum of the topic being explored by the current study. The special equipment required to record these communication processes separately is expensive and therefore since the current research has been self-funded, such an infrastructure could not be in place.

The second main limitation of this research has resulted from practical and methodological constraints. Ideally, greater sample involvement in the experiments could have occurred, but unfortunately, this was not possible due to time constraints of parties involved. A larger sample size would have provided more accurate mean values and would have allowed to increase the significance level of the findings. In addition, it would have enabled to identify outliers easily and would have provided a smaller margin of error.

5.5 Directions for Future Research

This Thesis raised numerous possible future avenues of investigation. Indeed, several directions for future research have been identified in Chapter Four. This Section presents the most promising ones.

An important direction for future research would be the application of the Collective Intelligence Maturity Assessment (CIMA) Model, developed and proposed by this Thesis. Since the current study aimed to propose a new maturity assessment model and was not concerned with the application of an existing one, the Thesis focussed solely on the development cycle. Figure 26, *Two sides of the same coin? Development and application cycle of maturity assessment models*, adopted from Mettler (2011), presents the development and application cycles of a maturity assessment model. The application cycle, in contrast to the development cycle, always starts with a business need, and it is concerned with the application of already established and validated models.

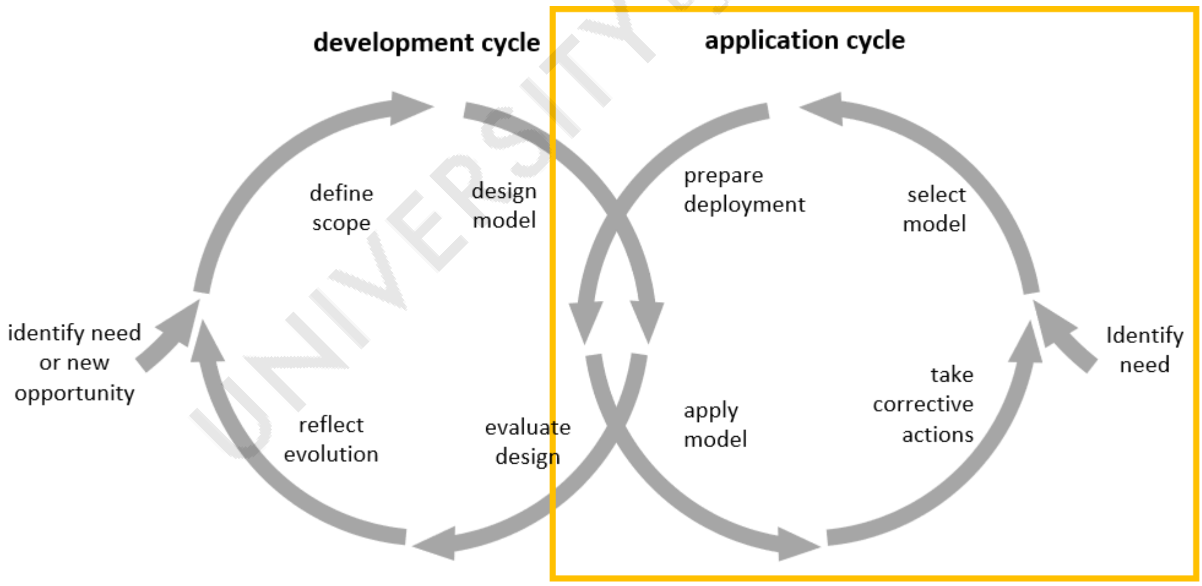


Figure 26: *Two sides of the same coin? Development and application cycle of maturity assessment models (adopted from Mettler, 2011)*

Additional promising directions for future research result due to the newness of the area of investigation. As mentioned in the previous section of this Chapter, this research is the first to examine Transactive Memory Systems in relation to Collective Intelligence. The lack of a visible correlation between CI and TMS in the present study could be due to the moderation occurring by a number of external conditions and constraints. Considerable future experimental studies that investigate further the dynamics between the two are needed since the comprehensive literature review conducted individually on Collective Intelligence, and the concept of Transactive Memory Systems points to the conclusion that both share common factors that are significantly correlated with their emergence in teams.

Furthermore, the current study is the first, to the best of the researcher's knowledge, to incorporate Folk Physics in the context of Collective Intelligence. Additional experimental research, therefore, could offer a precise understanding of the dynamics of the relationship between Folk Physics and Collective Intelligence and its impact on Collective Performance in relation to specific task characteristics. In addition, investigating the dynamics that govern the relationship between Folk Psychology (as measured by the Reading the Mind in the Eyes Test RME) and Folk Physics (as measured by the Folk Physics Test), within the spectrum of the topic being explored by the current study, and their collective, as well as independent impact on the emergence and success of CI and Collective Performance, is a path worth exploring further. In relation to the above, the researcher supports Truninger's et al. (2018) remark that further studies are needed to examine how Emotional Intelligence/social causality (as measured by the Reading the Mind in the Eyes Test), may relate differently to performance depending on the type of the task.

The extensive investigation of the impact of different dimensions of diversity on Collective Intelligence and Collective Performance, in relation to specific task characteristics, within the spectrum of the topic being explored by the current study, is also a promising direction for future research. Moreover, future studies can focus on the development of a methodological standardization in regards to how studies on diversity are conducted. Such a methodological standardization can offer reproducible and comparable results.

Additional studies that examine the relationship and dynamics between personality, as well as the diversity in personality traits, and performance within the context of managing LoPHIEs with the use of CI, would also be valuable. The empirical results of the present study show that diversity in Extraversion within team members is the only consistent primary factor, influencing positively both CI and Collective Performance. Investigating this finding further could offer a better understanding of the dynamics of the relationship between the diversity in Extraversion and CI as well as Collective Performance in relation to the management of LoPHIEs.

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Appendices

Appendix I: Comparative assessment of existing approaches and methods used for the anticipation and management of LoPHIEs

(adopted from Diakou and Kokkinaki, 2013)

EXISTING RELEVANT APPROACHES & THEIR IDENTIFIED LIMITATIONS

LIMITATIONS

- Judgment or Decision-Making Biases
- Process and Content ambush
- Heavy dependence on out-of-date information
- Data Quality Sensitive
- Lack of empirical testing
- Additional research needed on the conditions under which the method is most useful
- No concrete evidence for success in producing well-calibrated probabilities for rare events
- Frame Blindness

CRITICAL ASSESSMENT OF METHODS ADDRESSING LOW PROBABILITY HIGH IMPACT EVENTS

- Scenario Planning
- Delphi Approach
- Prediction Markets
- Reference Classes
- Statistical Forecasting with Judgmental Intervention or Adjustment
- Frame Predictions
- Expert Judgmental Forecasting
- Red Teaming
- Simulation Platforms
- Thesis-Antithesis-Synthesis
- Disaster Management Metamodel (DMM)
- Risk-Oriented-Process Evaluation (ROPE)
- Combining Forecasts
- Causal Models
- Judgmental Bootstrapping
- Structured Judgment
- Simulated Interaction (role playing)
- Structured Analogies
- Judgmental Decomposition
- Structured Judgmental Adjustments
- Rule Based Forecasting
- Data Mining
- Neural Nets

Appendix II: World Natural Catastrophes, 2018

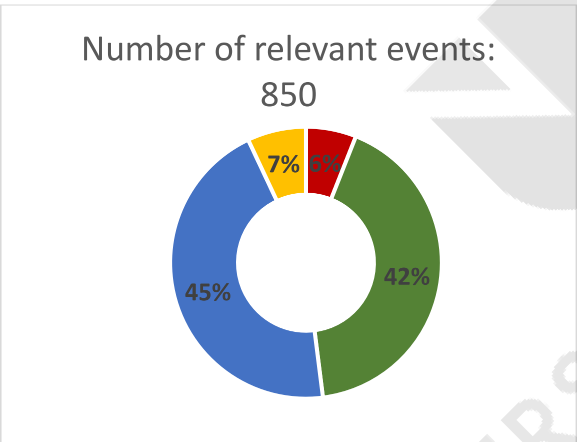
(adapted from: Facts and Statistics: Global Catastrophes report, The Insurance Information Institute - https://www.iii.org/fact-statistic/facts-statistics-global-catastrophes)

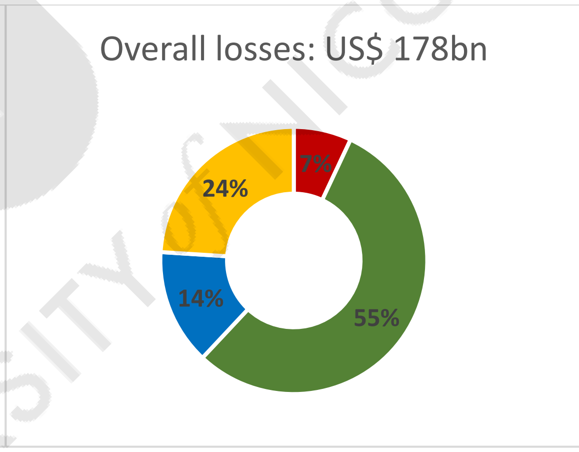
World Natural Catastrophes by Type of Event, 2018 (Percentage distribution)

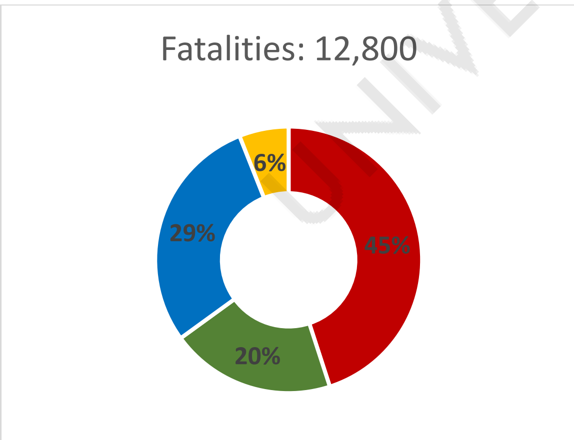
	Geophysical events (Earthquake, tsunami, volcanic activity)
	Meteorological events (Tropical storm, extratropical storm, convective storm, local storm)
	Hydrological events (Flood, mass movement)
	Climatological events (Extreme temperature, drought, forest fire)

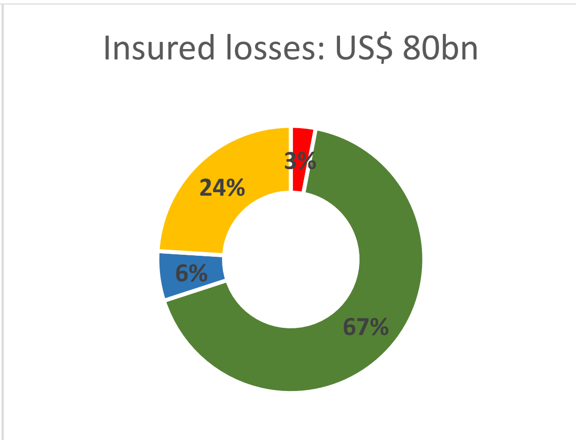
Accounted events have caused at least one fatality and/or produced normalized losses ≥ US$ 100k, 300k, 1m, or 3m (depending on the assigned World Bank income group of the affected country).

Inflation adjusted via country-specific consumer price index and consideration of exchange rate fluctuations between local currency and US$.









Appendix III: Existing mobile and web-enabled applications enriched with CI for the management of LoPHIEs

Name of the platform	Main features	Link
Ushahidi	A platform that supports crisis management works using ICT based crowdsourcing. The platform enables users to crowdsource crisis information, create reports from social media updates, direct information, and conventional media activities accompanied by GPS location. It offers a channel for citizens to report on their needs and urgent assistance they need, allowing others (humanitarian organizations or community members), to more effectively respond.	https://www.ushahidi.com/
SwiftRiver	An open-source platform that helps people make sense of large amounts of information in a short amount of time. Enables users to discover authentic and accurate information and create reports by gathering and filtering information from a variety of channels, drawing insights from the collected data and creating buckets of information.	https://wiki.ushahidi.com/display/WIKI/SwiftRiver
Crowdmap	A tool that allows users to crowdsource information from cell phones, news, and the web. All information is collected into a single platform and can be visualized on an interactive map and timeline. Crowdmap has analytical tools that help users make sense of incoming data in real-time.	https://crowdmap.com/welcome
Sahana Eden	An open-source humanitarian platform that can be used to provide solutions for Disaster Management, Development, and Environmental Management sectors. It can be rapidly customized to adapt to existing processes and integrate with existing systems to provide practical solutions before the occurrence of a crisis and also during a crisis. Designed to help Disaster and Emergency Management practitioners to prepare for, respond to, and recover from disasters more effectively and efficiently.	http://eden.sahanafoundation.org/ http://sahanafoundation.org/products/eden/
CrisisTracker	A geospatial open-source platform and reporting project that facilitates collaborative social media analysis, for disaster response in the remote border region encompassing the northeastern Democratic Republic of Congo and eastern Central African Republic. It can be used to track armed group activity and conflict-related incidents. Users can directly contribute tags that make it easier for other users to retrieve information and explore reports by similarity.	https://lracrisistracker.com/
OpenIR	An ICT tool that maps environmental risks. The risks are exposed using infrared satellite data. It offers algorithms for flood risk map generations and a web map application with environmental feature classification.	http://openir.media.mit.edu/main/
ArcGIS	An online mapping platform, that includes a living atlas of the world. It combines reference and thematic maps with many topics relating to people, earth, and life. It explores maps from Esri and enriches them with users' own data to create new maps and map layers. It enables the analysis and quantification of geographic relationships in users' data.	http://www.esri.com/software/arcgis
Recovers	A software that connects local government, organizations, and residents, making disaster preparedness and recovery	https://recovers.org/

	smarter. It can be used before a disaster to prepare communities but can also be used during and after a disaster to organize volunteers and manage donations etc.	
Google Crisis Map	Developed to help people find, use, and share critical emergency information when they need it most. It includes the latest satellite imagery and available information like storm paths, flood zones, evacuation routes, shelter locations, and power outages. Via the 'Person Finder' feature, Google Crisis Map connects friends and loved ones following a disaster, when traditional communication lines are down.	https://www.google.org/crisismap/weather_and_events
GeoChat	A flexible open-source tool for group communications that helps team members stay connected, synchronized, and aware. It enables the easy deployment of crowdsourced interactive mapping applications and helps users to react quickly to events by offering a smart and straightforward way to connect headquarters to staff in the field, and field staff to each other. GeoChat indexes online, multi-way conversations geographically.	https://instedd.org/technologies/geochat/
Indonesian Scenario Assessment for Emergencies (InaSAFE)	A free and open-source software, that produces realistic natural hazard impact scenarios for better planning, preparedness, and response activities. It offers insights into the possible impacts of future disaster events, by combining data from scientists, local governments, and communities.	http://inasafe.org/
LEEDIR (Large Emergency Event Digital Information Repository)	A cloud-based platform for crowdsourcing, management, and analysis of eyewitness photos, videos, and information. It allows law enforcement and relief agencies who adopt it to solicit and gather videos and photos of major emergency event from the public.	http://www.leedir.com/
Geo-pictures (GP)	It provides solutions to emergency responders and environmental monitoring initiatives, with the use of satellite technology and geographic information systems (GIS). The application can be used to acquire geo-tagged photos. The collected photos and assessments are coupled with near real-time satellite image delivery and analysis, as well as meteorological observations.	http://www.geo-pictures.eu/
CrisisNET	It provides easy access to critical government, business, humanitarian, and crowdsourced information. Finds, formats, and exposes crisis data in a simple, intuitive structure that's accessible anywhere.	http://crisis.net/

Appendix IV: Reading the Mind in the Eyes RME Test

(*developed by prof. Simon Baron-Cohen at the University of Cambridge)*

For all users of the revised version of the Adult "Reading the Mind in the Eyes" Test.

Enclosed you will find

the adult version of the above test
the word definition handout,
the correct answers.
A copy of the paper describing the test in full

As you know, publication details of the original version appeared in the Journal of Child Psychology and Psychiatry, 38, 813-822 (1997). The revised version which we have sent you was published in the Journal of Child Psychiatry and Psychiatry, 42, 241-252 (2001).

A child version of this test has also been developed and is available upon request. It was published in the Journal of Developmental and Learning Disorders, 5, 47-78 (2001).

We would, of course, appreciate hearing of any results you obtain with this test.

Thank you.

Best wishes

Simon Baron-Cohen

Adult Eyes Instructions

For each set of eyes, choose and circle which word best describes what the person in the picture is thinking or feeling. You may feel that more than one word is applicable but please choose just one word, the word which you consider to be most suitable. Before making your choice, make sure that you have read all 4 words. You should try to do the task as quickly as possible but you will not be timed. If you really don’t know what a word means you can look it up in the definition handout.

WORD DEFINITIONS

ACCUSING	blaming The policeman was accusing the man of stealing a wallet.
AFFECTIONATE	showing fondness towards someone Most mothers are affectionate to their babies by giving them lots of kisses and cuddles.
AGHAST	horrified, astonished, alarmed Jane was aghast when she discovered her house had been burgled.
ALARMED	fearful, worried, filled with anxiety Claire was alarmed when she thought she was being followed home.
AMUSED	finding something funny I was amused by a funny joke someone told me.
ANNOYED	irritated, displeased Jack was annoyed when he found out he had missed the last bus home.
ANTICIPATING	expecting At the start of the football match, the fans were anticipating a quick goal.
ANXIOUS	worried, tense, uneasy The student was feeling anxious before taking her final exams.
APOLOGETIC	feeling sorry The waiter was very apologetic when he spilt soup all over the customer.
ARROGANT	conceited, self-important, having a big opinion of oneself The arrogant man thought he knew more about politics than everyone else in the room.
ASHAMED	overcome with shame or guilt The boy felt ashamed when his mother discovered him stealing money from her purse.

ASSERTIVE	confident, dominant, sure of oneself The assertive woman demanded that the shop give her a refund.
BAFFLED	confused, puzzled, dumbfounded The detectives were completely baffled by the murder case.
BEWILDERED	utterly confused, puzzled, dazed The child was bewildered when visiting the big city for the first time.
CAUTIOUS	careful, wary Sarah was always a bit cautious when talking to someone she did not know.
COMFORTING	consoling, compassionate The nurse was comforting the wounded soldier.
CONCERNED	worried, troubled The doctor was concerned when his patient took a turn for the worse.
CONFIDENT	self-assured, believing in oneself The tennis player was feeling very confident about winning his match.
CONFUSED	puzzled, perplexed Lizzie was so confused by the directions given to her, she got lost.
CONTEMPLATIVE	reflective, thoughtful, considering John was in a contemplative mood on the eve of his 60th birthday.
CONTENTED	satisfied After a nice walk and a good meal, David felt very contented.
CONVINCED	certain, absolutely positive Richard was convinced he had come to the right decision.
CURIOUS	inquisitive, inquiring, prying Louise was curious about the strange shaped parcel.
DECIDING	making your mind up The man was deciding whom to vote for in the election.

DECISIVE	already made your mind up Jane looked very decisive as she walked into the polling station.
DEFIANT	insolent, bold, don't care what anyone else thinks The animal protester remained defiant even after being sent to prison.
DEPRESSED	miserable George was depressed when he didn't receive any birthday cards.
DESIRE	passion, lust, longing for Kate had a strong desire for chocolate.
DESPONDENT	gloomy, despairing, without hope Gary was despondent when he did not get the job he wanted.
DISAPPOINTED	displeased, disgruntled Manchester United fans were disappointed not to win the Championship.
DISPIRITED	glum, miserable, low Adam was dispirited when he failed his exams.
DISTRUSTFUL	suspicious, doubtful, wary The old woman was distrustful of the stranger at her door.
DOMINANT	commanding, bossy The sergeant major looked dominant as he inspected the new recruits.
DOUBTFUL	dubious, suspicious, not really believing Mary was doubtful that her son was telling the truth.
DUBIOUS	doubtful, suspicious Peter was dubious when offered a surprisingly cheap television in a pub.
EAGER	keen On Christmas morning, the children were eager to open their presents.
EARNEST	having a serious intention Harry was very earnest about his religious beliefs.

EMBARRASSED	ashamed After forgetting a colleague's name, Jenny felt very embarrassed.
ENCOURAGING	hopeful, heartening, supporting All the parents were encouraging their children in the school sports day.
ENTERTAINED	absorbed and amused or pleased by something I was very entertained by the magician.
ENTHUSIASTIC	very eager, keen Susan felt very enthusiastic about her new fitness plan.
FANTASIZING	daydreaming Emma was fantasizing about being a film star.
FASCINATED	captivated, really interested At the seaside, the children were fascinated by the creatures in the rock pools.
FEARFUL	terrified, worried In the dark streets, the women felt fearful.
FLIRTATIOUS	brazen, saucy, teasing, playful Connie was accused of being flirtatious when she winked at a stranger at a party.
FLUSTERED	confused, nervous and upset Sarah felt a bit flustered when she realised how late she was for the meeting and that she had forgotten an important document.
FRIENDLY	sociable, amiable The friendly girl showed the tourists the way to the town centre.
GRATEFUL	thankful Kelly was very grateful for the kindness shown by the stranger.
GUILTY	feeling sorry for doing something wrong Charlie felt guilty about having an affair.
HATEFUL	showing intense dislike The two sisters were hateful to each other and always fighting.

HOPEFUL	optimistic Larry was hopeful that the post would bring good news.
HORRIFIED	terrified, appalled The man was horrified to discover that his new wife was already married.
HOSTILE	unfriendly The two neighbours were hostile towards each other because of an argument about loud music.
IMPATIENT	restless, wanting something to happen soon Jane grew increasingly impatient as she waited for her friend who was already 20 minutes late.
IMPLORING	begging, pleading Nicola looked imploring as she tried to persuade her dad to lend her the car.
INCREDULOUS	not believing Simon was incredulous when he heard that he had won the lottery.
INDECISIVE	unsure, hesitant, unable to make your mind up Tammy was so indecisive that she couldn't even decide what to have for lunch.
INDIFFERENT	disinterested, unresponsive, don't care Terry was completely indifferent as to whether they went to the cinema or the pub.
INSISTING	demanding, persisting, maintaining After a work outing, Frank was insisting he paid the bill for everyone.
INSULTING	rude, offensive The football crowd was insulting the referee after he gave a penalty.
INTERESTED	inquiring, curious After seeing Jurassic Park, Hugh grew very interested in dinosaurs.
INTRIGUED	very curious, very interested A mystery phone call intrigued Zoe.

IRRITATED	exasperated, annoyed Frances was irritated by all the junk mail she received.
JEALOUS	envious Tony was jealous of all the taller, better-looking boys in his class.
JOKING	being funny, playful Gary was always joking with his friends.
NERVOUS	apprehensive, tense, worried Just before her job interview, Alice felt very nervous.
OFFENDED	insulted, wounded, having hurt feelings When someone made a joke about her weight, Martha felt very offended.
PANICKED	distraught, feeling of terror or anxiety On waking to find the house on fire, the whole family was panicked.
PENSIVE	thinking about something slightly worrying Susie looked pensive on the way to meeting her boyfriend's parents for the first time.
PERPLEXED	bewildered, puzzled, confused Frank was perplexed by the disappearance of his garden gnomes.
PLAYFUL	full of high spirits and fun Neil was feeling playful at his birthday party.
PREOCCUPIED	absorbed, engrossed in one's own thoughts Worrying about her mother's illness made Debbie preoccupied at work
PUZZLED	perplexed, bewildered, confused After doing the crossword for an hour, June was still puzzled by one clue.
REASSURING	supporting, encouraging, giving someone confidence Andy tried to look reassuring as he told his wife that her new dress did suit her.

REFLECTIVE	contemplative, thoughtful George was in a reflective mood as he thought about what he'd done with his life.
REGRETFUL	sorry Lee was always regretful that he had never travelled when he was younger.
RELAXED	taking it easy, calm, carefree On holiday, Pam felt happy and relaxed.
RELIEVED	freed from worry or anxiety At the restaurant, Ray was relieved to find that he had not forgotten his wallet.
RESENTFUL	bitter, hostile The businessman felt very resentful towards his younger colleague who had been promoted above him.
SARCASTIC	cynical, mocking, scornful The comedian made a sarcastic comment when someone came into the theatre late.
SATISFIED	content, fulfilled Steve felt very satisfied after he had got his new flat just how he wanted it.
SCEPTICAL	doubtful, suspicious, mistrusting Patrick looked sceptical as someone read out his horoscope to him.
SERIOUS	solemn, grave The bank manager looked serious as he refused Nigel an overdraft.
STERN	severe, strict, firm The teacher looked very stern as he told the class off.
SUSPICIOUS	disbelieving, suspecting, doubting After Sam had lost his wallet for the second time at work, he grew suspicious of one of his colleagues.
SYMPATHETIC	kind, compassionate The nurse looked sympathetic as she told the patient the bad news.

TENTATIVE	hesitant, uncertain, cautious Andrew felt a bit tentative as he went into the room full of strangers.
TERRIFIED	alarmed, fearful The boy was terrified when he thought he saw a ghost.
THOUGHTFUL	thinking about something Phil looked thoughtful as he sat waiting for the girlfriend he was about to finish with.
THREATENING	menacing, intimidating The large, drunken man was acting in a very threatening way.
UNEASY	unsettled, apprehensive, troubled Karen felt slightly uneasy about accepting a lift from the man she had only met that day.
UPSET	agitated, worried, uneasy The man was very upset when his mother died.
WORRIED	anxious, fretful, troubled When her cat went missing, the girl was very worried.

		Answers - Adults			
P	jealous	**panicked**	arrogant	hateful	M
1	**playful**	comforting	irritated	bored	M
2	terrified	**upset**	arrogant	annoyed	M
3	joking	flustered	**desire**	convinced	F
4	joking	**insisting**	amused	relaxed	M
5	irritated	sarcastic	**worried**	friendly	M
6	aghast	**fantasizing**	impatient	alarmed	F
7	apologetic	friendly	**uneasy**	dispirited	M
8	**despondent**	relieved	shy	excited	M
9	annoyed	hostile	horrified	**preoccupied**	F
10	**cautious**	insisting	bored	aghast	M
11	terrified	amused	**regretful**	flirtatious	M
12	indifferent	embarrassed	**sceptical**	dispirited	M
13	decisive	**anticipating**	threatening	shy	M
14	irritated	disappointed	depressed	**accusing**	M
15	**contemplative**	flustered	encouraging	amused	F
16	irritated	**thoughtful**	encouraging	sympathetic	M
17	**doubtful**	affectionate	playful	aghast	F
18	**decisive**	amused	aghast	bored	F
19	arrogant	grateful	sarcastic	**tentative**	F
20	dominant	**friendly**	guilty	horrified	M
21	embarrassed	**fantasizing**	confused	panicked	F
22	**preoccupied**	grateful	insisting	imploring	F
23	contented	apologetic	**defiant**	curious	M
24	**pensive**	irritated	excited	hostile	M
25	panicked	incredulous	despondent	**interested**	F
26	alarmed	shy	**hostile**	anxious	M
27	joking	**cautious**	arrogant	reassuring	F
28	**interested**	joking	affectionate	contented	F
29	impatient	aghast	irritated	**reflective**	F
30	grateful	**flirtatious**	hostile	disappointed	F
31	ashamed	**confident**	joking	dispirited	F
32	**serious**	ashamed	bewildered	alarmed	M
33	embarrassed	guilty	fantasizing	**concerned**	M
34	aghast	baffled	**distrustful**	terrified	F
35	puzzled	**nervous**	insisting	contemplative	F
36	ashamed	nervous	**suspicious**	indecisive	M

practice

jealous

panicked

arrogant

hateful

1

playful comforting

irritated bored

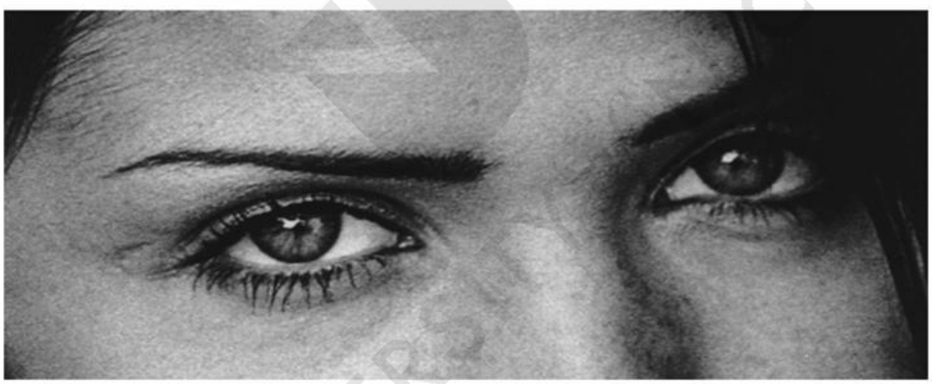
2

terrified upset

arrogant annoyed

3

joking flustered



desire convinced

4

joking

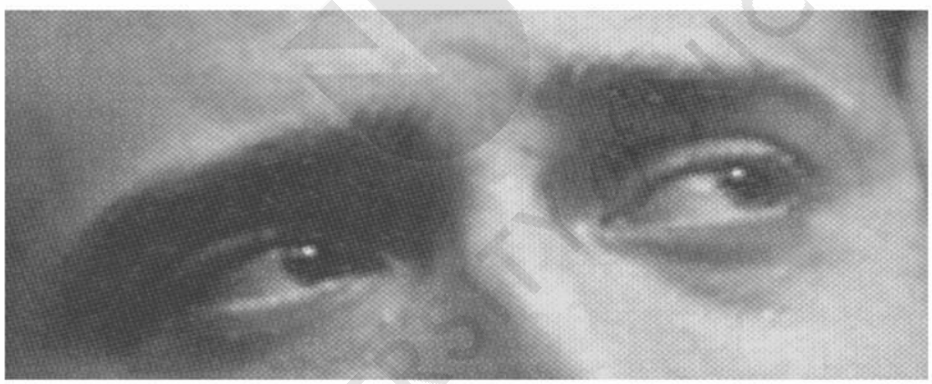
insisting

amused

relaxed

5

irritated sarcastic



worried friendly

6

aghast fantasizing

impatient alarmed

7

apologetic friendly

uneasy dispirited

8

despondent relieved

shy excited

9

annoyed hostile

horrified preoccupied

10

cautious

insisting

bored

aghast

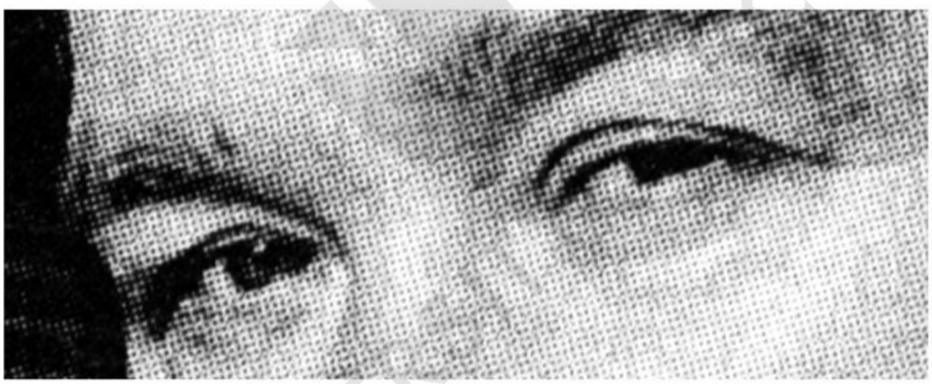
11

terrified amused

regretful flirtatious

12

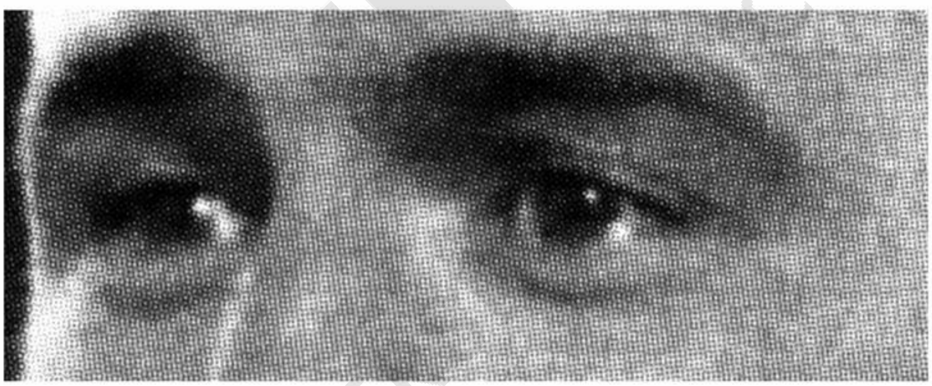
indifferent | embarrassed



sceptical | dispirited

13

decisive anticipating



threatening shy

14

irritated disappointed

depressed accusing

15

contemplative | flustered

encouraging | amused

16

irritated thoughtful

encouraging sympathetic

17

doubtful affectionate

playful aghast

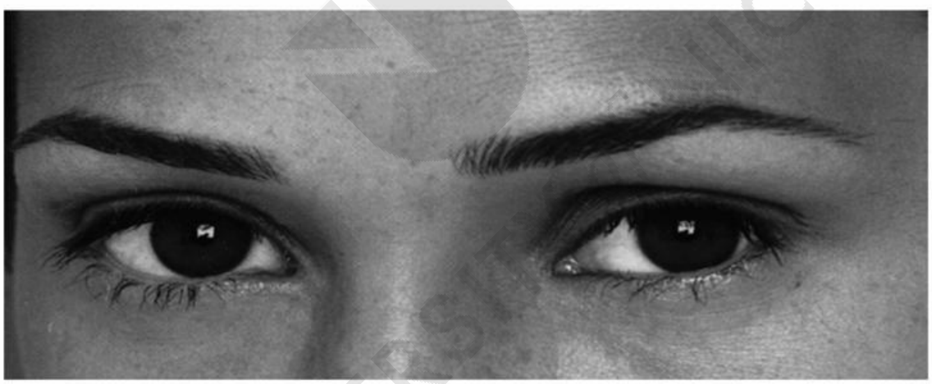
18

decisive | amused

aghast | bored

19

arrogant grateful



sarcastic tentative

20

dominant

friendly

guilty

horrified

21

embarrassed fantasizing

confused panicked

22

preoccupied grateful

insisting imploring

23

contented apologetic

defiant curious

24

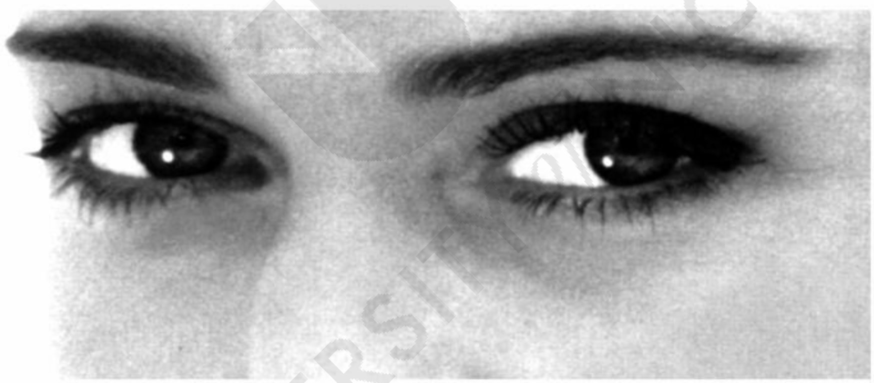
pensive | irritated

excited | hostile

25

panicked

incredulous

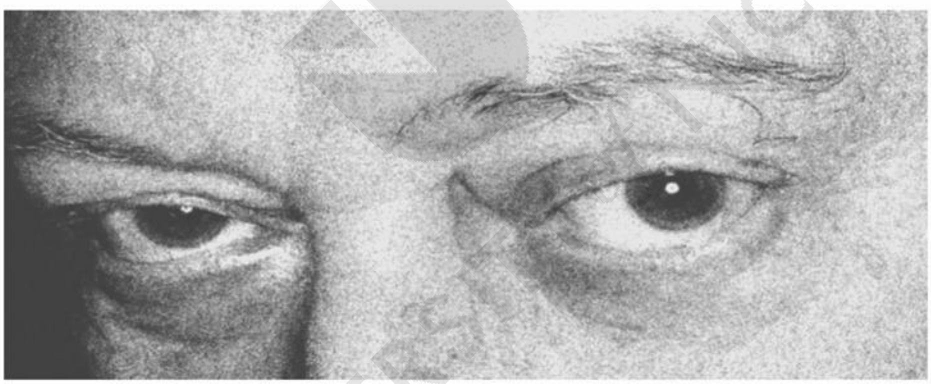


despondent

interested

26

alarmed shy



hostile anxious

27

joking cautious

arrogant reassuring

28

interested joking

affectionate contented

29

impatient aghast

irritated reflective

grateful flirtatious

hostile disappointed

31

ashamed confident

joking dispirited

32

serious ashamed

bewildered alarmed

33

embarrassed guilty

fantasizing concerned

34

aghast baffled

distrustful terrified

35

puzzled nervous

insisting contemplative

36

ashamed nervous

suspicious indecisive

Reading the Mind in the Eyes Test

For each set of eyes, choose and circle which word best describes what the person in the picture is thinking or feeling. You may feel that more than one word is applicable but please choose just one word, the word which you consider to be most suitable. Before making your choice, make sure that you have read all 4 words. You should try to do the task as quickly as possible but you will not be timed.

Reference Number (Student ID) ______________________

Today's Date ______________________

Degree Subject/Occupation ______________________

Date of Birth ______________________

Nationality ______________________

Gender Male ☐ Female ☐

P	jealous	panicked	arrogant	hateful
1	playful	comforting	irritated	bored
2	terrified	upset	arrogant	annoyed
3	joking	flustered	desire	convinced
4	joking	insisting	amused	relaxed
5	irritated	sarcastic	worried	friendly
6	aghast	fantasizing	impatient	alarmed
7	apologetic	friendly	uneasy	dispirited
8	despondent	relieved	shy	excited
9	annoyed	hostile	horrified	preoccupied
10	cautious	insisting	bored	aghast
11	terrified	amused	regretful	flirtatious
12	indifferent	embarrassed	sceptical	dispirited
13	decisive	anticipating	threatening	shy
14	irritated	disappointed	depressed	accusing
15	contemplative	flustered	encouraging	amused

16	irritated	thoughtful	encouraging	sympathetic
17	doubtful	affectionate	playful	aghast
18	decisive	amused	aghast	bored
19	arrogant	grateful	sarcastic	tentative
20	dominant	friendly	guilty	horrified
21	embarrassed	fantasizing	confused	panicked
22	preoccupied	grateful	insisting	imploring
23	contented	apologetic	defiant	curious
24	pensive	irritated	excited	hostile
25	panicked	incredulous	despondent	interested
26	alarmed	shy	hostile	anxious
27	joking	cautious	arrogant	reassuring
28	interested	joking	affectionate	contented
29	impatient	aghast	irritated	reflective
30	grateful	flirtatious	hostile	disappointed
31	ashamed	confident	joking	dispirited
32	serious	ashamed	bewildered	alarmed
33	embarrassed	guilty	fantasizing	concerned
34	aghast	baffled	distrustful	terrified
35	puzzled	nervous	insisting	contemplative
36	ashamed	nervous	suspicious	indecisive

Appendix V: Folk Physics Test

(adapted from Baron-Cohen et al., 2001b)

- Folk Physics Test – Part I
- Folk Physics Test – Part II

Folk Physics Test – PART I

This Test aims to find out whether you can easily understand how things work and function.

Each question has a diagram below, from which the answer can be worked out. After each question there is a choice of answers. Only one is correct. When you think you have found the correct answer, please indicate your choice by putting a circle around it. An example is shown below.

Please try to answer all the questions as quickly and as accurately as you can and then enter the total time taken to complete the test in the box at the end.

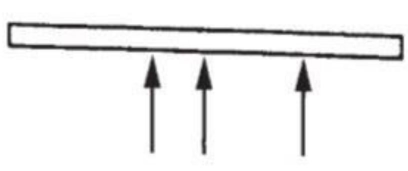
Reference Number (Student ID) ________________
Today's Date ________________
Degree Subject/Occupation ________________
Date of Birth ________________
Nationality ________________

Gender Male ☐ Female ☐

Example

Which arrow will balance the beam?

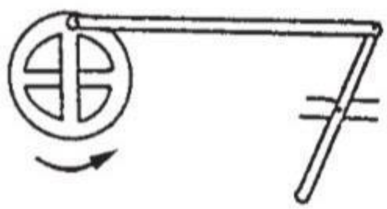
(a) A (b) B (c) C (d) all equal



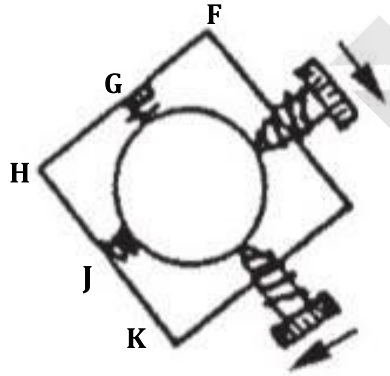
NOTE THE TIME BEFORE YOU START ____________________

Questions

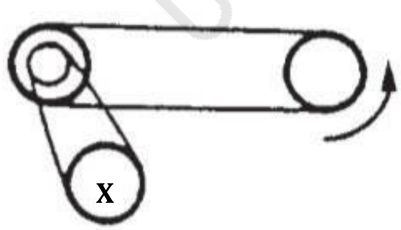
1. If the wheel rotates as shown, P will
   (a) move to the right and stop
   (b) move to the left and stop
   (c) move to and fro
   (d) none of these



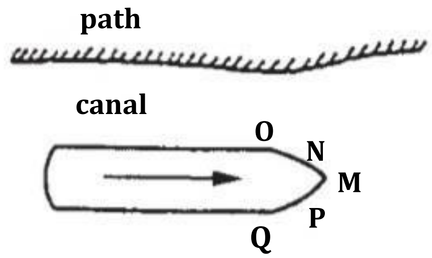
2. When the two screws are turned the same amount as shown, the ball will move towards
   (a) F (b) G (c) H (d) J (e) K



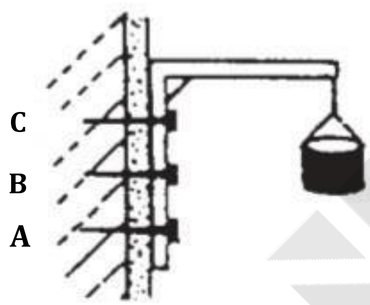
3. Which way does wheel X move?
   (a) either (b) (c) (d) stays still



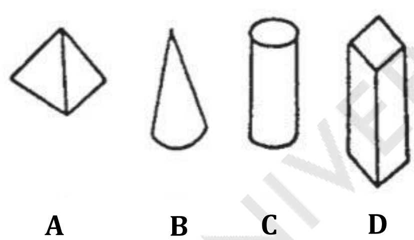
4. To move the boat easily in the direction shown, the rope would be best attached to
(a) M (b) N (c) O (d) P (e) Q



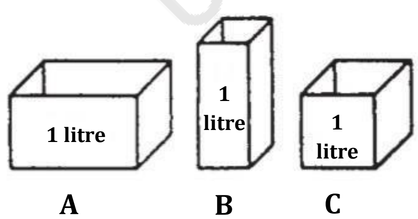
5. Which nail is most likely to pull out of the wall?
(a) A (b) B (c) C (d) all equally likely



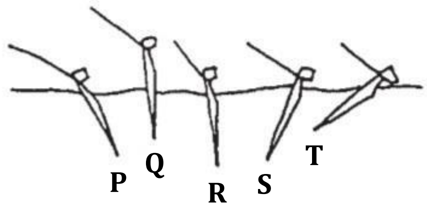
6. If each block weight the same, which one will be most difficult to push over? (a) A (b) B (c) C (d) D



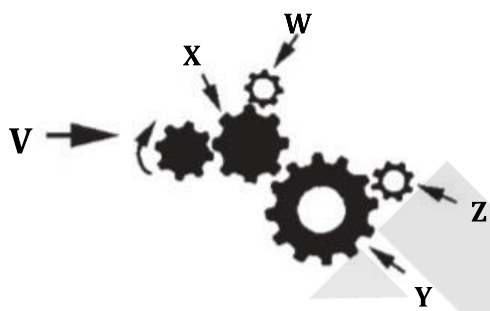
7. Which tank will cool the water faster? (a) A (b) B (c) C (d) all equally



8. Which tent peg will give the best hold in soft ground? (a) P (b) Q (c) R (d) S (e) T



9. Which gear wheel goes in the same direction as the driver, V?
(a) X (b) Y (c) Z



10. In question 9, which gear goes round faster?
(a) W (b) X (c) Y (d) Z

NOTE THE TIME AT THIS POINT ______________________________

Time taken to complete this Section ______ mins

Folk Physics Test – PART II

This Test aims to find out whether you can easily understand how things work and function.

Each question has a diagram below, from which the answer can be worked out. After each question there is a choice of answers. Only one is correct. When you think you have found the correct answer, please indicate your choice by putting a circle around it. An example is shown below.

Please try to answer all the questions as quickly and as accurately as you can and then enter the total time taken to complete the test in the box at the end.

Reference Number (Student ID) ________________

Today's Date ________________

Degree Subject/Occupation ________________

Date of Birth ________________

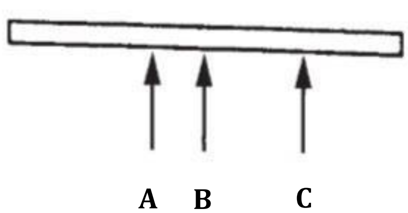
Nationality ________________

Gender Male [ ] Female [ ]

Example

Which arrow will balance the beam?

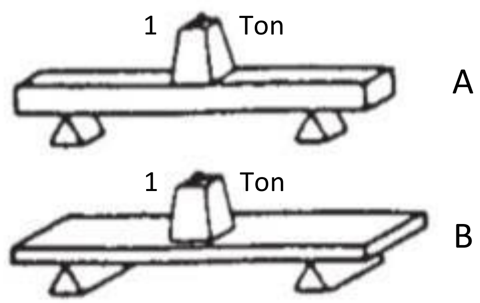
(a) A (b) B (c) C (d) all equal



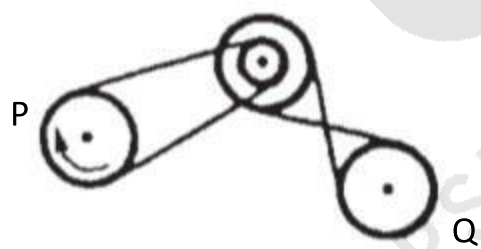
PART II

NOTE THE TIME BEFORE YOU START ____
Questions

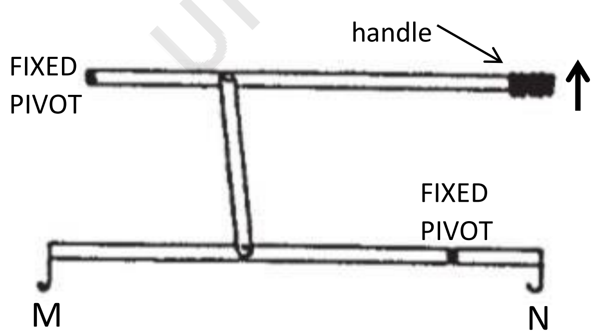
11. Which plank is more likely to break?
(a) A
(b) B
(c) either



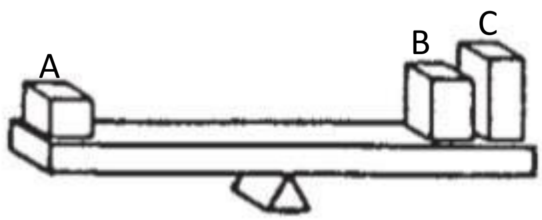
12. Which way will wheel Q turn when wheel P rotates as shown?
(a) ↶ (b) ↷ (c) either



13. If the handle is moved as shown, how will the hooks M and N move?
(a) M up, N down (b) M down, N up (c) M up, N up (d) M down, N down
(e) M up, N still

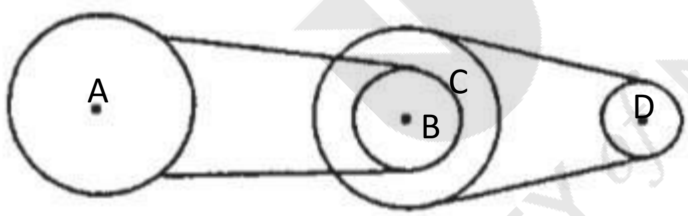


14. Which box is the heaviest?
(a) A (b) B (c) C (d) all equal



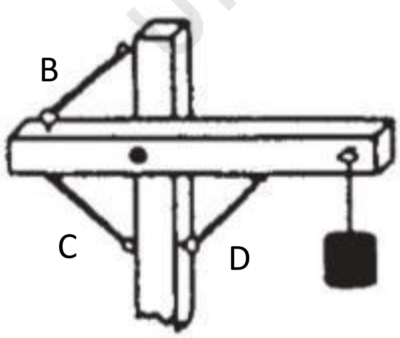
15. The diameter of pulleys A and C is 10cm and the diameter of pulleys B and D is 5cm. When pulley A makes a complete turn, pulley D will turn (a) once (b)

twice (c) 4 times (d) 6 times (e) 8 times

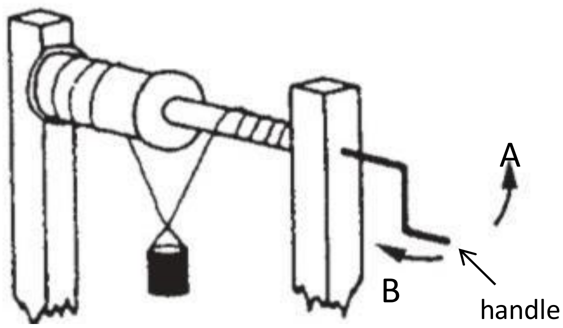


16. In question 15, if pulley D is the driver, (i.e. pulley D rotates) which pulley turns slowest?
(a) A (b) B (c) C (d) all the same

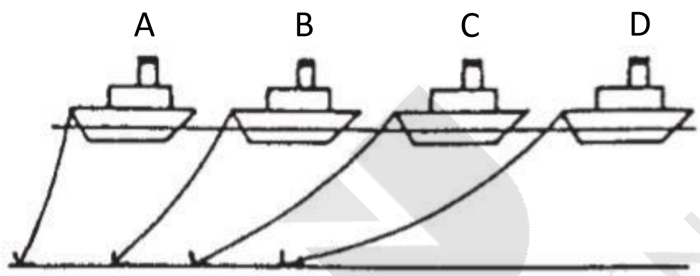
17. Which chain would support the weight by itself?
(a) any equally (b) B (c) C (d) D



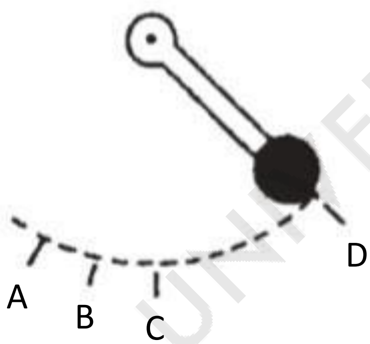
18. Which way would the handle have to turn to raise the bucket?
(a) A (b) B (c) either



19. Which boat has the safest anchorage?
(a) A (b) B (c) C (e) D



20. Where is the pendulum moving faster?
(a) A (b) B (c) C (d) D



NOTE THE TIME AT THIS POINT ____

Time taken to complete this Section ______ mins

Appendix VI: Big Five Personality Test

(Endorsed by the Open-Source Psychometrics Project)

Big Five Personality Test

Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. So that you can describe yourself in an honest manner, your responses will be kept in absolute confidence. Indicate for each statement whether it is 1. Very Inaccurate, 2. Moderately Inaccurate, 3. Neither Accurate Nor Inaccurate, 4. Moderately Accurate, or 5. Very Accurate as a description of you.

Reference Number (Student ID)	
Today's Date	
Degree Subject/Occupation	
Date of Birth	
Nationality	

Gender Male ☐ Female ☐

	Very Inaccurate	Moderately Inaccurate	Neither Accurate Nor Inaccurate	Moderately Accurate	Very Accurate
1. Am the life of the party.	○	○	○	○	○
2. Feel little concern for others.	○	○	○	○	○
3. Am always prepared.	○	○	○	○	○
4. Get stressed out easily.	○	○	○	○	○
5. Have a rich vocabulary.	○	○	○	○	○
6. Don't talk a lot.	○	○	○	○	○

	Very Inaccurate	Moderately Inaccurate	Neither Accurate Nor Inaccurate	Moderately Accurate	Very Accurate
7. Am interested in people.	○	○	○	○	○
8. Leave my belongings around.	○	○	○	○	○
9. Am relaxed most of the time.	○	○	○	○	○
10. Have difficulty understanding abstract ideas.	○	○	○	○	○
11. Feel comfortable around people.	○	○	○	○	○
12. Insult people.	○	○	○	○	○
13. Pay attention to details.	○	○	○	○	○
14. Worry about things.	○	○	○	○	○
15. Have a vivid imagination.	○	○	○	○	○
16. Keep in the background.	○	○	○	○	○
17. Sympathize with others' feelings.	○	○	○	○	○
18. Make a mess of things.	○	○	○	○	○
19. Seldom feel blue.	○	○	○	○	○
20. Am not interested in abstract ideas.	○	○	○	○	○
21. Start conversations.	○	○	○	○	○

	Very Inaccurate	Moderately Inaccurate	Neither Accurate Nor Inaccurate	Moderately Accurate	Very Accurate
22. Am not interested in other people's problems.	○	○	○	○	○
23. Get chores done right away.	○	○	○	○	○
24. Am easily disturbed.	○	○	○	○	○
25. Have excellent ideas.	○	○	○	○	○
26. Have little to say.	○	○	○	○	○
27. Have a soft heart.	○	○	○	○	○
28. Often forget to put things back in their proper place.	○	○	○	○	○
29. Get upset easily.	○	○	○	○	○
30. Do not have a good imagination.	○	○	○	○	○
31. Talk to a lot of different people at parties.	○	○	○	○	○
32. Am not really interested in others.	○	○	○	○	○
33. Like order.	○	○	○	○	○
34. Change my mood a lot.	○	○	○	○	○
35. Am quick to understand things.	○	○	○	○	○
36. Don't like to draw attention to myself.	○	○	○	○	○

	Very Inaccurate	Moderately Inaccurate	Neither Accurate Nor Inaccurate	Moderately Accurate	Very Accurate
37. Take time out for others.	○	○	○	○	○
38. Shirk my duties.	○	○	○	○	○
39. Have frequent mood swings.	○	○	○	○	○
40. Use difficult words.	○	○	○	○	○
41. Don't mind being the center of attention.	○	○	○	○	○
42. Feel others' emotions.	○	○	○	○	○
43. Follow a schedule.	○	○	○	○	○
44. Get irritated easily.	○	○	○	○	○
45. Spend time reflecting on things.	○	○	○	○	○
46. Am quiet around strangers.	○	○	○	○	○
47. Make people feel at ease.	○	○	○	○	○
48. Am exacting in my work.	○	○	○	○	○
49. Often feel blue.	○	○	○	○	○
50. Am full of ideas.	○	○	○	○	○

Appendix VII: Experiment 2 / Task 1 – Emergency Planning Activity – Case Study

EMERGENCY PLANNING ACTIVITY

Case Study: Why Plan?

Instructions: *Read the following case study and brainstorm to answer the questions that follow the case study. Supporting material is provided to help you answer the questions. → (20 minutes)*

At 6:53 p.m. on Friday, October 6, Hurricane Frieda slammed into the Carolinas. A Category 3 hurricane, Frieda dumped 12 inches of rain in as many hours, causing coastal flooding that, combined with wind speeds of 115 m.p.h., demolished 1,000 homes, seriously damaged 25,000 others and left 150,000 people homeless. Mass evacuation in coastal counties was required.

Evacuation in most counties went well. Prior to the hurricane, Green County had conducted a study to estimate the time required to evacuate its population, and the actual time to evacuate was less than planned. Additionally, inland residents were able to survive on their own for several days, thanks to functioning county emergence services.

However, evacuation in Washington and Jefferson Counties, which had no emergency plans, was itself a disaster. The decision to recommend evacuation was made too late and was broadcast insufficiently. Furthermore, evacuation routes were not specified. Traffic on westbound two-lane roads crawled to a standstill, and many drivers had to abandon their cars in rising water and proceed on foot in high winds. There were many casualties among those trying to reach shelter. These counties had to request State help immediately to rescue residents. After the storm, these counties were not eligible for the full amount of State aid to rebuild because of their failure to create an emergency plan.

---

1. What advantages to emergency planning can you list from this case study?

2. What consequences resulted from a lack of planning?

3. Threat profiles should address each threat's :

   a) Sector population.
   b) Quantification of risk.
   c) Seasonal pattern.
   d) Event severity.

4. The first step in a threat analysis is to:

   a) Divide the community into emergency management sectors.
   b) Create scenarios to test response capabilities.
   c) Develop a list of threats, the community may face.
   d) Quantify the community's risks from identified threats.

SUPPORTING MATERIAL

The Emergency Planning Process

Emergency planning is not a one-time event. Rather, it is a continual cycle of planning, training, exercising, and revision that takes place throughout the five phases of the emergency management cycle (preparedness, prevention, mitigation, response, and recovery).

The planning process does have one purpose - the development and maintenance of an upto-date emergency operations plan (EOP). An EOP can be defined as a document maintained by various jurisdictional levels describing the plan for responding to a wide variety of potential hazards.

Although the emergency planning process is cyclic, EOP development has a definite starting point.

There are six steps in the emergency planning process:

1. Form a collaborative planning team - Using a team or group approach helps organizations define their perception of the role they will play during an operation. One goal of using a planning team is to build and expand relationships that help bring creativity and innovation to planning during an event. This approach helps establish a planning routine, so that processes followed before an event occurs are the same as those used during an event.

2. Understand the situation - Hazards and threats are the general problems that jurisdictions face. Researching and analysing information about potential hazards and threats a jurisdiction may face brings specificity to the planning process. If hazards and threats are viewed as problems and operational plans are the solution, then hazard and threat identification and analysis are key steps in the planning process.

3. Determine goals and objectives - By using information from the hazard profile developed as part of the analysis process, the planning team thinks about how the hazard or threat would evolve in the jurisdiction and what defines a successful operation. Starting with a given intensity for the hazard or threat, the team imagines an event's development from prevention and protection efforts, through initial warning (if available), to its impact on the jurisdiction (as identified through analysis) and its generation of specific consequences (e.g., collapsed buildings, loss of critical services or infrastructure, death, injury, or displacement).

4. Develop the plan - The same scenarios used during problem identification are used to develop potential courses of action. For example, some prevention and protection courses of action can be developed that may require a significant initial action (such as hardening a facility) or creation of an on-going procedure (such as checking identity cards.). Planners consider the needs and demands, goals, and objectives to develop several response alternatives.

5. Prepare, review, and approve the plan - The planning team develops a rough draft of the base plan, functional or hazard annexes, or other parts of the plan as appropriate. As the planning team works through successive drafts, the members add necessary tables, charts, and other graphics. A final draft is prepared and circulated to organizations that have responsibilities for implementing the plan to obtain their comments.

6. Implement and maintain the plan - Exercising the plan and evaluating its effectiveness involve using training and exercises and evaluation of actual events to determine whether the goals, objectives, decisions, actions, and timing outlined in the plan led to a successful response. Similarly, planners need to be aware of lessons and practices from other communities.

The planning process is all about stakeholders bringing their resources and strengths to the table to develop and reinforce a jurisdiction's emergency management and homeland security programs. Properly developed, supported, and executed operational plans are a direct result of an active and evolving program.

Who Should Be Involved?

Emergency planning is a team effort because disaster response requires coordination between many community agencies and organizations and different levels of government. Furthermore, different types of emergencies require different kinds of expertise and response capabilities. Thus, the first step in emergency planning is identification of all of the parties that should be involved.

Obviously, the specific individuals and organizations involved in response to an emergency will depend on the type of disaster. Law enforcement will probably have a role to play in most events, as will fire, emergency medical services (EMS), voluntary agencies, and the media. On the other hand, hazardous materials (hazmat) personnel may or may not be involved in a given incident but should be involved in the planning process because they have specialized expertise that may be called on.

Appendix VIII: Experiment 2 / Task 3 – Tsunami Disaster Scenario

Tsunami Fast Facts

What is a tsunami?

A tsunami, from the Japanese word for ''harbour wave'' is a series of giant, long ocean waves (10 or more) created by an underwater disturbance such as an earthquake, landslide, volcanic eruption or meteorite. A tsunami can move hundreds of miles per hour in the ocean and smash into land with waves as high as 100 feet or more.

What are the elements most a risk during a tsunami:

- All structures within 200 m of low lying coastal area are most vulnerable to direct impacts of tsunami waves, and the debris brought by these waves. Settlements in adjacent areas will be vulnerable to floods and scour.
- Structures constructed of wood, mud, thatch, sheets, and structures without proper anchorage to foundations are at risk from tsunami waves and flooding.
- Other elements at risk are infrastructure facilities like ports and harbors, telephone and electricity poles, and cables. Ships and fishing boats near the coast may also be damaged / destroyed.
- Earthquakes and tsunami waves may damage both structural and non-structural elements within the built environment. Essential infrastructure (roads, harbors, power plants, banking, etc.) can be damaged which will shut down a community.

How can communities be more protected against tsunamis?

Here are some things that can be done to protect homes and communities from the damage caused by tsunamis:

<u>Before the tsunami</u>

Reinforce building structures:

- Remove homes and buildings to higher land that is away from the coastline. All structures within 200 meters of low lying coastal areas are most vulnerable to the impact of tsunami waves.
- Important buildings, such as schools and hospitals, should be built at higher locations.

- Designate tsunami hazard areas. A hazard map should be prepared, showing areas that could be damaged by flooding caused by tsunami waves. Development in these areas should be avoided, or kept to a minimum.

Take some shore line protections:
(Build structures to help protect the shoreline from tsunami damage)

- Seawalls and revetments are structures that can be built along the shoreline to help protect the shore from storm waves. Seawalls are vertical walls made of strong material, such as concrete, that can withstand the power of storm surges.
- Breakwaters may also protect the shoreline from waves. They are constructed some distance away from the coast in shallow water, to protect gently sloping beaches.
- Build and/or protect natural wave barriers. Natural barriers may help to protect the shore, and they also provide important habitat for fish and wildlife. However, because tsunami waves are so powerful, these measures cannot be relied on alone to protect from the biggest waves.
- Sand dunes may be built to act as a buffer from waves. Existing dunes may be stabilized by planting grasses, shrubs and trees.
- Maintain and/or construct mangroves (tree formations found along tropical and sub-tropical coastlines). These act as natural shock absorbers, soaking up destructive waves.
- Protect coral reefs. They act as natural wave-breakers.
- Shrubs, grasslands, and marshes will not provide adequate protection against tsunami waves, but will help to absorb flood water.
- Sea cliffs act as a natural wall against approaching waves, helping to break their power.

Raise community awareness about tsunami risk:

- Make sure there is a hazard map prepared with designated areas expected to be damaged by flooding caused by tsunami waves.
- Make sure the community has an evacuation plan, and practice it!
- Make sure the public knows that when sea waters recede noticeably, everyone must head for high land. This is nature's warning of an approaching tsunami.
- Place tsunami evacuation signs along roadways clearly indicating the direction inland or to higher ground. These signs will assist coastal residents and visitors in finding safer locations if a tsunami strikes.

Make sure there is a working early warning system in place

Tsunami early warning systems exist for many countries around the Pacific Ocean, and in certain other tsunami-prone areas. These systems give the public advance warning of tsunami waves, enabling communities to take the appropriate precautions. Make sure that early warning systems warn all communities of coastal areas when there is the threat of a tsunami. Tsunami warnings should be disseminated at all levels (local, regional, national, international).

TSUNAMI SCENARIO

There are approximately 20 minutes until a tsunami disaster.

You are presented with a map, which is an overview of the current area you are requested to work on. An example of Risk Map & Risk Level Exposure as well as Fast Facts about tsunamis, are provided to help you solve the task. → *(20 minutes)*

Team Members

1	Reference Number (Student ID)	
	Date of Birth	
2	Reference Number (Student ID)	
	Date of Birth	
3	Reference Number (Student ID)	
	Date of Birth	
4	Reference Number (Student ID)	
	Date of Birth	
5	Reference Number (Student ID)	
	Date of Birth	

1. The map below, which is an overview of the current area you are requested to work on, encompasses 5 levels of risk.
   Based on which factor/s is the map separated into different levels risk?

2. In relation to the above map (item 1), using the colouring pencils provided, indicate in the map below the level of risk, each tile is exposed to.

The risk map has 5 levels of risk which range from green to pink as shown below:

Pink tiles are at most risk, green at the least risk (1 Green, 2 Yellow, 3 Orange, 4 Red, 5 Pink).

1	2	3	4	5

3. Indicate with ‘’ X ’’ the best location (tile) on the map, to build a hospital and explain why?

Example - Risk Map & Risk Level Exposure

(The map below is related to a wildfire disaster scenario and it is only provided in this task as a reference)

Appendix IX: TMS Measurement Model

(adapted from Lewis, 2003)

Transactive Memory System

Indicate for each statement whether you 1. Strongly Disagree, 2. Disagree, 3. Neutral, 4. Agree, or 5. Strongly Agree.

Reference Number (Student ID) ______________________

Today's Date ______________________

Degree Subject/Occupation ______________________

Date of Birth ______________________

Nationality ______________________

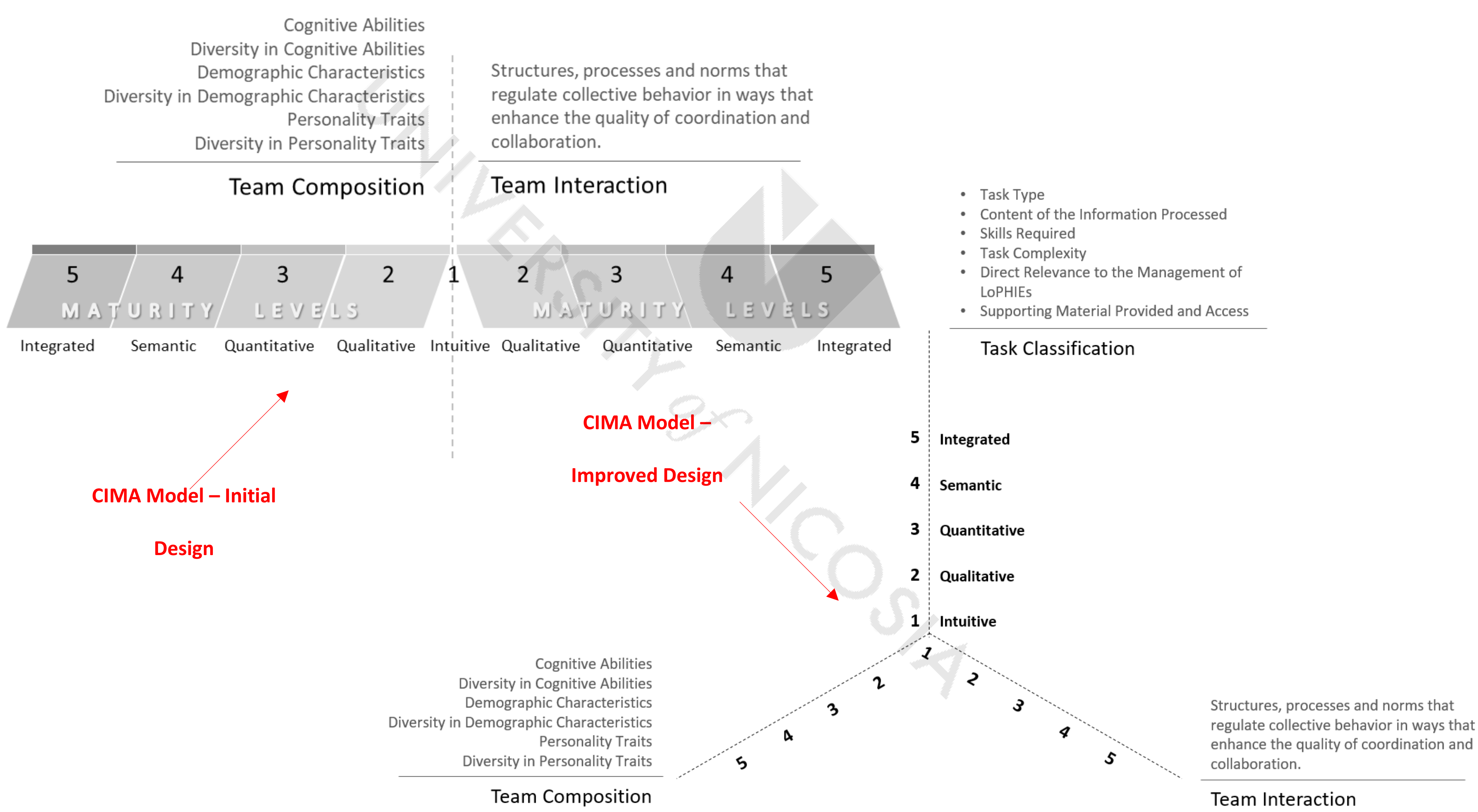
Gender Male [ ] Female [ ]

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
<u>Specialization</u>					
1. Each team member has specialized knowledge of some aspect of our project.	○	○	○	○	○
2. I have knowledge about an aspect of the project that no other team member has.	○	○	○	○	○
3. Different team members are responsible for expertise in different areas.	○	○	○	○	○
4. The specialized knowledge of several different team members was needed to complete the project deliverables.	○	○	○	○	○
5. I know which team members have expertise in specific areas.	○	○	○	○	○

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Credibility					
1. I was comfortable accepting procedural suggestions from other team members.	○	○	○	○	○
2. I trusted that other members' knowledge about the project was credible.	○	○	○	○	○
3. I was confident relying on the information that other team members brought to the discussion.	○	○	○	○	○
4. When other members gave information, I wanted to doublecheck it for myself.	○	○	○	○	○
5. I did not have much faith in other members' "expertise."	○	○	○	○	○
Coordination					
1. Our team worked together in a well-coordinated fashion.	○	○	○	○	○
2. Our team had very few misunderstandings about what to do.	○	○	○	○	○
3. Our team needed to backtrack and start over a lot.	○	○	○	○	○
4. We accomplished the task smoothly and efficiently.	○	○	○	○	○
5. There was much confusion about how we would accomplish the task.	○	○	○	○	○

Appendix X: Evolution of the CIMA Model after the Completion of the First Development Cycle

Evolution of the CIMA Model after the Completion of the First Development Cycle



Appendix XI: Teams

- Results of EXPERIMENT 1 by TEAM (aggregated over team)
- Results of EXPERIMENT 2 by TEAM
- Results of EXPERIMENT 3 by TEAM (aggregated over team)

Results of EXPERIMENT 1 by TEAM (aggregated over team)

team	Agreeableness	Conscientiousness	Emotional Stability	Extraversion	Intellect or Imagination	Folk Physics (Part 1)	RME TOTAL
TEAM 1	41.25	34.50	28.25	33.00	34.75	5.00	23.25
TEAM 2	44.00	40.00	28.67	31.67	42.00	5.00	23.00
TEAM 3	33.33	34.33	26.33	31.33	36.00	5.67	23.67
TEAM 4	40.25	43.00	34.00	32.25	37.00	6.25	25.00
TEAM 5	40.25	36.75	27.50	33.75	36.75	5.00	22.50
TEAM 6	40.00	36.00	27.25	30.75	39.75	6.00	25.50
TEAM 7	42.50	38.50	27.75	31.25	38.25	5.50	22.50
TEAM 8	38.50	39.25	29.50	28.75	35.25	6.25	24.00
TEAM 9	35.50	38.25	28.25	27.25	35.00	4.00	21.00
TEAM 10	36.50	34.00	30.50	35.50	36.25	5.50	25.25
TEAM 11	41.00	30.67	34.33	37.67	32.67	6.00	24.67
TEAM 12	36.33	33.00	29.67	34.67	38.00	6.00	25.67
TEAM 13	34.67	30.67	28.33	37.00	35.00	5.33	22.33
TEAM 14	34.67	39.33	36.33	37.00	37.00	5.33	21.00

Results of EXPERIMENT 2 by TEAM

team	TASK 1 (Emergency Planning Activity)	TASK 2 (Folk Physics)	TASK 3 (Tsunami Disaster Scenario)	Team Interaction Score - TASK 1	Team Interaction Score - TASK 2	Team Interaction Score - TASK 3	Total Team Interaction Score	Total Task Score (scaled)
TEAM 1	5	7	83	5	5	4	14	1.07
TEAM 2	6	6	67	5	5	4	14	0.77
TEAM 3	5	5	19	3	3	2	8	-0.79
TEAM 4	5	5	67	3	3	4	10	0.27
TEAM 5	4	7	56	2	2	3	7	0.20
TEAM 6	3	6	71	5	5	5	15	0.03
TEAM 7	2	6	68	4	5	5	14	-0.32
TEAM 8	4	5	59	4	5	5	14	-0.18
TEAM 9	2	7	35	5	5	5	15	-0.82
TEAM 10	4	6	57	4	5	4	13	0.00
TEAM 11	5	6	58	5	5	5	15	0.30
TEAM 12	6	7	74	5	5	5	15	1.15
TEAM 13	4	7	61	4	5	5	14	0.31
TEAM 14	5	5	43	5	5	5	15	-0.26

Results of EXPERIMENT 3 by TEAM (aggregated over team)

team	Coordination	Credibility	Specialization	Total TMS
TEAM 1	4.15	4.10	3.70	11.95
TEAM 2	4.27	4.27	3.73	12.27
TEAM 3	3.27	3.67	3.53	10.47
TEAM 4	4.65	4.40	3.50	12.55
TEAM 5	4.20	4.10	2.30	10.60
TEAM 6	4.80	4.05	3.50	12.35
TEAM 7	4.00	3.95	4.05	12.00
TEAM 8	3.95	3.45	2.75	10.15
TEAM 9	4.25	3.85	3.05	11.15
TEAM 10	3.05	3.15	2.80	9.00
TEAM 11	2.80	2.80	3.93	9.53
TEAM 12	3.47	3.40	3.13	10.00
TEAM 13	3.93	3.80	2.33	10.07
TEAM 14	3.60	3.33	2.93	9.87

Appendix XII: Model for Total Task Score on Experiment 1 variables and demographics

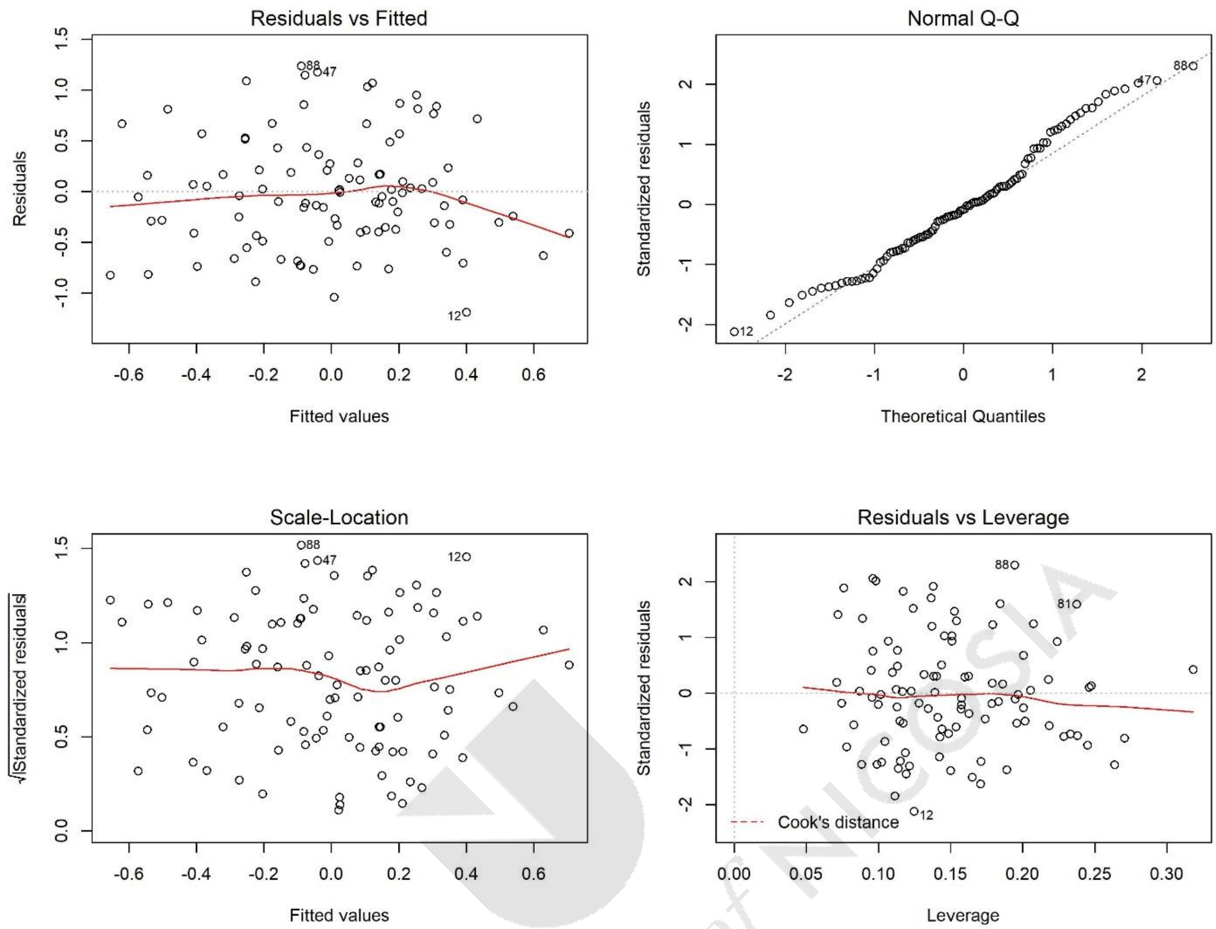
Model assumptions

```
# Variance Inflation Factors
car::vif(model_100)

##                    GVIF Df GVIF^(1/(2*Df))
## mode_of_part   2.316407  1        1.521975
## age            1.629635  1        1.276572
## gender         1.446915  1        1.202878
## risk_relevance 4.073941  4        1.191933
## rme_total      1.199534  1        1.095233
## b5_ex          1.395305  1        1.181230
## b5_ag          1.296361  1        1.138578
## b5_co          1.351065  1        1.162353
## b5_em_st       1.217943  1        1.103604
## b5_in_or_im    1.193156  1        1.092317
## folk_ph_part_i 1.329472  1        1.153027

#residual analysis
par(mfrow=c(2,2))
plot(model_100)
```

94.


Residuals vs Fitted
Residuals
Fitted values
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Scale-Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Cook's distance
Leverage

Appendix XIII: Team Interaction and Effective Communication Questionnaire

(adopted from: The Blake Group Organizational Consulting LLC)

Instructions: The current questionnaire aims to measure personal characteristics of team interaction and communication and should be completed by all team members.

There are no best ratings on this questionnaire - it is an instrument that offers a way to assess your strengths and weaknesses and to evaluate areas where your perceptions are congruent or inconsistent with those of others.

For each term listed below, indicate the degree to which you think the term describes you. The other members of your team are requested to rate your strength in these same characteristics by completing the questionnaire anonymously.

1. Articulate: Communicates effectively with others.
2. Listening: Active, empathetic listener.
3. Verbal/Non-verbal: Consistent communication, both verbally and non-verbally.
4. Clear: Communication is easy to understand.
5. Two-way: Encourages feedback and questions to ensure mutual understanding.
6. Unity, harmony, resolution: Communicates to strengthen understanding and achieve group goals.
7. Openness: Welcomes conversation concerning team goals and objectives.
8. Concise: Uses appropriate communication vehicles and achieves brevity.
9. Body Language: Movements convey clear messages that reinforce verbal content.
10. Tone: Conveys clear messages through voice inflection.
11. Open: Encourages knowledge sharing.
12. Follow-up: Communicates at critical/key points to ensure understanding.
13. Intuitive: Understands others' level of commitment.

Please pick one of the following responses to indicate the strength of your opinion:

5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree

Name of the team member being assessed: ____

	Rating Sheet					
	Team Member 1	Team Member 2	Team member 3	Average	Self	Difference
1. Articulate						
2. Listening						
3. Verbal/Non-verbal						
4. Clear						
5. Two-way						
6. Unity, harmony, resolution						
7. Openness						
8. Concise						
9. Body Language						
10. Tone						
11. Open						
12. Follow-up						
13. Intuitive						
TOTAL						

Scoring Interpretation: The score you received on this questionnaire provides information about how you see yourself and how others see/perceive your communication. The rating sheet allows a comparison between your perceptions and those of others.

Appendix XIV: Situation Awareness Register

(The register is examined for evaluation and validation)

Instructions: The current register is an instrument that offers a way to assess the situation at hand based on specific characteristics. It aims to measure collective task representations and to record situation awareness. Clarification, when needed, is provided. Team members are requested to complete the register collectively.

Please, indicate with ‘ X ‘ the most suitable answer in relation to the situation at hand.

Team Name: ___________________________________

1. The task is:	
a) Closed	
*Clarification The task exhibits the following characteristics: • Has one correct answer/solution. • A specific skill or procedure or one specific piece of knowledge is needed for its completion. • Does not offer the opportunity to demonstrate problem-solving strategies, thinking and higher levels of understanding.	
b) Open-ended	
*Clarification The task exhibits the following characteristics: • Has a range of appropriate responses/solutions. • A range of knowledge and skills are required for its completion. • Offers the opportunity to demonstrate problem-solving strategies, thinking and higher levels of understanding.	
c) A combination of both	
*Clarification The task exhibits both closed and open-ended characteristics.	
2. The content of the information needed to be processed in the task is based on:	
a) The social-cognitive domain	

*Clarification The task exhibits the following characteristics: • Involves interpersonal interaction. • Requires social information processing to be completed.	
b) The analytic (non-social) cognitive domain	
*Clarification The task exhibits the following characteristics: • Involves reasoning about the mechanical or underlying properties of lifeless objects. • It is concerned with arithmetic and abstract concepts. • Requires nearly no social skills to be completed.	
3. The type of skills required for the completion of the task are:	
a) Accuracy	
b) Coordination	
c) A combination of both	
*Clarification The type of skills required for the completion of the task can be determined by two factors: 1. The type of the task (whether it is a closed, open-ended, or a combination of the two), and 2. The content of the information needed to be processed (whether based on the social or analytic cognitive domain).	
4. The task has a direct relevance to the management of LoPHIEs:	
a) Yes	
b) No	
5. Supporting material for the completion of the task has been provided:	
a) Yes	
b) No	
6. Access to the supporting material provided is allowed during the completion of the task:	
a) Yes	
b) No	
7. The complexity of the task is:	
a) Low	
b) Medium	
c) High	
*Clarification The complexity of the task can be determined based on the type of the task (whether it is a closed, open-ended or a combination of the two), the content of the information needed to be processed (whether based on the social or analytic cognitive domain), the direct relevance to the management of LoPHIEs and on whether supporting material is provided or not and based on what fashion knowledge is distributed.	

Appendix XV: **Backward Design Template with Descriptions**

(adapted from Bowen, 2017)

<table>
<tr><th colspan="3">Stage 1 – Desired Results</th></tr>
<tr><td rowspan="6">ESTABLISHED GOALS

The enduring understandings and learning goals of the lesson, unit, or course.</td><td colspan="2">Transfer</td></tr>
<tr><td colspan="2">Team members will be able to independently use their learning to…

Refers to how team members will transfer the knowledge gained from the lesson, unit, or course and apply it outside of the context of the course.</td></tr>
<tr><td colspan="2">Meaning</td></tr>
<tr><td>UNDERSTANDINGS
Team members will understand that…

Refers to the big ideas and specific understandings team members will have when they complete the lesson, unit, or course.</td><td>ESSENTIAL QUESTIONS

Refers to the provocative questions that foster inquiry, understanding, and transfer of learning. These questions typically frame the lesson, unit, or course and are often revisited. If team members attain the established goals, they should be able to answer the essential question(s).</td></tr>
<tr><td colspan="2">Acquisition</td></tr>
<tr><td>Team members will know…

Refers to the key knowledge team members will acquire from the lesson, unit, or course.</td><td>Team members will be skilled at…

Refers to the key skills team members will acquire from the lesson, unit, or course.</td></tr>
<tr><th colspan="3">Stage 2 – Evidence and Assessment</th></tr>
<tr><td>Evaluative Criteria</td><td colspan="2">Assessment Evidence</td></tr>
<tr><td rowspan="2">Refers to the various types of criteria that team members will be evaluated on.</td><td colspan="2">PERFORMANCE TASK(S):

Refers to the authentic performance task(s) that team members will complete to demonstrate the desired understandings or demonstrate they have attained the goals. The performance task(s) are typically larger assessments that coalesce various concepts and understandings like large projects or papers.</td></tr>
<tr><td colspan="2">OTHER EVIDENCE:

Refers to other types of evidence that will show if team members have demonstrated achievement of the desired results. This includes quizzes, tests, homework, etc. This is also a good point to consider incorporating self-assessments and student reflections.</td></tr>
<tr><th colspan="3">Stage 3 – Learning Plan</th></tr>
<tr><td colspan="3">Summary of Key Learning Events and Instruction

This stage encompasses the individual learning activities and instructional strategies that will be employed. This includes lectures, discussions, problem-solving sessions, etc.</td></tr>
</table>

Appendix XVI: R Markdown Document

The statistical analysis was performed in R version 3.5.1 and it is fully reproducible: an R markdown document is available online in the following links:

https://www.dropbox.com/sh/ruruo3bw2a8dlwn/AACZexvkzpPEM7HVp48vF9NSa?dl=0

https://1drv.ms/u/s!AgN7OfT5QYvahx20PZd7hw8s_4E2?e=WV8R8q