An Analysis of Data-Driven Decision-Making Capabilities of Managers in Banks

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DECLARATION

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ABSTRACT

The vast volume of data generated by modern organizations could be used to gain a competitive advantage through the application of data analytics techniques. As such, many organizations are adopting data analytics and business intelligence tools with the aim of obtaining information more easily, gaining important insights, forecasting future events, and getting timely and reliable information to aid them in their decision making. While these tools are becoming mature, affordable, and easier to use, it is also important to understand whether the contemporary managers in these organizations are ready for Data-Driven Decision Making (DDDM). Therefore, it is imperative to understand to what extent the Decision Makers (DMs) are utilizing these data and tools, whether they can interpret the various forms of outputs from these tools, and gauge their ability to apply those insights to gain a competitive advantage. This study aims to answer these questions through a qualitative survey and a detailed analysis of several cases where such data analytics tools were used. This research uses Straussian's grounded theory as the tool to analyze and build the theory for this investigation. The analysis focused on commercial banks in Sri Lanka and interviewed DMs at branch and regional levels, and the CTO, CIO, and Head of IT of six banks. It was identified that in many occasions, the DMs' intuition overrules the DDDM due to uncertainty, lack of trust, knowledge, and the unwillingness towards risk-taking. It was also found that while experienced DMs prefer intuition-based decision-making, novice DMs are more adept at DDDM. Moreover, it was identified that quality of visualizations and presentations had a significant impact on the use of intuition by overruling DDDM. Subsequently, a set of recommendations are provided on the adoption of BI tools and on overcoming the struggles faced while performing DDDM.

Keywords: Data-Driven Decision Making; Decision Makers; Data Literacy; Business Intelligence Tools

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BA	Business Analytics
BI	Business Intelligence
DDD	Data Driven Decisions
DDDM	Data Driven Decision Making
DM	Decision Maker
DMs	Decision Makers
IT	Information Technology
ML	Machine Learning
PR	Pattern Recognition
Stat	Statistical Method
STEM	Science, Technology, Engineering, and Mathematic

1. INTRODUCTION

1.1. Background

Contemporary businesses are trying to become more data-driven while increasing their decision-making efficacy so that those decisions will help them outsell their competitors (Hall & Jia, 2015). Many organizations are re-evaluating how to run smarter, be more agile and competent by using the right data to support efficient and effective decision making. In Data-Driven Decision Making (DDDM) we take data (structured or unstructured), analyze it, and make a decision based on the analysis (Agrawal, 2014). DDDM is also known as “the practice of basing decisions on the analysis of data rather than purely on intuition”. According to Ransbotham et al. (2015), Decision Makers (DMs) must make critical decisions based on the data to gain a competitive advantage in dynamic business environments. Hence, DMs are now seeking assistance from various tools and technologies to assist their decision-making process.

There are many tools and techniques supporting different steps of the decision-making process. Such tools are known as *Business Intelligence* (BI) tools, which is an umbrella term that refers to architectures, tools, databases, applications, and methodologies with the goal of analyzing data to support decisions of business managers. BI tools provide descriptive and predictive analytics of data with varying type of visualizations to reduce the complexity of data analysis. For example, these tools can provide summary reports, dashboards, balanced scorecards, and several other types of information to support the managers in the DDDM process to support the managers in the DDDM process. Faster and better decision making, as well as new insight creation, are among the top features where organizations intend to adopt BI tools (Hall & Jia, 2015). Therefore, organizations invest in expensive BI tools to support the DMs to process data and derive insights (Ransbotham et al., 2015; Tingling & Brydon, 2010).

Banking has been a prolific industry for innovation in the spheres of information systems and technologies. Credit evaluation, branch’s performance, e-banking, and customer segmentation and retention are some areas where a wide variety of BI concepts and techniques such as Data Mining, data warehouses, and Decision Support

Systems (DSS) can be applied (Hensman & Sadler-Smith, 2011; Moro et al., 2015). Moreover, the rapid growth in data volumes, structured and sensible data, and the increasing availability of data have further influenced the banking industry to focus more on evidence-based decision making (Hensman & Sadler-Smith, 2011).

However, to perform DDDM, DMs require a specific set of skills and capabilities such as data literacy, data interpretation, understanding of reports, and visualization of outputs from BI tools (Davenport et al., 2013; 2010; 2001; Dykes, 2017). While banks have invested heavily in BI tools and expect DMs to perform DDDM by using their outputs, the effectiveness of such investments is being questioned as DMs seem to struggle to perform DDDM activities. Therefore, it is becoming increasingly imperative to understand the underlying issues in DDDM, as well as identify suitable remedies for them.

1.2. Motivation

Senior management in banks is gradually recognizing the importance of using BI tools to create business value. However, under such dynamic and complex business conditions, the question is, how can managers with limited analytical expertise become adept consumers of analytics (Ransbotham et al., 2015). Even though the DMs have BI tools that provide insights and support decision making, the question yet to be raised is: do the DMs know what they are looking for in the data and is the analysis output supportive in enough to their decision making? Therefore, the frequency in which data are transformed into valuable insight and business decisions are applied to gain competitive advantages in a dynamic banking environment is also a major concern for banks. Many researchers have found that most organizations fail to use BI tools for DDDM; hence, they lack in strategic changes, the capabilities needed to perform DDDM, cultural impact on the DDDM process, and the human realm of analyzing data and then acting on insights (Davenport et al. 2001, 2010; Dykes, 2017; Ransbotham et al., 2015). Therefore, insights and information provided by BI tools is a waste if the DMs are unable to understand and interpret the information in the context of the business environment (Sharma et al. 2014).

Many BI tool vendors and IT departments are puzzled with questions such as why business managers are not utilizing available tools for DDDM, and what should DMs be aware of to make sure that their decisions are based on numbers, not intuition. On the other hand, DMs have the concern of "can we trust the tools and depend on what the BI tool says?" According to Davenport et al., (2010), many CIOs of leading companies stated that DMs spent a considerable time on verifying the outputs provided by BI tools due to a lack of trust and confidence on these tools. These concerns are not surprising given that most DMs do not have a strong STEM (Science, Technology, Engineering, and Mathematics) background that is required to interpret complex relationships in data. Moreover, decision-making habits are often learned by trial and error (Davenport et al. 2001). Thus, DMs in organizations need to learn and master the skills through deliberate and systematic effort.

Hall and Jia (2015) identify several key factors that negatively influence DDDM practices, such as: the organization culture and attitude towards DDDM, strategic changes required in the organization to perform DDDM, business process changes to perform DDDM, factors preventing DMs in practicing DDDM, and the complexity of BI tools used in organizations. Hence, it is imperative to understand the ability of DMs to understand and interpret data in the current business context, as well as the skill gap in DMs to drive the decision-making process based on evidence rather than pure intuition (Ransbotham et al., 2015; Yates & de Oliveira, 2016).

Most existing studies do not focus on finding the struggles DMs face during the adoption and practice of DDDM, neither do they specify suitable measures to address those pain points. The primary focus of this research is to identify the struggles that DMs face and evaluate the DDDM capability of DMs in banking organizations under complex business environments. Furthermore, identifying how banks can support DMs to improve and practice more DDDM for successful decision making is also a point of interest in this study.

1.3. Outline

The rest of the thesis is organized as follows. Chapter 2 presents an extended literature review on related topics, DDDM, data analytics, data-driven decision maker's characteristics, the impact on developing a DDDM-based culture, and DDDM in the banking domain. Chapter 3 formulates the problem statement, objectives, and research significance based on the literature review. Chapter 4 discusses the research methodology, where it presents the proposed research method, population and sampling, data collection, interview questions, and the data analysis approach. Chapter 5 presents a summary of the data analysis using the grounded theory approach. Chapter 6 provides recommendations, a conclusion of the study, research limitations, and future work.

2. LITERATURE REVIEW

As data analytics in decision making has become a trend, organizations are now adopting analytics and Business Intelligence (BI) tools with the aim of performing Data-Driven Decision Making (DDDM). This chapter discusses related work on DDDM. Section 2.1 describes DDDM, its components, how to build such capabilities, and the technological improvements needed to perform DDDM. Why modern businesses need analytics-driven decision making and how it can improve decision making is discussed in Section 2.2. Section 2.3 aims to differentiate a data-driven decision maker from an ordinary decision maker, based on their characteristics, as well as identify factors that can improve and reduce the discomfort in practicing DDDM. It further discusses a framework to build analytical capabilities among DMs and how to measure their DDDM ability. The cultural impact of a DDDM environment and how to build such a culture in an organization (and in individual DMs), is presented in Section 2.4. Section 2.5 describes how DDDM can be used in the banking domain and its anticipated challenges therein.

2.1. Data-Driven Decision Making

DDDM is defined as the systematic collection, analysis, examination, and interpretation of data to derive practices and policies in any domain (Mandinach, 2012). This is a generic process that can be applied to data from any domain to improve decision making, as well as administration and strategy-implementation across different levels of operations. However, it is important to have the right data and tools to support efficient and effective decision making (Davenport et al., 2010). DDDM is an art where DMs need to collaborate with data-driven evidence, as well as their own experience and intuition.

However, the most important question is: do DMs depend on what the data says? Do managers feel that they have all the data they need to make decisions in a dynamic business environment? Addressing these issues is complex and challenging for many organizations. Francioni, Musso, and Cioppi, (2015) found that DMs tend to follow a more rational strategic decision-making process depending on their education level and attitude towards risk. However, this study does not aim to find out the type of education and its extent required for DDDM. Alternatively, Mandinach, (2012), Mandinach, Honey, & Light, (2014) discussed the importance of data literacy in DDDM, however, how to improve data literacy and how much data literacy is required, is still a question.

2.1.1. Data-driven decision-making approaches and process

A leader's approach to decision making needs to be transformed to perform DDDM. DDDM is a blend of data analytics or evidence-based decision-making, along with the intuition and experience of the DM. The DDDM approach could be considered as a supportive element to make intuition-based decisions more concrete. However, to perform such decisions, DMs should have the ability to interpret data, domain knowledge, and the intention to practice the insight generated by the data. Therefore, Sharma et al. (2014) and Lycett (2013) highlighted that DMs should be able to transform data to insight, insight to the decision, and decision to value, to obtain competitive advantages for organizations.

Generating insights from an organization's data is challenging and needs many actors to perform these activities (Sharma et al., 2014). The composition of such a team is often an outcome of using the organization's data assets and a set of managerial DMs with the knowledge of the business domain. The outcome of these teams is influenced by the existing decision-making routines. Sharma et al. (2014) argue that effect of team compositions and existing structures on decisions and decision making are difficult to interpret in terms of business values, but such decisions are more powerful than intuition-based decisions. Data insight generation is no longer a human task and BI tools have replaced the involvement of DMs in processing data into insight (Mandinach et al., 2014; Ransbotham et al., 2015). However, understanding and interpreting the insights are still major responsibilities of DMs.

Understanding insights and making decisions is more critical today because, the course of action influenced by the insight could either lead to success or failure (Lycett, 2013; Sharma et al., 2014). Insights include an understanding of trends, operations, interpreting the data that is are likely to suggest multiple options for exploiting them and converting them into value. However, choosing the correct option remains a question for DMs due to the uncertainty and lack of trust on BI tools. While many organizations and DMs have reasonable facts to believe that there is a relationship between the use of business analytics and its ability to derive better insights and decisions, it is not clear when and in what situations those better outcomes will be observed (Lycett, 2013; Sharma et al., 2014; Smith et al., 2016).

Sharma et al., (2014) argue that transforming insights into decisions is dependent on the organizational decision-making process. However, Francioni et al. (2015) argue that transforming insights into decisions is more influenced by the DMs characteristics (personality, socio-demographic, and competencies) rather than the organizational decision-making process. Still, many DMs perform intuition-based decision making simply because their organizational decision-making process is complex, or when DMs are more experienced in decision making, they tend to be more comfortable with their intuition (Mandinach, 2012).

The ability of DMs in capturing insights and making decisions using BI tools are being discussed widely. However, whether those decisions can be implemented successfully remains a question for organizations as well as researchers. Lycett (2013) and Sharma et al. (2014) argue that in order to be considered "good", a decision should at least fulfill two criteria, namely the quality and acceptance of the decision. The q*uality of a decision* is about whether the decision can achieve its objectives, while *acceptance of the decision* is its level of acceptability by subordinates and other stakeholders.

While BI tools can help to improve the quality of the decision, it is not clear whether they can be used to improve the acceptance of a decision. Nevertheless, decision-to-value creation is a cyclic process where organizations and DMs have to analyze the feedback from subordinates and other stakeholders to ensure the quality and the acceptance of the decision (Mandinach, 2012). Mandinach (2012) further argues that in order for decisions to be accepted, it is a must to provide the knowledge of DDDM to decision implementers and other stakeholders in an organization. Furthermore, authors argue that as this process is expensive and time-consuming, most organizations are not interested in providing the adequate training and knowledge to its employees.

While numerous processes for DDDM have been proposed, they have several components in common such as; collecting, analyzing and integrating data; preprocessing and processing data; visualizing and analyzing data; decision making; and implementing and evaluating decisions. However, the DMs ability to interpret these insights or perform DDDM is not being addressed.

According to Mandinach (2012) and Mandinach et al., (2014), the objective of a DDDM process is to analyze the data, examine performance trends, drill down to item-levels, and look at aggregated and disaggregated data to try and make sense of performance patterns. Mandinach et al. (2014) developed a conceptual framework to perform DDDM. It consists of six key elements, namely data collection, organizing data, analyzing data, extracting information and summarizing them, and finally, synthesize and prioritize the data. While this framework is developed for DDDM in a school, it could be adopted to any domain for DDDM. BI tools can automate these six steps. Therefore, DMs do not have to consider these elements in the DDDM process and their focus should be on deciding and implementing the outcomes of the framework.

However, according to (Hall and Jia 2015), this framework does not consider the assessment and evaluation of decision implementation and the embeddedness of decision making in core business process. Moreover, they further argued that the proposed framework does not consider the external business environment, as an organization is not isolated from the society or its business environment. Hence, the authors derived an alternative framework because they argue that DDDM is a continuous process that includes collecting data, transferring data into information and ultimately knowledge, making decisions based on the knowledge, monitoring the implementation of decisions, and providing feedback for each of the processes. Moreover, the proposed framework screens data from external environments and data disclosure for the external environment. Furthermore, the proposed framework also has several levels of information such as organization, supply chain, and external environments.

However, in today's context, the above DDDM process models are outdated as BI tools have automated many more steps in the DDDM process. These two frameworks do not address the ability of a decision maker to interpret data. While (Hall and Jia 2015), (Mandinach, 2012) frameworks major missing component is the data interpretation ability of DMs. Figure 2.1 shown below is an effort to derive a new framework from (Hall and Jia, 2015; Mandinach, 2012) frameworks and incorporating a DM's data interpretation ability. It highlights the DMs' involvement and DMs' data interpretation, decision making, decision implementation characteristics and influence from external environments. Thus, the framework enables an organization to analyze the DMs' capabilities and characteristics for DDDM.

2.1.2. Components of Data-Driven Decision Making

The two major components of DDDM making are the practical guide to technological tools and the human capacity (Mandinach, 2012). Many organizations are required to perform DDDM with structured or unstructured data, tools and technology, meaningful data analysis, measurements and monitoring, benchmarking, integration of systems, and well-trained managers. While many of these key factors have been studied extensively, relatively less attention is given to the actual use of tools and to what extent the managers understand the output and their data literacy. The two comments can be further described as follows:

- Tools – The volume of data that organizations are confronted with continues to grow and increase in complexity. This growth has gone beyond the human handling capacity, hence, necessitating tools and solutions to support DDDM is key. Today, analysts, managers, and DMs have access to a variety of tools for data analysis, data mining, ad-hoc reporting, and visualization. Such DDDM tools should fulfill the four V's (Volume, Velocity, Variety, and Value) of big data (Lycett, 2013). While many tools are available, choosing the correct tool is still a challenge for organizations.

- Human capacity and data literacy – DDDM is an IT-driven sense-making process, which is known as a DMs' ability to interpret data. (Lycett, 2013).

Understanding data includes the DMs ability on how they interpret data into insight and then into business values in terms of:

a. the nature of how and why aspects are singled out from the stream of experience; and

b. How interpretations are made explicit through concrete activity.

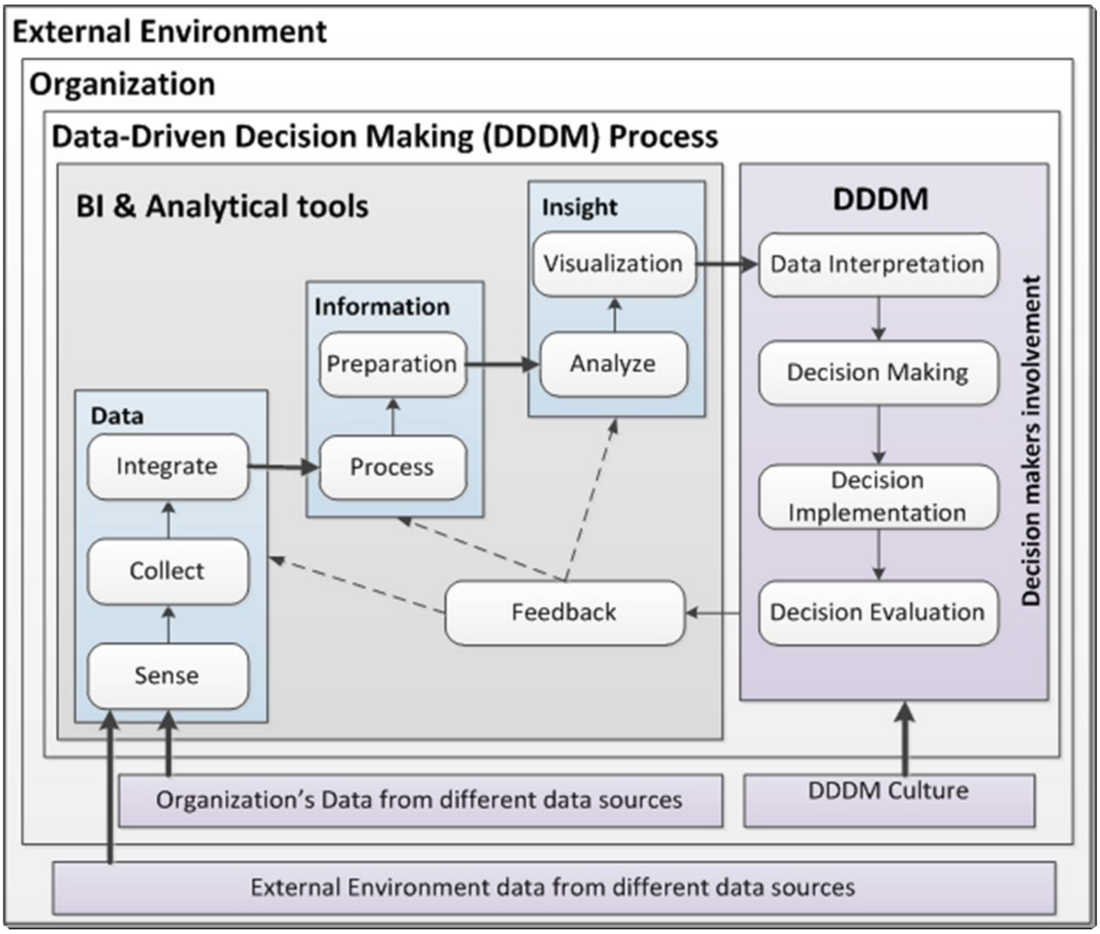

Figure 2:1 DDDM process with decision makers' involvement.

Source : (Hall and Jia, 2015; Mandinach, 2012)

However, the problem is that many DMs do not have the adequate training to understand, analyze, and interpret data, which hinders the DDDM. The lack of formal and informal mechanisms by which DMs can gain the skills and knowledge needed to become data literate is also a problem (Mandinach, 2012). Only a few organizations provide structured and professional development around DDDM. However, there is still no agreement among researchers and practitioners whether professional development providers require specific training to be data iterate so that they can perform DDDM.

2.1.3. Building analytical capabilities in decision makers

It has been identified through several studies that there is a lack of data literacy and analytical capabilities among DMs, and this is a major factor that leads towards failure in DDDM adoption (Mandinach, 2012; Mandinach et al., 2014; Marsh & Farrell, 2014). Hence, researchers have identified key facts to build analytical capabilities in DMs. Marsh et al. (2014) and Hamilton et al. (2006) identified the following as key factors to be addressed in a DDDM environment to guide DMs to adapt, develop and improve their analytical capabilities:

i. Understanding how to build a DMs analytical capability – a key component to the implementation of DDDM is to build human capability around data and data literacy (Mandinach et al., 2014). However, the major concern is that this area is still receiving less attention and limited funding from organizations. Hall and Jia (2015) recommend focussing on improving the capability of visualization, exploration, and explanatory skills. Moreover, Venkatraman et al. (2015) defined these factors as descriptive, prescriptive and predictive analysis techniques. However, Keim et al. (2010) argued that improving descriptive, prescriptive and predictive capabilities will not be effective when DMs are unable to interpret the visualization; hence, visualization capability a must. Yet, how and to what extent the visualization capability should be improved is unclear.

ii. Identify specific practices administrators might need to employ – to improve and develop analytical capabilities, organizations need to focus on both organizational and the DMs' perspectives. Many organizations fail to identify their own level of capabilities, which leads to failures (Tingling, et al., 2010). Organizations need systematic and comprehensive approaches, and methodologies to identify process and practice changes required to develop their internal analytical capabilities (Dunn, et al., 2013; Hall & Jia, 2015).

iii. When to employ these practices in the DDDM process – organizations have concrete ideas that analytical capabilities are a must for DDDM. However, they also have a phobia of failure, thereby preventing them from investing in BI tools. Marsh and Farrell (2014) identified the root cause for this phobia as the organization's concern on "when to employ analytical practices in a DDDM process". When to enforce new practices to improve or adapt DDDM, is a key factor for failure of implementing DDDM processes and techniques in firms. However, this is a strategic failure of adapting DDDM. Hence, it is recommended to have a strategic framework for adapting DDDM and enforcing the change to DMs in the organization (Dunn et al., 2013).

iv. Evaluating how these mechanisms may build or improve the DMs knowledge and skills – evaluating an implemented system based on feedback, performance, availability, and reliability is a key to success of any implementation. Evaluation mechanisms support DMs and organizations to improve and establish a stable system to cater to the organization's needs (Davenport et al., 2010; Dunn et al., 2013; Marsh, et al., 2014).

2.1.4. Improving technology and data quality for DDDM practice

Analytics must gain trust from DMs - this is essential to provide accurate analytics for DMs. While providing 100% accurate analytics is a challenge in a dynamic business environment, efforts should be taken to improve the accuracy of analytics data (Ransbotham et al., 2015). Davenport et al. (2001) identified the following key focus areas to consider in improving the technical environment and data quality:

i. Create an IT strategy that supports decisions as well as transactions – When practicing a DDDM approach for decision making a question arising among senior managers is whether to standardize the use of analytical tools and applications or not.

ii. Maintain a stable technical environment to the extent as possible – The rapid pace of technological change is a major obstacle to learn and embrace technology; hence, it is important to resist the temptation to continually upgrade the technical environments to provide a stable atmosphere for DMs.

iii. Match technical sophistication to business need – Most DMs are concerned about whether they have the adequate amount of data for decision making (Ransbotham et al., 2015). Resist the temptation to give every user infinite access and unlimited options for every business problem, even though DMs require a high degree of analytical skills and investigative environments to proceed.

iv. Integrate decision making with business processes – Linking data, analytic tools, and a transactional-based process into a single application can help ensure that decisions are executed consistently, and the desired outcome is achieved. However, it is essential to involve the DMs in early stages of implementing DDDM to ensure its success.

v. Let the strategic value of decisions drive the ‘make or buy’ choice – deciding whether an analytical application lends your organization a competitive advantage can greatly simplify the ‘make or buy’ choice. Organizations can decide on purchasing a standard software or building a custom software to facilitate their DDDM practice.

2.2. Data Analytics

The definition of the term analytics is diverse and depends on perspectives and business needs. The most commonly used definition is “the extensive use of data, statistical and quantitative analysis, exploratory and predictive models, and fact-based management to drive decisions and actions” (Davenport et al., 2010). It is not a technology in and of itself, but rather, a group of tools that are used in combination with one another to gain information, analyze that information, and predict the outcomes of the suggested solutions (Bose, 2009). Analytics can be categorized as Data Analytics and Visual Analytics.

Data is the underlying resource for DDDM tools in an organization; hence, the data should consist of the following characteristics to perform DDDM (Lycett, 2013):

i. Volume – There are key benefits of being able to process large volumes of data. Many underlying analytical solutions and tools recommend that more data beats better models. Key considerations here are scalability, distribution, and the ability to process data.

ii. Velocity – Data flow rate is important, not least in relation to the feedback loop to action. Key considerations here include the granularity of data streams, understanding what can be discarded, the latency acceptable in relation to data, decision making, and action taking.

iii. Variety – Data is messy in reality; data in an organization is extracted from different environments and sources in the organization and as well as outside the organization, that are often unstructured, error-ridden and inconsistent in nature. Key considerations here include the degree of information loss in cleanups, semantic integration, and versatility in representation. Data inconsistency can lead the DDDM to disastrous outcomes.

iv. Value – Having data after the above 3 V's does not give an organization any outcomes. To achieve and make DDDM, the data must be used by the DMs to cater to their needs.

There are three main approaches to data analytics as follows (Trindade, Ochoa, & Freitas, 2016):

i. Retrospective / Descriptive Data Analyses – Using historical data to find and understand patterns and results to make inferences about the future.

ii. Predictive analyses – Using simulation models to generate scenarios based on historical data to understand the future.

iii. Prescriptive data analysis – Using planned, quantitative analyses of real-time data that might trigger events.

Descriptive analytics outline what has happened, predictive analytics will outline what will happen, and prescriptive analytics will determine what should happen. An extensive range of data analytics algorithms can be applied to convert raw data into structured information and knowledge. The most common algorithms are classified into Artificial Intelligence (AI), Machine Learning (ML), Statistical Method (Stat), and Pattern Recognition (PR).

2.2.1. Emergence of Business Analytics (BA) for DDDM

With the advancement of data storage and processing techniques, organizations can now collect and leverage data to change intuition-based decision making into a more process and data-oriented decision-making. According to Cao et al. (2015), advancement in IT, organizations' need for BA to gain competitive advantage, and the confluence of big data are the key reasons contributing to the emergence of BA. This enables DMs to perform DDDM by visualizing what was previously invisible. While organizations tend to believe that with the emergence of BA, DMs and organizations will be equipped with more resources, new directions, and efficiency in the decision-making process, the emergence of BA seems to be having negativity among DMs (Bose, 2009) themselves. DMs are resisting the adoption of DDDM due to many reasons such as complexity, analytical phobia, lack of risk taking ability and lack of knowledge in analytics (Yates & de Oliveira, 2016). Hence, the emergence and embracing of analytics have caused human-related problems, which need to be critically addressed.

2.2.2. Visual Analytics

Visual Analytics (VA) is the science of analytical reasoning supported by interactive visual interfaces (Keim, Mansmann, & Thomas, 2010). Over the past decade, data was produced at incredible rates. However, the representation of the processed data in a humanly understandable manner has made the visualization more critical and thus, the need for visual analytics methods emerges (Kinkeldey, et al., 2017). Therefore, the goal of VA is to reduce information overload and simplify the information to DMs to perform real-time or offline decision making. VA methods enable DMs to combine the flexibility, creativity, and background of a particular domain knowledge with the enormous storage and processing capacity of today's computer systems to gain insight into complex problems (Keim, Mansmann, & Thomas, 2010). VA has the capability to transform a DM's daily work process and make it more effective and efficient. Information visualization technologies are often applied to help users obtain and maintain an overview in various situations, such as summarization and visualizing the information, and visualizing category based information, (Romanenko & Artamonov, 2014).

However, the most challenging task in VA is the ability to visualize the requirement of DMs and simplifying the data output for DMs for better understanding. Understanding and mapping the visualization outputs to the business context have become a nightmare for many DMs. Davenport et al. (2010) argue that DMs are not used to VA and therefore, they struggle to interpret the visual outputs and prefer data tables with numbers. This has been identified as a root cause for the failure of BI tools in many domains including banking (Keim et al., 2010; Kinkeldey et al., 2017).

The uncertainty of visualization has a greater impact on the DM's usage of visualization in the process of decision making. Uncertainty can be defined as an umbrella term for concepts like inaccuracy, imprecision, ambiguity, vagueness, subjectivity, or error (unknown or not quantified error) (Kinkeldey et al., 2017). However, visualization differs from domain to domain, where each domain will have different needs and aspects of visualization. For instance, a dashboard in banking domain differs to one in a retail store.

2.2.3. Analytical gap

Analytical gaps emerge when there is a gap between the ability of an organization's BI tools to produce analytical results, and the ability of its DMs to apply those results to solve business issues. According to Ransbotham et al., (2015), with more access to useful data, companies are using sophisticated analytical methods increasingly, which means that there is often a gap between an organization's capacity to produce analytical results and its ability to apply them effectively to business issues.

How can DMs with limited knowledge and analytical expertise become adept to analytics under such conditions? This question has become an important management issue as senior is now management increasingly recognizing the importance of creating a business value for analytics while dealing with the failure of DMs in understanding analytics. Based on a survey of 2,000 business executives, Ransbotham et al., (2015) identified the followings as leading issues faced by organizations in practicing and embracing DDDM:

- Translating analytical insights into business actions remains a difficulty for many organizations.

- Analytical skills are improving among managers, but the increasing sophistication of analyses is outpacing the increases in managers' analytical skills.
- The resulting gap creates the need for managers to become comfortable in applying analytical results they do not fully understand.

Analytical tool vendors claim to have given considerable attention to developing the tools, systems, and methods. However, Dykes (2017) highlighted that all of the rich data visualizations and intelligence built into today's self-service analytics tools can be negated by a simple deficiency in data literacy. Hence, organizations need to figure out methods on how, when and where to develop the data literacy of DMs, which can help to create a balance between the improvement in BI tools and the DMs' analytical skills.

Even though Ransbotham et al., (2015) have summarized the above findings, the most important underlying issues such as data literacy, measuring a DMs DDDM ability, human, technological, and process changes required are not being addressed.

2.3. Data-driven decision makers

A data-driven decision maker is different from a traditional decision maker. Data-driven decision making could be defined as "the ability of organizational managers to choose between a competing course of actions based on careful evaluation of the alternatives" (Amankwah-Amoah, 2015; Balleine, 2007). Whereas Levin and Datnow (2012) define a data literate leader or decision maker as one who is able to, (a) think about the purpose of data, (b) recognize sound and unsound data, (c) possess knowledge about statistical and measurement concepts, (d) make interpretation paramount, and (e) pay attention to reporting and to audiences.

As per the above analysis, a data-driven decision maker can be defined as one who "makes decisions based on data and evidence with the consideration of facts and figures to ensure and logically confirm the decisions accuracy". This definition could be changed based on the view of the person who defines it. The most ideal definition would be to consider the data-driven decision maker in terms of the characteristics and the specific domain. Next, we elaborate and discuss the characteristics of a decision maker, as well as the characteristics that a data-driven decision maker should have.

2.3.1. Decision makers characteristics

Decision maker's characteristics can be analyzed in different dimensions. According to Francioni et al. (2015), DMs characteristics are their personality (need of achievement and risk attitude), socio-demographic characteristics (education and age), and competencies (belonging to a network and experience). Stoian et al. (2010) define managerial characteristics as demographic, industry and management know-how, international experience, language skills, risk tolerance, and innovativeness. However, Amankwah-Amoah (2015) argues that a set of cognitive and psychological attributes of a decision maker, namely; powerlessness, meaninglessness, obsolescence and institutional linkages, and interactions to precipitate business failures, are a set of characteristic to focus on.

In a dynamic business environment, DMs are forced to make decisions based on data, hence DMs require skills on data knowledge, data interpretation and data observation, mapping data interpretations with business environment, and recognizing the limitations of data (Dykes, 2017; Ransbotham et al., 2015; Tingling & Brydon, 2010). Moreover, Yates and de Oliveira (2016) argue that a DM's characteristics in modern days are driven by culture. One dimension of culture that receives substantial attention is individualism or collectivism. However, measuring the cultural impact on DDDM still remains a question.

The moral judgment of a DM is a challenging factor in terms of performing DDDM in the organization's business environment (Haines, 2007). Hence, moral judgment behavior drives the DMs. A DM's intent is influenced by their moral judgment of behavior and their personal feeling of obligation to perform or not to perform the behavior, as well as their demographic characteristics.

Furthermore, Cosgrave (1996) described that a DM's characteristics differ based on the environment in which the decision is made. For example, decision making in an emergency requires a set of unique characteristics. Moreover, researchers argue that a DM's characteristic of classifying a problem is a key to a successful decision. Problem characterization includes actions such as, determining the quality of a decision, its acceptance, and its urgency. It is essential to have problem characterization in a DM to decide which decision to make first and how to make the decision in a way that would be acceptable to its stakeholders.

Acedo et al., (2011) hypothesizes that the characteristics of a DM can be categorized into four groups of variables from the perspective of a DMs behavior, as follows:

i. Behavioral dispositions – Also known as the personal characteristics of a DM; (a) cognitive style (intuitive thinking or rational thinking), (b) tolerance and ambiguity (situations of high uncertainty), and (c) proactiveness (entrepreneurial characteristics).

ii. Perceived behavioral control – Beliefs or perception of DMs on the risks and opportunities of DDDM; (a) perception of ease/difficulty and (b) perception of control over the result.

iii. Intention – Stimuli motivation for deciding as proactive and reactive.

iv. Behavior – Behavior and the culture of the firm on decision making.

Furthermore, Dykes (2017) argues that democratizing data throughout the organization supports all levels of employees in the organization to perform their job faster, better and smarter. However, data literacy is a characteristic every decision maker requires for DDDM. Data knowledge, data assimilation, data interpretation, and data skepticism and curiosity are characteristics that are essential for DDDM in DMs.

Figure 2.2 and Table 2.1 below are used to summarize and highlight the DM's characteristics observed by the above researchers and combining the key characteristics to define a data-driven decision maker. Figure 2.2 and Table 2.1 lists a DMs' characteristics influencing DDDM. While there are findings to prove that these characteristics influence DMs negatively or positively, there is a lack of study on how to change this negativity into positive manner to motivate DDDM.

Table 2: 1 Key factors to identify a DDDM.

Characteristic	**Description**
Personality Characteristics (need of achievement, Risk attitude, Cognitive style, Morals)	• Need for achievement as the aspiration of individuals to achieve better results from their actions and feel responsible for them (Entrialgo et al., 2000; Watson 2005). High need of achievement has the propensity of attracting DMs more towards DDDM. • Risk attitude is a characteristic that mostly leads to a resistance in DDDM; DMs' resist to perform DDDM due to the lack of confidence and trust on the accuracy of the data (Acedo et al., 2011). • Morals of a DM influence for a positive or a negative perception of DDDM, (Russell Haines, 2007). • Cognitive style is a mode of thinking and convincing the decision based on intuition or rational based or a combination of both by DMs (Acedo, et al., 2011).
Socio-demographic characteristics (Age, Level of formal education, Domain knowledge)	• The confidence level of domain knowledge is a characteristic which builds upon the experience, trial and error in decision making and continuous learning (Yates & de Oliveira, 2016). • Domain knowledge is a factor that influences DDDM in positive and negative aspects of the business environment. (Acedo et al., 2011) .
Competencies (Years of experience, perception on DDDM)	• DMs experience is negatively related to rationality and positively related to political behavior and intuition-based decision making (Acedo, et al., 2011; Francioni et al., 2015). • DMs' perception on DDDM is clumsy, many researchers have been conducted to identify why DMs prefer intuition-based decision making over DDDM. • Perception of DMs on DDDM is influenced by DMs' personal, socio-demographic, competencies, culture and data literacy characteristics (Acedo, et al., 2011; Stoian et al., 2010). • Even though many DMs' perceptions of DDDM is not positive, complexity in the business environment has forced many DMs to use data, statistics and analytical methods that they do not understand fully (Ransbotham et al., 2015).
Culture (Individualism or collectivism cultural influence of a decision maker)	• Cultural impact on DDDM is broadly discussed by researchers; however, culture on analytics is discussed in few perspectives. According to Yates & de Oliveira (2016), the dimension of culture in DDDM receives substantial attention on individualism or collectivism. • Individualism cultures; uniqueness and self-expression are generally valued in such cultures, whereas DMs tend to value personal goals. • According to Russell Haines (2007) and Yates & de Oliveira (2016), individualism or collectivism are somewhat correlated. With collectivism cultures being tighter than individualistic cultures, in decision making, collectivists often weigh input from others more than individualistic.
Data literacy	• As per Dykes (2017), Mandinach (2012), Ransbotham et al. (2015) DMs in the modern era are forced to make decisions based on data, statistical and analytical methods. However, many DMs are unable to take analytical decisions due to lack of data literacy.

Characteristic	Description

	• Among many organizations, the most challenging question on adopting DDDM is "to what extent do DMs understand data and analytics to perform DDDM?"
	• According to Dykes' (2017) analysis, data literacy can encompass a wide spectrum of skills, however at a minimum level, DMs will need the skills in the below area,
	  o Data knowledge – The more the DMs understand the organization's data in a business perspective, the better the position they are in to apply those data for DDDM. Actions based on data, knowledge making and analytical insights more digestible to DMs can help yield better business decisions (Dykes, 2017; Ransbotham et al., 2015). Nevertheless, Mandinach (2012) argues that the knowledge of data has a high positive correlation with the years of experience in the particular business or organization, also defined as the domain related knowledge.
	  o Data assimilation – Known as the first step of DDDM, when data is interpreted using analytical tools for DMs, DMs should get familiarized with unfamiliar data before consuming it (Dykes, 2017). However, Deussen, Ertl, & Keim, (2010); Kinkeldey et al., (2017) identify the ability to understand the visualizations of data provided by data analytics tools, as the major challenge that DMs encounters when performing DDDM. Dykes (2017) describes several obvious factors that a DMs should focus in data assimilation such as; titles & labels, time frame, data source, unit(s) of measurements, scales, calculates metric(s), dimensions, filters, sorting and targets. (These factors are described based on a table data and charts of data interpretation).
	  o Data interpretation – Tan et al. (2015) and Zeni et al. (2016) define data interpretation as a part of data analytics in terms of a technical perspective. However, considering the business aspect, data interpretation is all about making sense of data for DMs to perform DDDM. Nevertheless, Staman et al., (2014) argue that data interpretation plays a key role in DDDM whereas many organization has faced worst case scenarios due to incorrect data interpretation from DMs.
	• According to Dykes, (2017) analysis, DMs should be able to interpret data when analytical tools provide visualization and analysis. DMs require the ability to make observations such as; trends, patterns, gaps, clusters, skewness, outliers, focus, noise, logical interpretation in order to perform DDDM. Major challenge organizations face today is the literacy required by a decision maker and how to train DMs to make these observations. This is among the least researched area when considering DDDM in the banking domain.
	• Data skepticism and curiosity – Analyzing and interpreting data does not make a decision into action. Too much trust on analytics can lead DMs to incorrect and unusable decision since DMs must think critically about what they interpret and what the insights give the decision maker (Davenport et al., 2010; Dykes, 2017; Keim et al., 2010). However, Dykes (2017) identifies several factors to consider in data skepticism and curiosity such as collection method, credibility, bias, the truthfulness of the data, assumptions made when presenting data,

Characteristic	Description
	context, comparisons, causations, significance, outliers in data and quality of data.
Problem characteristics (Quality, acceptance, urgency)	• DMs should have the capability to identify the problems and prioritize the problems to solve. According to Cosgrave (1996), determining the quality and urgency of the problem will lead DMs to prioritize the problems and acceptance will support DMs to identify the mode to solve the problem, either intuition based or data based.
Firm	• Firm culture and behavior, availability of data in the organization, cultural impact and developing a data-based culture.
Environment the organization is operating	• Improving technology and data quality for DDDM practice.

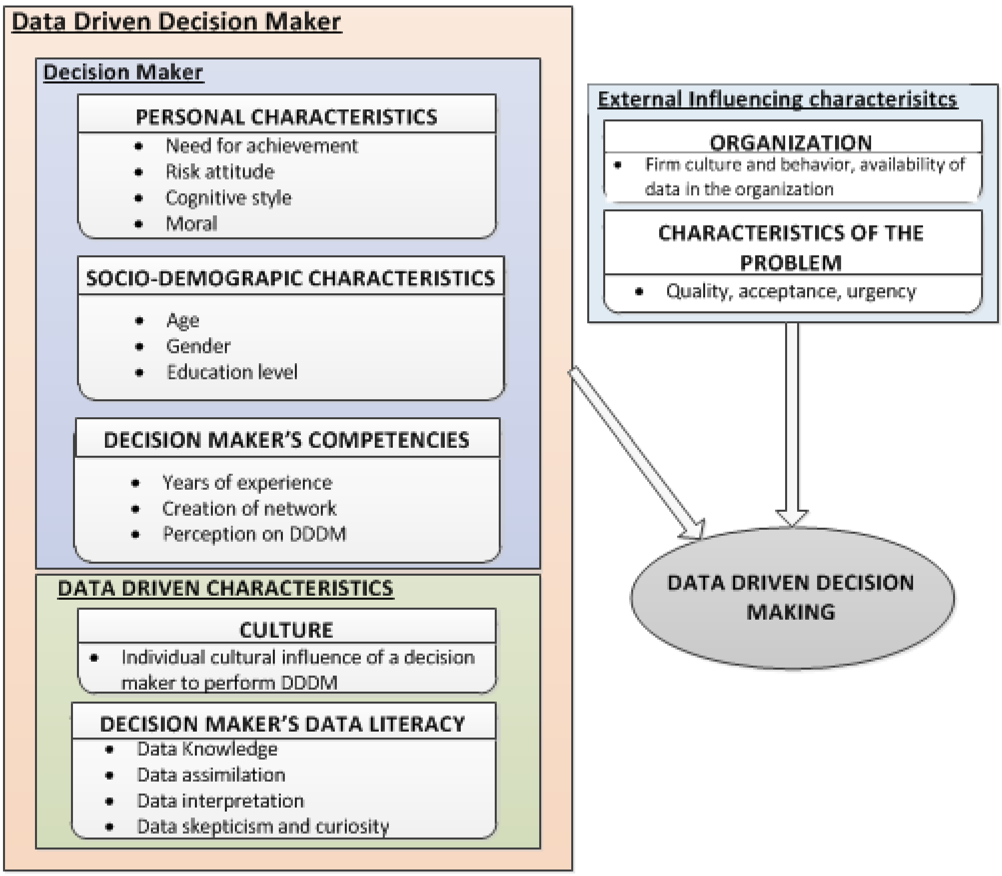

Figure 2:2 Characteristics influencing a DM to perform DDDM.

2.3.2. Factors that reduce discomfort in data interpretation

DMs need to improve their data interpretation ability and reduce their discomfort in practicing DDDM. DMs are required to have training and development on data interpretation to perform DDDM. Dykes (2017), Ransbotham et al. (2015), and Tingling & Brydon (2010) argue that a DM's lack of fundamental knowledge in data is a key factor that increases their discomfort to interpret data for decision making,

According to Ransbotham et al., (2015) "when an organization's capacity to produce increasingly sophisticated analytics outpaces its managers' abilities to understand, discomfort is created - managers find that they must make decisions based on complex analytical insights that they do not fully understand". Authors defined the following key factors to improve the ability of data interpretation in managers:

i. Bolstering knowledge base – Even though DMs are not able to become experts in analytics, they are demanding for the fundamental knowledge to understand analytical results. Understanding analytics is an incremental process of analyzing, interpreting and critical evaluation (Hall & Jia, 2015; Hora, Bouwma-gearhart, & Park, 2017; Ransbotham et al., 2015; Tingling & Brydon, 2010). However, to meet the increasing need for a knowledge base (Ransbotham et al. 2015) proposed that DMs can familiarize themselves with concepts such as descriptive, predictive and prescriptive analytics, and learn through observation on what other organizations are doing with analytics. The bolstering knowledge base among DMs is a fundamental requirement when an organization is adopting DDDM over intuition-based decision making. However, many organizations are faced with the question of, to what extent, how and when does the DMs' knowledge base need to be improved".

ii. Building off prior experience – Prior experience increases the DMs' confidence level in analytics. Experience builds trust in the producers of analytical results, repeated communication with analytical producers improves the DMs' abilities to frame the right questions, and experience builds familiarity with an organization's data (Ransbotham et al., 2015).

iii. Capitalizing on domain knowledge – The lack of analytical capabilities and understanding is a disadvantage for DMs. However, the DMs' broader understanding in business functionalities and business environment is a key advantage, even though the analytics is not completely understood, the resulting insight or information should resonate with the DMs when analytics successfully releases the important underlying business mechanism (Ransbotham et al., 2015). Organizations can improvise on the broader domain knowledge in DMs to understand analytics better and faster in the business environment. This approach is suitable for a closed-culture organization to adopt DDDM.

iv. Recognizing the limitations of models – Analytics is not a bailout ticket for DMs, but a facilitator for decision making in complex and dynamic business environments (Vanlommel, et al., 2017). DMs overestimate the ability of data where they expect the analytics make the decision on behalf of humans. Whereas, DMs are required to use their knowledge in business to identify the discrepancies and limitations of analytical models in a dynamic business environment.

2.3.3. Framework to build analytical capabilities

Several frameworks are proposed to build capabilities in DMs based on different aspects and factors that can influence the capability of skill-building (Acedo & Galan, 2011; Davenport et al., 2010; Dunn et al., 2013; Hall & Jia, 2015; Mandinach et al., 2014). As such, Davenport et al., (2001), (2010) proposes a model for building analytical capability model has used as a core for other frameworks.

Davenport et al. (2001), (2010) proposed a model to improve one's analytical capabilities. This model consists of three major elements, namely context, transformation, and outcomes. This framework can be used to determine different capability levels in an organization, such as the primary level. The model can be applied to describe or understand how to transform data into decisions and perform decision making. It can be used to develop an ongoing capability in an area of a business with carefully selected data and business objectives. The model can understand an organization's broader capability for turning data into knowledge and results. An organization should focus on the four underlying components in building the analytical capability of the organization, as shown in Figure 2.3. The key focus of this research is on individual DMs perspective. Apart from that, as argued by Dunn et al., (2013) and Marsh and Farrell (2014), it is essential to focus on culture, technology, and data when developing the analytical capability of DMs.

Figure 2:3 A model to building analytical capabilities.

Source: Davenport et al. (2001, 2010)

2.3.4. Critical factors in developing skills for analytical capability

Davenport et al., (2010) defined that the skills and experience needed to analyze transaction data are vastly different from the skills and experience needed to record transaction data. Thinking about decisions in analytic terms is very different from thinking about them based on prior experiences.

Dunn et al., (2013) defined the following three determinants in building analytical capability which interlock each other:

i. Knowledge – Many DMs lack the requisite training to understand and connect data to a business environment for DDDM. However, this is influenced by factors such as fundamental technology skills, statistical modeling and analytical skills, knowledge about data, knowledge on business, and lack of communication skills. It is recommended to develop an individual strategy to identify and measure the knowledge factors listed above. For example, a structured and semi-structured survey and a practical evaluation can be used to determine a DM’s skills (Dunn et al., 2013; Mandinach et al., 2014; Ransbotham et al., 2015).

ii. Concerns – Concerns are a set of feelings, perceptions, preoccupations, considerations, satisfaction and frustrations related to adopting and building capabilities of DDDM practices. Concerns influence the DMs to resist or embrace DDDM practices (Acedo & Galan, 2011). According to Mandinach et al., (2014), concerns among DMs arise when organizations perform a knowledge test to measure their level of data literacy. Therefore, researchers recommend identifying the level of knowledge through surveys, practical examinations, and interviews.

iii. Efficacy – DDDM efficacy reflects the DMs’ beliefs in their ability to successfully engage in DDDM. Like concerns, researchers indicate that efficacy is a powerful predictor of future DMs’ actions and a trainable DM characteristic. The set of skills that a DM should develop to build individual analytical capability are (1) technology skills, (2) statistical modeling and analytical skills, (3) knowledge of data, and (4) knowledge of the business. Moreover, Keim et al. (2010) recommend improving visualization and interpretation as an analytical capability.

Even though Davenport et al. (2010) suggested the above factors, they did not discuss how to improve or to what extent a DM requires these skills to perform DDDM. This research will focus on building a model on how a DM can improve these skills.

2.3.5. Measuring the DDDM ability of decision makers

There seems to be little work on measuring the DDDM ability of DMs. Amankwah-Amoah, (2015); Dykes, (2017); Yates, et al., (2016) have taken the approach of measuring DMs’ abilities based on the characteristics of a DDDM. Subsequently, Amankwah-Amoah (2015) recommended the development of a set of hypotheses based on the DMs' characteristics and an analysis of these using a quantitative approach. Alternatively, Davenport et al. (2001, 2010) and Amankwah-Amoah (2015) also questioned the practicality of measuring the ability to interpret data through a statistical method.

In this research, the aim is to identify the ability of interpretation and other underlying factors in DDDM, as mentioned in the sections above. The author recommends using a practical method to evaluate data interpretation using structured interviews. This research does not use a quantitative survey due to the practical implementation issues in conducting a survey.

2.4. Cultural impact and developing DDD based culture

62% of managers believe that the cultural factor is a significant barrier to getting the return on their investment on DDDM (Davenport et al. 2001; 2010). Nevertheless, many organizations have achieved success by creating a cultural value system that supports the DDDM practice. According to Yates & De Oliveira (2016), culture and decision making address variations in how and why people from different cultures sometimes tend to make decisions differently. Moreover, those authors identified the following fundamental issues that could influence the DDDM practice in organizations:

i. Need – DMs tend to question the need of DDDM when current decision making is successful and meeting the expectations of the organization (Amankwah-Amoah, 2015; Yates & de Oliveira, 2016). However, it is the responsibility of the management to create the need for DDDM by providing tools, data literacy, and knowledge to all DMs (Davenport et al., 2010).

ii. Mode – Who will make this decision? How will they decide? It is found that DMs are more comfortable when practicing DDDM in a collectivist culture, where the responsibility is distributed to the team. However, many DMs tend to make intuition-based decisions in an individualistic culture.

iii. Investment – What resources will be invested in decision making? DDDM practices require an investment of financial and human resources as the need for expert knowledge rises. However, defining the borderline of how much and how long this expert knowledge will be required remains unclear (Amankwah-Amoah, 2015; Davenport et al., 2010; Yates & de Oliveira, 2016). The challenge for organizations is “How much expertise will be required for DMs to build their analytical capability, and for how long?”

iv. Judgment – Which of the things that could happen would happen? Decisions are shaped by predictions, opinions, and projections. Therefore, it is important to evaluate their accuracy and determine how much weight to give them (Yates, et al., 2016). Many DMs perform descriptive and predictive analytics with intuition, which is considered as a key component of judgment. It is believed that educating DMs with the use of DDDM practices to reduce human effort will breach the cultural barriers (Tingling, et al., 2010; Trindade et al., 2016).

v. Value – How much would beneficiaries care, positively or negatively, if an outcome was realized? Analytics and the DDDM practice would not replace the human ability of decision making. However, DDDM will allow DMs to recognize, process and identify data to gain valuable insights that are beyond the human processing capacity. Therefore, organizations should clearly communicate the vision of DDDM to DMs to calm their fear of DDDM (Mandinach et al., 2014; Yates & de Oliveira, 2016).

vi. Tradeoffs – Every potential action has strengths and weaknesses and need to be evaluated. Using tradeoff tools to identify the issues and resolving them (Yates & de Oliveira, 2016) is recommended in such cases.

vii. Acceptability – How can we get stakeholders to agree to a decision and the procedure that created it? When implementing and enforcing DDDM, there are DMs who might object to the practice. Identifying these individuals and convincing them using techniques such as Kotler’s Change Management process (Yates & de Oliveira, 2016) becomes key. Education and strategic approaches in imposing a DDDM practice can reduce the objection from DMs (Davenport et al., 2010; Mandinach, 2012; Yates & de Oliveira, 2016).

viii. Implementation – The decision has been made. How can we ensure that it will be carried out? Creating awareness on decisions made using DDDM is essential, and evaluating the decision made through DDDM in comparison with intuition and experience of DMs to ensure the decision made is accurate (Davenport et al., 2010; Ransbotham et al., 2015; Yates & de Oliveira, 2016) can also be beneficial.

Apart from the above factors, Davenport et al., (2001); (2010) have identified several key factors to develop a DDDM culture such as (1) cultivate executive sponsorship, (2) start with understanding the existing norms and practices, (3) start small, and (4) recognize that data based culture change is a long-term initiative.

2.5. DDDM in Banking domain

Increasing customer bases, the number of transactions locally and internationally, technological improvements and dynamic business environments have all forced banks to adopt analytics and DDDM practices to cater to their needs. Banking is a vitally important sector of the global economy, and decisions taken by banking and finance executives have a gravity and importance which can dwarf other organizational processes They have an impact not only on employees and organizations, but also shareholders, depositors, and the wider economy (Hensman & Sadler-Smith, 2011). Modern banking aspects, online banking, mobile banking, and credit cards have given banks vast amounts of data as an asset. The rapid growth of data analytics has given the DMs a helping hand to overcome data processing and converting data into information and insights (Sun, et al., 2014). A high degree of importance in decision making has influenced many small and medium level banks. Financial institutions sometimes tend to use intuition-based decision making as a means of risk and failure avoidance (Hensman & Sadler-Smith, 2011; Moro et al., 2014).

Sun, et al., (2014) argue that with the availability of vast volumes of structured and unstructured data from both internal and external sources, there is an increased pressure and focus on obtaining an enterprise view for banking and financial institutes. However, as per Davenport et al., (2001), the major drawback is that turning data into knowledge just does not happen often enough in banks, and even if a bank does manage to transform data into knowledge and then into results, its rarely a sustained or widespread process.

Although DMs in banks intend to use intuition-based decision making, they seek the support of analytics to ensure that their intuition-based decision is supported by the past actions of the organization. However, researchers argue that the banks need to move beyond this point and collaborate DDDM with intuition-based decision making to enforce a DDDM culture within the organization (Davenport et al., 2001; Hensman & Sadler-Smith, 2011; Sun et al., 2014). While many large-scale banks have the capacity to invest on expensive analytical tools and technology, to gain the advantage of this investment, organizations have to ensure that correct analytics are applied in the organization (Davenport et al., 2001; Sun et al., 2014).

2.6. Summary

Decision making is considered as an art as well as a science. However, modern decision making has become more complex and competitive with dynamic business environments such as in those in the banking domain. After a comprehensive literature analysis, below are a few key findings:

Intuition-based decision making is known as the most preferred decision-making method among DMs. However, influencing DMs to perform DDDM depends on their characteristics (personality, socio-demographic, competencies, data literacy, and culture), the perspective of their behavior (behavioral dispositions, perceived behavior control, intention), and their analytical capabilities. There are many struggles faced by DMs when performing DDDM, such as the inability to perform data interpretation, understanding the data, and mapping the outcomes to the business.

Organizations are investing in BI tools and technology to support the DMs to perform DDDM. However, the DMs' use of BI tools to perform DM is limited, so the ROI of those investments are being questioned by the management.

Even though the use of BI tools and adoption of BI tools for decision making is being extensively studied, the DMs perspective in DDDM is not a focused area of the researchers. Hence, the main intention of this research is to focus on the banking industry to identify the struggles faced by DMs when performing DDDM and how they can overcome those struggles. Also, another major area of focus is to identify the factors to measure the DDDM ability of DMs and capabilities of understanding the analytics produced by tools and technology to perform DDDM.

3. RESEARCH PROBLEM FORMULATION

Decision Makers (DMs) perform decision making in a unique style. However, intuition-based decision making has dominated throughout the banking domain. Section 3.1 elaborates the problem statement of this research. Section 3.2 lists the objectives of this research, and Section 3.3 briefly discusses the significance of this research and its planned contribution.

3.1. Problem Statement

Many organizations want DMs to switch from intuition-based decision making to Data-Driven Decision Making (DDDM). However, this is a complex process where many underlying issues need to be addressed, from both the organizational and the DMs' perspectives. While the DM's perspective plays a major role in this transformation, factors such as discomfort in practicing DDDM, impact of organizational culture on DDDM, complexity of BI tools and their outputs, uncertainty due to performing intuition-based decision making over DDDM, the DMs ability to interpret data, and data literacy have gained the least attention by researchers. While facts such as the challenges faced by DMs due to their inability to interpret data, their struggles due to the lack of data knowledge, data assimilation, data interpretation, data skepticism, and curiosity, are less explored. Moreover, initiatives required by organizations to reduce the discomfort of DMs remain unclear. These facts could cause difficulties and an analytical gap between DMs in using an organization's BI tools. Moreover, it is important to understand how DMs can overcome these problems to perform DDDM in complex business environments. Therefore, the problem to be addressed by this research can be stated as follows:

What are the challenges faced by data-driven decision makers and how to overcome them?

This research specifically focusses on the banking industry and how DMs use DDDM in this industry. This domain was chosen because the banking industry has access to lots of data, the need to analyze data for decision making has been widely recognized, many international banks are known to be adopting DDDM, and banks tend to invest heavily in BI tools to support their DMs.

3.2. Research Objectives

The objective of this research is to explore and analyze the ability of DMs to make decisions based on data, rather than purely on experience and intuition. The following are the specific objectives of this study:

- Identify factors that can be used to measure the DDDM ability of DMs
- Understand the challenges faced by DMs when adopting and performing DDDM
- Identify human, technological and process changes required by managers to improve their DDDM ability
- Develop a framework that can be used to improve DMs' ability to adapt, improve and practice DDDM

There are several factors that restrict DMs in performing DDDM, such as the lack of data availability, lack of BI tools, and the incompetency of DMs themselves. However, during this research, the author assumes that the required data and BI tools are available for the DMs to perform DDDM.

3.3. Research Significance

This research aims to create awareness and provide insights on how, when, and what actions are to be taken to improve a DM's data literacy. It plans to provide insights for organizations as to why DMs make decisions based on prior experience and intuition rather than data-based decision making, and how both managers and organizations can impose DDDM to DMs, as well as the process and technological changes, or improvements that need to be met before imposing DDDM.

Human resource improvement is a key to perform DDDM, and this research will provide guidelines to managers and businesses as to which areas DMs need to be trained on and how to go about providing these improvements. This research plans to identify specific characteristics of DMs that need to be strengthened to perform DDDM. Many DMs have an uncertainty and lack of trust on BI tools and therefore, tend to do manual calculations on the outputs provided by the BI tools to verify the accuracy of the information. This could occur due to lack of data literacy, trust on the team that generates BI reports, and the inability to interpret data. Therefore, this research will further provide insights to managers on how to create awareness, build trust, as well as provide training and development to DMs on data literacy and data interpretation.

The ability of DDDM in decision making to translate outputs from BI tools to business values is something that DMs need to be trained in. Performing DDDM requires technological and process changes such as modifying current processes to collect, organize, and analyze data. Therefore, this research plans to provide managers with a framework on how to build their capability and discuss the key dimensions that need to be addressed to build it.

3.4. Summary

DMs struggle when performing DDDM in the banking domain and their major struggle is with the ability to map data to the business environment. The author identified four objectives to achieve from this study, which are: identify factors that can be used to measure the DDDM ability of DMs; understand the challenges faced by DMs when adopting and performing DDDM; identify human, technological, and process changes required by managers to improve DDDM ability; and, develop a framework to improve DMs' ability to adapt, improve, and practice DDDM. This study focuses on the struggles faced by DMs and how to overcome those struggles, as well as providing insights and recommendations to the banks' management as to how to build upon the analytical and DDDM skills among the DMs in the banks.

4. RESEARCH METHODOLOGY

This chapter describes the steps, process, and procedures practiced during the data gathering, interviews, and analysis of the research. Related work is used to gather the factors and identify the research gap, which was essential in formulating the research methodology. This chapter is broken down as follows. Section 4.1 provides the research method and approach. Section 4.2 illustrates the prefigured factors of the research, while Section 4.3 explains the theoretical sampling of the study. Section 4.4 describes the method and the approach that was used for data collection. Interview questions are presented in Section 4.5. Section 4.6 and 4.7 elaborate the use of grounded theory in this research and how theory is generated based on the grounded theory, respectively.

4.1. Research Method and Approach

The literature review and a few pilot interviews conducted by the author provided the platform for the problem definition of this research. It was found that Decision Makers (DMs) struggle to perform Data-Driven Decision Making (DDDM) due to the lack of data literacy and DDDM capabilities. However, it is also important to identify the DM's current state of data literacy and DDDM capability.

Figure 4.1 illustrates the research methodology. An extensive literature review and a set of pilot interviews were conducted to identify the problem statement of this research. Based on the pilot interviews and literature, the author identified the key struggles and characteristics that DMs face and the support they require for DDDM. Then, a set of interview questions were derived based on the key characteristics that a DM requires to perform DDDM. Further, through theoretical sampling, a set of banks was chosen to conduct interviews with the aim of collecting data for the study. The data collected from these interviews were then analyzed using the grounded theory approach to prepare a list of observations, findings, and recommendations.

4.2. Prefigured factors

A set of issues were found through the initial literature review and the pilot interviews and those are the struggles which have been considered as the factors that impact DMs in practicing DDDM. These problems are categorized as socio-demographic characteristics, personal characteristic, the DMs' data literacy levels and competencies, and the external characteristics influencing the DMs. Table 4.1 shows the independent, moderating and dependent variables according to the initial literature and pilot interviews findings.

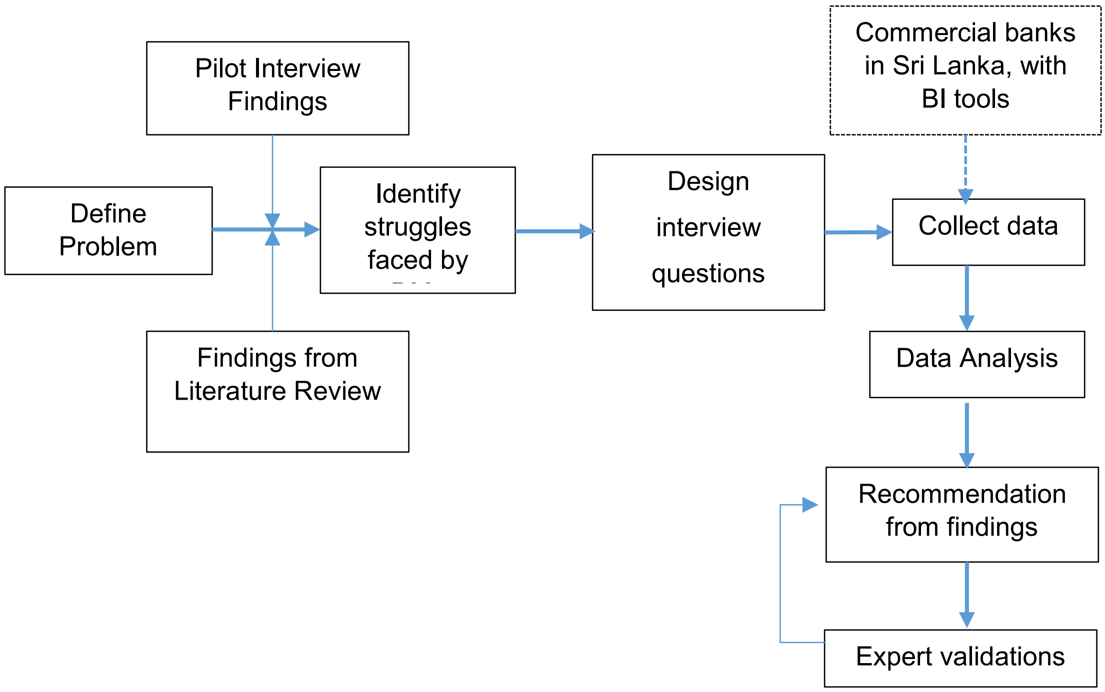

Figure 4:1 Research methodology.

Expert Validation

In this study author conducts an expert validation on the study's Findings and recommendations, In this case, experts are considered as the managers who are performing DDDM on a daily basis and they are considered as the managers who overlooking the DDDM process and practicing in the organization. The researcher has conducted a face to face interview with two experts after driving the findings and recommendations from grounded theory approach discussed below. These interviews are conducted based on the questions in Appendix B.

Table 4:1 Dependent, moderating and independent factors

Independent	Moderating	Dependent
Socio demographic characteristics	Organization's culture	Decision maker's DDDM ability
Personal characteristics		
Decision makers' data literacy		
Decision makers' competencies		
External characteristics influencing DMs		

Dependent Variable

The dependent variable in this research focuses on the variable which responds to the changes in independent variables - in this case, the DDDM ability of DMs is the dependent variable will not change throughout the research study.

Independent Variables

The independent variables considered for the research focuses on key factors uncovered through reviewing the literature and during pilot interviews. The independent variables defined in Table 4.2 have a direct impact on the dependent variable.

Table 4: 2 Derivation of Independent factors through open and axial coding

Selected	Axial	Open
Typical decision makers' characteristics	Personal characteristics of DMs	• Need of achievement
		• Risk-taking attitude
		• Cognitive style
		• DMs morals
	Socio-demographic characteristics of DMs	• Age
		• Gender
		• Education level
		• Location of service
	Competencies of DM	• Years of experience
		• Creation of network
		• Perception of DDDM
		• Decision-making approach

Unique characteristics of DDDM	Data literacy of DMs	• Data knowledge
		• Data assimilation
		• Data interpretation
		• Data skepticism and curiosity
Influencing factors of DMs towards DDDM	External factors influencing DDDM	• The individual culture of DM
		• Organizational culture
		• Quality, acceptance, and urgency of need

4.3. Theoretical and population sampling

Theoretical sampling is a process of data collection to generate a theory where the researcher collects, codes, and analyzes the data and decides what data to collect next and where to find them. Apart from the factors identified from the literature review, a set of pilot interviews were also conducted with four managers from two different banks to identify the key factors in the Sri Lankan context, to base the final interview questions on. After the initial interviews were conducted, the collected data were coded and analyzed to guide the interview process further to gather more data needed for the research.

The authors identified a set of banks which use BI tools for decision making. Figure 4.2 represents the breakdown of population and sampling. As per the Central Bank of Sri Lanka (CBSL, 2017), there are 25 licensed commercial banks in Sri Lanka, where 18 banks are known to use BI tools. With the aim of selecting from a set of different types of banks in Sri Lanka, the author selected three local private banks, two state banks, and an international bank. To collect the opinion from different levels of decision making, the author selected a branch level manager, a regional level manager, and a CTO/CIO (the head of IT).

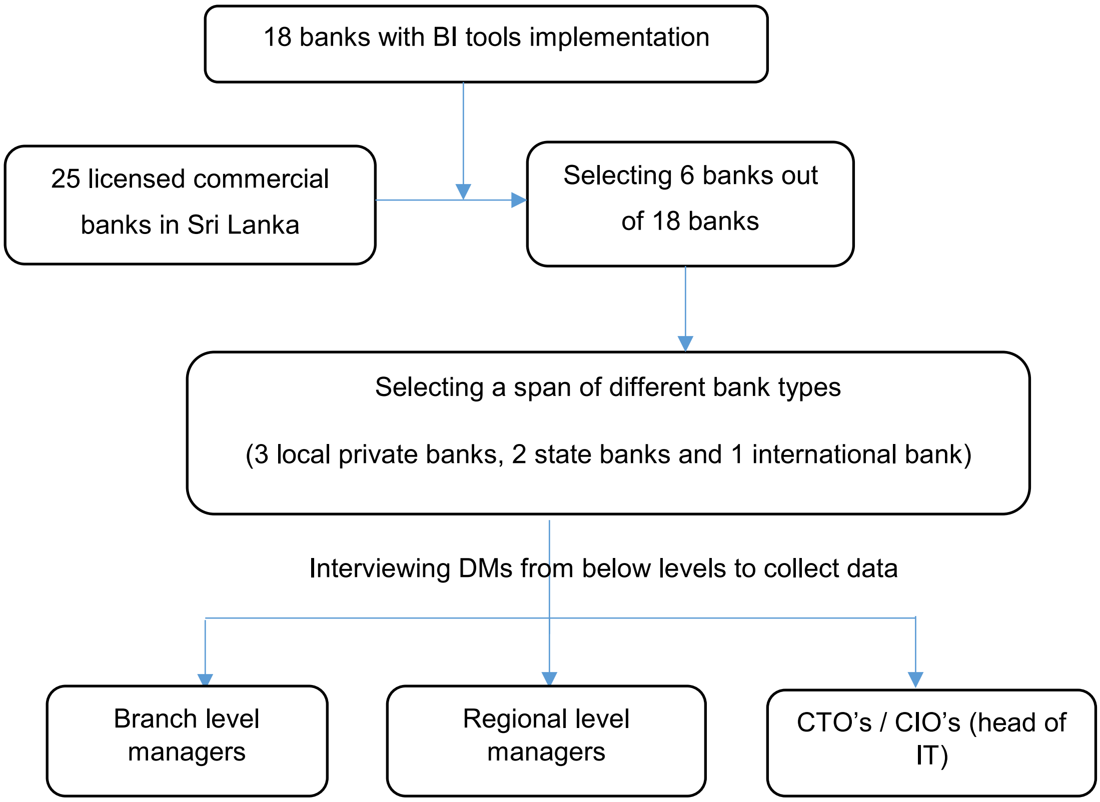

Figure 4:2 model of population sampling for the study representing Sri Lankan banks.

4.4. Data collection

The data collection strategy for this research was to interview key DMs from several levels of the banks' decision-making hierarchy such as branch and regional level managers, and CTO's/CIO's (the head of IT) to get opinions from different levels of DMs. Three different types of banks were selected for the study, namely private local banks, state banks, and an international bank, to ensure that the study covers all the types of banks with BI implementations.

A quantitative approach was not suitable for this study because measuring the struggles and DDDM related issues faced by DMs would be difficult to quantify. Hence, this study focuses on a qualitative approach where each interviewee's ideas and opinions are taken as a case and analyzed for findings, observations, and recommendations.

Data gathering is the most critical part of this study, and it was carried out through a set of interviews. The target population is identified through the theoretical sampling based on the BI implementations in Sri Lankan banks. Interview questions (see

Appendix A) were formed based on literature reviews and pilot interviews. There was no significant related work on the area of study, neither was there any literature to identify a framework or a model to capture the DDDM related issues faced by the DMs. Hence, the aim of this study is to develop, create, or identify a theory. In this case, Glaser & Strauss (1967) is well known for developing a theory grounded in data. Therefore, the author used the Straussian theory (Glaser & Strauss, 1967) to guide the research, which emphasizes the importance of coding data and identifying the critical findings through memo writing immediately after an interview.

In this research, the author personally conducted face-to-face interviews. During the interviews, some features of BI tools were observed, and the author also requested the DMs to show samples of reports and dashboards, with the aim of observing the interpretation ability of the DMs. Observations were recorded in the form of notes or memos, which were used to analyze the data. Further interviews were carried out using personal interaction skills and by framing questions in a proper manner, which were found to be equally important. Based on the response to the first few interviews, some interview questions were modified, and a few new questions were added to ensure that the interviews focused on the right areas.

4.5. Interview questions

This study relies on interviews as the primary method of data collection, as the research aims to get the opinions of the DMs and identify the struggles they face during day-to-day decision making, with the assistance of BI tools. The list of interview questions (see Appendix A) consists of open-ended questions which were designed to get detailed information from each interviewee. Open-ended questions also helped to capture more information from the interviewee and gave them the freedom to express their honest ideas on the questions asked. With this approach, interviewees were able to communicate their perspectives freely, which in turn provided the author with more accurate outputs and findings for the research.

4.6. Data analysis using grounded theory

Glaser & Strauss's (1967) grounded theory was used to analyze the unstructured data to bring meaning to it and ultimately develop a theory. This section describes how the data was analyzed based on the approach of the grounded theory within its stages such as open coding, axial coding, and selected coding.

Coding

According to Strauss & Corbin (2008), the researcher should begin with open coding after immediately conducting an interview. *Open coding* is the process of analyzing textual contents, breaking the data into parts, identifying the key terms and comparing the key terms to identify the categories. Open coding uses words, statements, and phrases from the collected data to develop concepts. These indicators are constantly compared with data being collected to identify new insights until theoretical saturation is reached, (Feeler, 2012).

Category and memo writing

Performing open coding for all the interview responses may result in many pages of codes as well as duplicates in coding. Therefore, the researcher must identify these discrepancies, find the similarities, omit the duplicate codes, group them into categories or subcategories, and then link them to categories. In this study, several categories were identified from the literature review and pilot interviews; and open coded data was assigned into subcategories and categories from the data collected from the interview questions.

Memo writing is a pivotal aspect of open coding because open coding with a few words is often not enough to describe the concept. The notes that are written based on the open coding and the analysis of gathered data is called a *memo*. Writing memos support the researcher to think more abstractly and theoretically to bring more depth into the study. A memo contains a set of sentences, paragraphs, or even more if needed.

4.7. Generating a theory

Generating a theory depends on the conceptual categories and identified core categories. Glaser & Strauss (1967) argued that hypotheses need to be developed before generating a theory. However, sometimes it may be difficult to generate hypotheses, concepts, and categories with the collected data. Strauss & Corbin (2008) explained that it is necessary to write a memo to locate more important ideas that will help to generate proper concepts, categories, and the theory from the data collected. There are cases where researchers will not be able to develop hypotheses to generate a theory. However, the researcher's findings can be presented as observations or recommendations. In general, data needs to be analyzed properly to generate a theory. Strauss & Corbin (2008) argued that a theory can be generated even from a single case, and research should identify categories and generate theories based on them. The process of generating a theory from data involves data collection, coding, and data analysis. It is important to be aware of the entire process from the beginning of the research methodology and until a theory is generated using the collected data.

4.8. Summary

The author proposed to use a qualitative analysis based on interviews to gather data and identified the struggles that DMs face when adopting and practicing DDDM, as well as how to overcome those struggles. This study follows a Straussian-grounded theory design to guide the collection and coding of interview data to identify emerging categories and generate critical factors to be considered in DDDM. Related work was utilized to identify the direction of the research, identify variables, and form the questionnaire for interviews. Both related work and the researcher's own observations of the pilot interviews were used to identify a set of prefigured categories. The interview questions were then derived based on these prefigured categories. A set of banks was then selected for interviewing, with DMs from different levels of the management hierarchy. Data gathered from these interviews was analyzed by coding, categorizing, comparing, and memo writing of the interview responses. Key findings, observations, and recommendations will then be derived from data analysis.

5. DATA ANALYSIS

This chapter presents the analysis of the collected data through 18 interviews. A qualitative approach was used, and data analysis was conducted based on Straussian's grounded theory approach. The rest of the chapter is organized as follows. Section 5.1 describes how the collected data was prepared for analysis using the grounded theory. Section 5.2 presents the data analysis broken down into several sub-sections, where the interview data was analyzed based on the DMs competencies (Section 5.2.1), the socio-demographic characteristics of DMs (Section 5.2.2), their personal characteristics (Section 5.2.3), and data literacy-related factors based on the collected data (Section 5.2.4). A summary of the overall data analysis is presented in Section 5.3.

5.1. Data Preparation for Analysis

This study is mainly driven by interviews among six selected Sri Lankan commercial banks and three managers from each bank, which includes a branch manager, a regional manager, and the CTO/ CIO or the Head of IT. Grounded theory was used to analyze the data to generate a substantive theory regarding the Data-Driven Decision Making (DDDM) capabilities of managers in banks.

Interviews were carried out face-to-face, and interview questions were based on the independent variables in Table 4.1. Interviews were conducted in a few stages, where after conducting the initial set of interviews, the outcomes were reviewed, and a couple of new questions were added with the aim of capturing the required information to achieve the objectives in Section 3.2. Appendix B contains the modified questions.

Axial coding was generated based on the open coding data gathered, and finally, main categories were extracted through selected coding after analyzing the results from the axial coding. A scale from zero to three (zero was considered as '*not applicable'*, one as '*disagree'*, two as '*neutral'*, and three as '*agree'*) was utilized to check and confirm the axial coding and final categories. The factors that got more than 50% as agreed or strongly agreed were categorized as a factor to consider when performing DDDM in banks. The factor selection matrix is given in Appendix B.

5.2. Data Analysis

This study used interviews to gather data and grounded theory was used to analyze the data to generate a concrete theory regarding the DDDM capabilities of managers in banks. Table 5.1 lists the summary of the interviewed managers' profiles, bank type, responsibility, experience, and most preferred decision-making method. Table 5.1 excludes the CTO/CIO or the head of IT profiles, as even their high-level profile details could be sufficient to identify them personally. This study focusses on the DMs who practice DDDM on a daily basis for decision making, hence the main aim of the research is to identify the struggles that DMs face and how to overcome them.

Table 5:1 Profiles of interviewed DMs.

Position	Responsibility	Bank Type	Experience Level
Asst. manager regional sales and development	• Improving business • Managing the branches	International	High
Branch manager – Colombo	• Following instructions and making short-term decisions to manage the branch	International	Mid-level
Regional manager Western region	• Responsible for a specific region's sales development	Semi-government	High
Branch manager – Colombo district	• Branch level operation and decisions to improve branch sales and performance	Semi-government	Low -level
Manager central region operations	• Managing the central region branches' operations • Developing sales and performance of branches and the region	Local Private	High
Branch manager - Kandy	• Managing branch operations and making short-term decisions for branch performance improvement	Local Private	Mid-level
Regional sales manager – Central region	• Improving the regional sales and creating strategies to gain new sales for the branch	Local private	High
Branch manager – Kandy	• Branch operations and short-term decision making	Local private	High
Business development manager	• Improving business in the bank and preparing strategic plans to gain new business for the bank	Local State	High
Branch manager	• Branch operations and short-term decision making	Local State	low-level

Manager sales and business development	• Creating strategies to improve sales and business; to develop and increase bank revenue	Local private	Mid-level
Branch manager – Colombo	• Branch operations and short-term decision making	Local private	Low-level

Through the grounded theory's open coding and axial coding, the author identified several key factors influencing the DMs' capabilities of practicing DDDM. These factors are analyzed in the following sections.

5.2.1. Decision makers competencies

Decision Maker's experience

As per the analysis of the interview data using the grounded theory, a relationship between the level of experience and intuition-based decision making is discovered as an insight. As a DM's experience grows, they tend to make decisions based on their intuition by overruling the DDDM process in the bank. A regional manager in a semi-government bank stated that:

"*While I gained experience, my decision making is always intuition-based but data is only used when I was unsure of a decision.*"

Moreover, a regional sale manager from an international bank mentioned the following:

"*Using data to support the decision depends on type decision and the person who approves the decision.*"

However, the most interesting finding is many managers make sure that the intuition-based decision is supported and explained using data or tend to use data to defend the intuition-based decision when it fails. This is counter-intuitive because, while we typically expect data to be used to derive a decision, many experienced managers seem to make intuitive decisions and then look for the data to support those decisions.

In a dynamic business environment like Sri Lanka, uncertainty is a dimension to be considered. Hence, many DMs in banks are forced to consider such uncertainties. This is a major root cause for DMs to overrule the DDDM process and make intuition-based decisions. These are recognized as the inabilities of BI tools available in the market. However, BI tool vendors must reconsider these aspects which have a negative impact on the DMs' perception of the BI tools. Table 5.2 indicates how the DM's experience is derived from open coding and axial coding.

As shown in Figure 5.1, an interesting observation is that most of the DMs have a habit of justifying their intuition-based decisions by conducting cross-references with the data, reports, and dashboards. Moreover, the lessons learned during their service period motivates intuition-based decisions rather than data-driven decisions. A private bank manager stated that:

"*I don't use data to make decisions. But I use data to explain and check my decisions in worst cases.*"

Furthermore, another important finding is that experienced DMs have a low need for data interpretation, even if they currently use DDDM. Also, this finding indicates that in many occasions, that DMs intentionally overrule the DDDM based on their experience. An experienced DM from a private bank stated:

"*Lessons learned from the years of decision making cannot be replaced by a data graph.*"

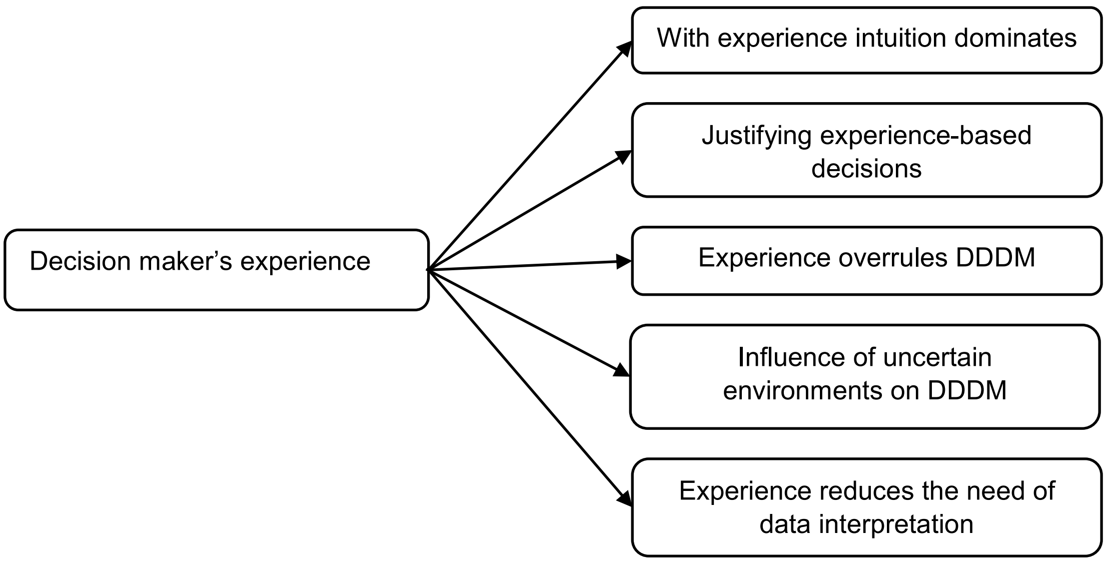

Figure 5:1 Dimensions related to DMs experience on DDDM

Decision maker's perception on DDDM

Even though DDDM has proven to be a successful approach in DM in modern business environments, DMs are not willing to change their decision-making approach. Nevertheless, some interviewees had a positive impression on DDDM approach. However, a regional sales manager of a state bank mentioned:

"My experience is more powerful than data and I don't trust data because there is an error percentage in data."

However, Intuition has overruled the DDDM approach due to factors such as uncertainty, lack of trust in the system reports and dashboards, lack of knowledge in system reports, and not willing to change the decision-making style as illustrated in Figure 5.2.

A branch manager of a private bank stated:

"*Even though I use data for decision making, sometimes I don't trust the data because from my experience I am confident that the data decision will fail.*"

Hence, DM's are not willing to make decisions beyond their comfort zone. A branch manager from a private raised the following question:

"*I was making decisions for last 15 years, but I didn't have data - why should we change successful decision making?"*

Table 5:2 Open and axial coding for DMs experience.

Selected	Axial Coding	Open Coding
Decision maker's experience	With experience, intuition dominates	• Intuition-based decision-making increases with experience • Experience improve intuition-based decisions quality • With experience, risk-taking ability decreases • Experience and intuition creates more uncertainty towards the DDDM process • Inexperience creates uncertainty towards intuition-based decision making
	Justifying the experience-based decisions	• Reports and dashboards are monitored to check and verify decisions • Self-reports are created to verify the decisions made • Reports are revalidated by DMs

	Experience overrules DDDM	• Eager to use data for decision making • Lack of trust on DDDM • The ego of personal experience vs. computers • The confidence of DMs in making successful decisions with intuition over DDDM
	Experience reduce the need for data interpretation	• With experience, DMs only refer to a graph's shape • DMs data interpretation need reduces since they are used to these graphs
	Influence of uncertain environment on DDDM	• Due to changes in the dynamic banking environment in Sri Lanka • Reports do not incorporate uncertainty • Different geographical locations will require different approaches to decision making

Moreover, DMs justify the decisions made by their intuition with data to ensure the decision is made based on data even though the decision is an intuition-based decision. This has been a challenge for CTOs/CIOs or Head of IT's in banks. One CTO from an international bank stated that:

"*Managers do not use the BI tools as expected, but most of the time they cross-check the decision with data. But this is not our real expectation.*"

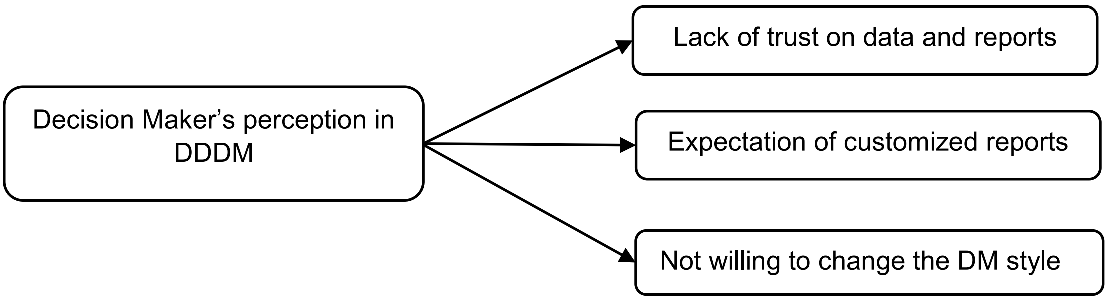

Figure 5: 2 Dimensions related to DMs perception on DDDM

High expectations of DM's cause many issues in the banking domain, due to the fact that the DMs' expectations are set beyond the abilities of DDDM, which is a misconception among the DM's in the banks. A branch manager of a private bank stated that:

"*I need BI tools to give me the decisions that I should implement but it seems like the BI tools are not providing decisions.*"

5.2.2. Socio-demographic characteristics

Table 5.3 indicates how the DMs' perception is derived from open coding and axial coding.

Table 5: 3 Open and axial coding for DMs Socio-demographic characteristics.

Selected	Axial coding	Open coding
Decision maker's perception in DDDM	Lack of trust on data and repots	• Lack of trust in the accuracy of the reports and dashboards • Verifying the data by manual calculations • Lack of trust in data guiding the decision-making process
	Expectations on customized reports	• The expectation of customized reports for decision-making • Self-service reports for decision making • Backing up intuition-based decisions using customized reports to ensure the accuracy of decisions

The socio-demographic characteristics of a DM have a high influence on DDDM. As per the grounded theory approach, analysis knowledge and exposure in banking domain, experience in managerial positions, working exposure in different banks, and acquaintance with different geographical locations have an impact on the DDDM capability of a DM, as illustrated in Figure 5.3. The knowledge of and exposure in the banking domain have significant influence on the DDDM approach, as with vast knowledge and exposure, the DM pretends to make more intuition-based decisions rather than practicing DDDM. A CTO from a private bank specifically mentioned that:

"*More than 50% of the decisions are made based on the gut feeling because the managers in the higher position are more experienced and they do not see the real value of the data most of the times.*"

Moreover, the opinion of many DMs is that the geographical location is key in choosing the decision-making approach.

According to open coding, a key factor identified was that the use of DDDM changes based on geographical location, Most of the DMs away from the financial capital is not satisfied with the forecasting reports provided by the system, as it does not consider the geographical location of the branch as a factor in its forecasting. A branch manager from an international bank pointed out that:

"*The system provides good data but since we are an international bank, the system is not a specifically designed for our purpose like other local banks, so some reports are immaterial to us.*"

The exposure to working with different systems has a key influence in adopting DDDM based on a few scenarios. For example, when a DM's previous job role did not have adequate support from the system to support DDDM, while the current system provides many reports and dashboards to support the decision making, then the DM tends to use more DDDM. A manager in private bank mentioned the following:

"*I worked in many banks and I really appreciate the BI tool in this bank and I am using it more frequently than I did in the previous places.*"

However, as a DM gains experience, recognizes patterns, and gets familiar with the system, he/she tends to make more intuition-based decisions.

Academic, professional, and domain-specific qualifications have a significant impact on a DM's approach in decision making. DMs with a STEM background are more influenced by their educational background to move towards DDDM compared to intuition-based decision making. As per the regional sales manager of a private bank:

"My subordinates with science and statistical degrees and very comfortable with data-oriented decision-making compared to others."

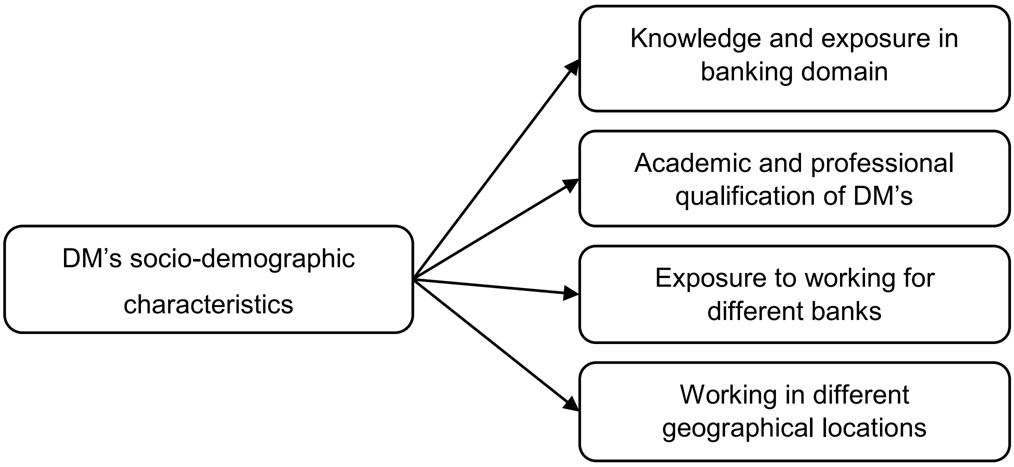

Figure 5: 3 Dimensions related to DMs socio-demographic characteristics

Therefore, a background in STEM will provide the skill of data and graph interpretation to a certain extent, and by combining the domain-specific knowledge, such DMs are comfortable in DDDM compared to other DMs who do not have a STEM background.

Table 5: 4 Open and axial coding for DMs personal characteristics

Selected	Axial coding	Open coding
Decision maker's socio-demographic characteristics	Knowledge and exposure in banking domain	• Level of experience in banking domain (highly experienced, mid-level and low experience) • Branch level management • Regional level management experience
	Academic and professional qualification of DMs	• Academic higher education • Professional education • Masters education in management • IBSL qualifications which are related to the domain knowledge • STEM-related knowledge
	Exposure to working in different banks	• Exposure to working with different banking systems • Comparing different systems' data and reports quality, and user-friendliness
	Working in different geographical locations	• Forecast reports do not consider geographical locations • Different business environment factors are not considered

5.2.3. Personal characteristics

A DM's personal character has a positive as well as a negative influence on adopting and performing DDDM. As per the data analysis, influencing individuals to use the DDDM approach is a challenge because the personal characteristics of a DM are unique to each person. Figure 5.4 illustrates personal characteristics such as a risk-taking attitude in decision making, decision-making style (cognitive style), DMs' moral and individual perception, and willingness to change the decision-making style.

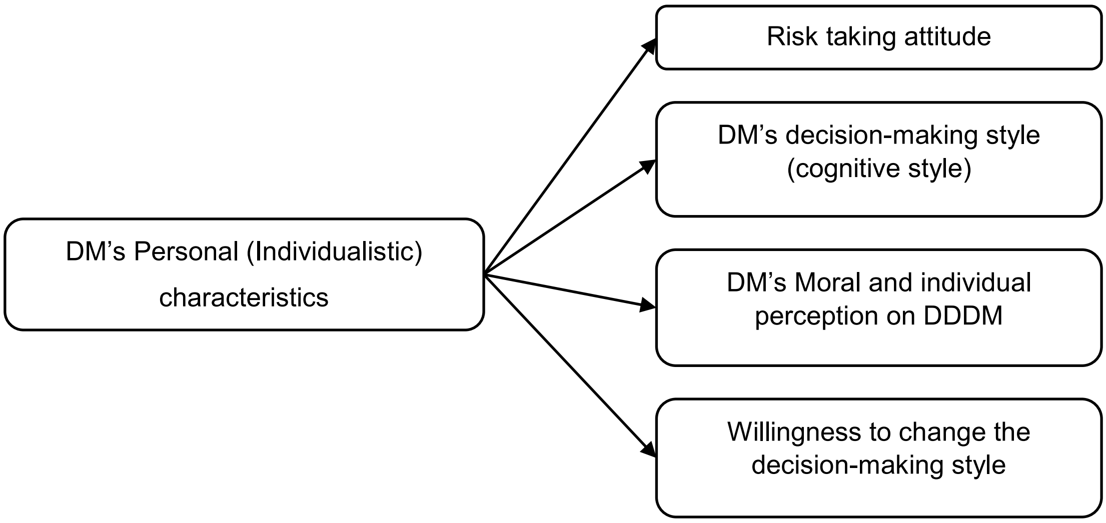

Figure 5: 4 Dimensions related to DMs personal characteristics

During the analysis, it was noticed that almost every decision maker is required to take a risk to achieve their Key Performance Indicator (KPI) targets. Some DMs are not willing to take risks due to bad experiences in the past. Alternatively, many inexperienced DMs are willing to take risks with the aim of achieving the KPIs, and these DMs expect support from data analysis and forecasting reports to mitigate any risks and ensure that the decision is supported by data analysis. A young manager from a private bank stated that:

"*We need data to make decisions and we have the ability to use data in decision making but a certain amount of support is needed to understand data in some situations.*"

Nevertheless, the underlying fact is that some DMs have the intention of using data and forecasting reports as a bailout from a worst-case scenario in case of a wrong decision. A DM's cognitive style is a major factor in influencing a DM to adopt or practice DDDM. According to the analysis, certain DMs are unable to move from a specific cognitive style to a different cognitive style. However, there are few factors that influence DMs to change their cognitive styles, such as gut-feeling based decision making, influenced by the senior management and a unique blend of DDDM and intuition-based decision making. As per the analysis, younger managers can be influenced more to change the cognitive style but they require more knowledge and support from data and the higher management to make successful decisions. An experienced manager with a strong knowledge of DDDM mentioned the following:

> "*I strictly request my subordinates to use data to make decisions and justify decisions; I always make sure they use this practice in decision making.*"

Table 5.5 indicates how a DM's perception is derived from open coding and axial coding.

The moral and perceptions of individual DMs on DDDM have a significant impact on their adoption of DDDM. While the researcher identified that some of the DMs are willing to change their cognitive style, there are several other underlying factors that restrains the DMs from changing this style. These include lack of trust, uncertainty, and lack of experience and knowledge in DDDM. Banks should focus on these dimensions to enforce DDDM on decision makers. Experienced DMs are more comfortable in making decisions. When a DM is more comfortable with making decisions based on intuition or gut-feelings and when those decisions were successful in the long run, DMs develop an ego which negatively influences the willingness to change their cognitive style. Table 5.6 indicates the cognitive style and willingness of the interviewed DMs to change their cognitive style of decision-making.

Table 5: 5 Open and axial coding for DMs data literacy.

Selected	Axial coding	Open coding
DM's personal (individualistic) characteristics	Risk-taking attitude	• Willing to take risks in decision making • Risk taking ability improves with experience • Inexperienced DMs require support and backing from data and reports for decision making
	DM's decision-making style (cognitive style)	• Unique style of decision making • Influence of the higher management on their cognitive style • Unique blend of DDDM and intuition-based decision making
	DM's moral and individual perception on DDDM	• Moral of using DDDM in a dynamic environment

		• Lack of moral in DDDM approach while gaining more experience
	Willingness to change the decision making (cognitive) style	• Uncertainty of DMs reduce their willingness to change • Due to lack of trust on DDDM • Lack of experience and knowledge on DDDM

5.2.4. Data literacy of decision makers

Data literacy is a key characteristic that is required to perform DDDM. A DM's level of data literacy influences a decision maker based on four different dimensions, namely data knowledge, data assimilation, interpretation and skepticism, and curiosity. Discomfort experienced in any of these dimensions restrains DMs when it comes to performing or adopting the DDDM approach.

According to Dykes (2017), every industry has its own set of unique data terms and data. It is required that DMs in the banking domain understand data in from a banking perspective. However, as per the data analysis conducted in this research, it is identified that most of the DMs do not have a clear idea of the data available in the bank. The Head of IT from a private bank mentioned:

"*Many managers struggle in matching data with business and making decisions, which is a major area to be focused.*"

This is a major drawback in enforcing DDDM in banks. As per the analysis, the ability to understand the data in business terms, the lack of basic statistical knowledge, and the lack of knowledge on banking domain-related data, are identified as major struggles faced by the DMs.

Table 5: 6 DMs willingness to change the cognitive style and most preferred DM method

Position	Experience Level	Most Preferred DM Method	Willingness to Change Cognitive Style
Asst. manager regional sales and development	High	Intuition and occasionally data driven	High
Branch manager – Colombo	Mid-level	Intuition based but decisions are supported by data to	High

Position	Experience Level	Most Preferred DM Method	Willingness to Change Cognitive Style
		convince the higher management	
Regional manager Western region	High	Highly dependent on data but intuition overrules in some situations	NA
Branch manager – Colombo district	Low -level	Highly dependent on data for decision making and performance analysis	NA
Manager Central region operations	High	Highly dependent on data-driven decisions. Use prescriptive and descriptive analysis for decision making	NA
Branch manager - Kandy	Mid-level	Influenced by the immediate manager to make data-driven decisions, but intuition is also used for decision making	Moderate
Regional sales manager – Central region	High	Highly dependent on data-driven decisions. However, intuition overrules in some scenarios.	Moderate
Branch manager – Kandy	High	Intuition-based decision making; rarely use data for decision making	Moderate
Business development manager	High	Highly dependent on intuition-based decision making	Low
Branch manager	low-level	Dependent on data but intuition overrules DDDM	Moderate
Manager sales and business development	Mid-level	Intuition based but decisions are supported by data to convince the higher management	Moderate
Branch manager – Colombo	Low-level	Highly dependent on intuition for decision making and performance analysis	Low

Banks encourage DM’s to gain domain knowledge by obtaining professional bank-related qualifications. The opinions of CTO/CIO or Head of IT were to conduct training and hands-on training sessions for the DMs, to breach their gap of data knowledge. Supporting this idea, a private bank’s regional sales manager mentioned:

"*I highly encourage my subordinates and colleagues in banking to get professional qualifications related to banking to get familiarized with data and terms in the banking domain.*"

Moreover, a branch manager from a state bank mentioned:

"The training given to us is limited so we struggle in using reports sometimes, so I think it is better to provide training continuously at regular intervals."

Table 5.7 lists the open, axial, and selected coding for a DM's data literacy. Dykes (2017) described that data assimilation is all about getting familiarized with the data and reports presented to the DM to make decisions. As per the analysis in this research, most DMs are not comfortable with the data and the reports presented to them for decision making, and they tend to request for customized reports. A CTO from an international bank mentioned:

"*30 to 40% of IT requests are received from managers to make changes to reports and dashboards or requesting new reports and dashboards.*"

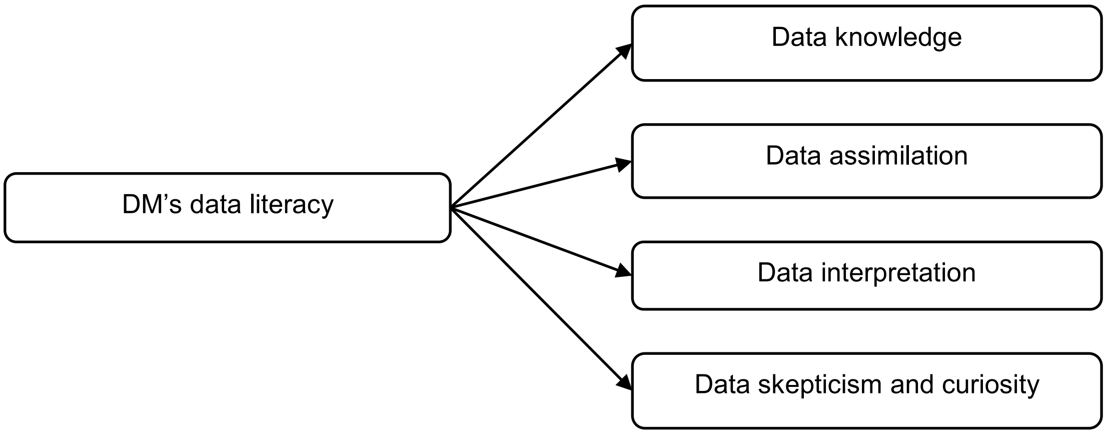

Figure 5. 5 Dimensions related to DMs data literacy

As per the discussions with the CTO, CIO, or the Heads of IT, it was identified that most of the changes or system upgrade requests they receive from DMs are related to customized reports or new reports, even though the existing reports can provide the required information. A CIO from a private bank mentioned the following:

"*Many managers have no idea what information is in what report, so they complain and request to add more information on to the same reports where they were more comfortable with that particular set of reports, rather than looking for the correct report.*"

The inability to familiarize themselves with the reports has caused DMs to make decisions using their intuition. DMs who have a statistical and STEM background were able to get more familiar with the data compared to DMs without this background. During the data analysis, it was discovered that as DMs gain more experience they also get more comfortable with DDDM and improve data assimilation. A branch manager from private bank mentioned:

"It took me a considerable amount of time and a few years of experience to get used to data; by the way, I had to play a lot with data to get familiarized with it."

However, there have been issues such as the conflict between the intuition-based DMs and data-driven DMs, and incorrect interpretations of data for decision making which leading towards failures. This is because DMs only consider the shape of the graph and do not consider the units of measurements or the metrics of the graph. Alternatively, CTOs, CIOs, and the Heads of IT recommend training younger managers with less experience, to make them understand the importance and usefulness of data assimilation, which could set the platform to improve their skills and result in the use of more DDDM in the bank under any environment.

After DMs are familiarized with data assimilation, they will ideally have the sufficient background to interpret data and perform DDDM. Depending on the type of data, the format, and the method of data presentation, DMs should have the ability to interpret the data more meaningfully. During the interviews, a regional sales manager was requested to show a graph and interpret the graph, however, his interpretation was:

"*I only need to see the shape of the graph - rest I can decide what to do with my experience.*"

The usage of data and reports are different during the entire process of decision making. Hence, the DMs' utilization of BI tools differs based on their decision-making style.

Table 5: 7 Open and axial coding for DMs data literacy

Selected	Axial coding	Open coding
DM's data literacy	Data knowledge	• Lack of ability to understand the data in terms of the business perspective • Not having a basic understanding of statistical concepts • Lack of basic understanding of data related to the banking domain
	Data assimilation	• Description of data tables and graphs are clear and understandable • Units of measurement and metrics are understandable • Clear understanding of the ratio, rates, other formulas • Dimensions and segmented data are clear and understandable • Filtering in the data and graphs are understandable • KPI and targets indicated in the graphs are understandable
	Data interpretation	• Identifying the trends, patterns, and clusters in the graphs • Interpretation ability of the DM • Can data help to answer a specific business question? • Reads only the chart or graph shape instead of the full interpretation • With experience, the need for interpretation is low • Assumption and intuition-based decisions are taken based on the shape of a graph
	Data skepticism and curiosity	• Credibility – how reliable is the data source • Truthfulness – is the data is misrepresented in the true meaning • Additional information needed for data understandability is missing • Practical significance of the data • Required period over period for comparison

Low-quality data visualization is another major finding that requires attention from IT departments. Many DMs complain about the quality of the visualization. For example, most DMs should be able to identify interest rate fluctuations. As observed during the interviews, DMs had difficulties in identifying the fluctuations clearly, due to the unclear visualization from the BI tools. In this case, a branch manager from a local bank mentioned:

“*Some reports are much needed ones, but the report is not clear, and I cannot clearly identify a change, so these reports are useless.*”

This has been a key reason for DMs to avoid DDDM and make intuition-based decisions, even during crucial times. Alternatively, the lack of quality in visualization and the DMs’ ability of data interpretation and relating interpretations to business, has created a new need among DMs. Hence, DMs suggest providing self-service BI tools for DDDM with the aim of developing customized reports to support the decision-making process. A branch manager from a private bank insisted:

“*I prefer customized reports as well as having my own reports which will ease my decision making instead of looking for data in different reports.*”

Nevertheless, CTOs, CIOs, and Heads of IT have a different view on providing self-service BI tools for DMs, as they believe that providing self-service BI tools will lead to more issues and probable failure in DDDM. This is because such customized reports and graphs will not be tested for accuracy and therefore, might mislead DMs in decision making. Moreover, these CTOs, CIOs, and Heads of IT have a concern about the accuracy of the data which will be produced by the self-service BI reports. A CTO from a private bank mentioned:

“*We can provide self-service BI, but this will be a disaster because many managers do not have an idea of the meaning of the data, and the reports built with self-service BI are not being tested for the accuracy, so this will be a disaster. I am not willing to take this risk at all.*”

Alternatively, the existing reports in the system are well tested and known to be accurate. However, DMs build the argument that the reports are not specific to a region or a location, where common reports produced by the system do not provide the required information or data to perform DDDM. Conversely, the counter argument by the CTOs, CIOs, and Heads of IT is that the system is providing the required reports, but the DMs are not aware of the availability of those reports and their uses. A senior regional manager from an international bank mentioned that:

"*Many subordinates are not aware of what report gives what information and where to look for data - this is a big issue I face.*"

Table 5: 8 comparison of DMs' views versus opinions of CTO's / CIO's or Heads of IT.

DMs requirement	Opinions of CTOs, CIOs, and Heads of IT
Provide self-service BI tools for creating custom reports	Self-service BI can lead to data misjudgment and inaccurate reports and dashboards, which could eventually lead to failure in decision making
Reports need a customized version for specific regions	Reports can be created for specific regions, but they will create overheads in systems
Using only the basic reports and dashboards	Other reports required to be self-learned; however, DMs have not considered self-learning
System reports do not have the necessary information required for decision making in one place	System reports have all the required information and data, but many DMs are not familiar with what data a report provides, and where the reports are in the system
Reports need to be modified and updated based on the user's need	It is difficult to update a report only based on a specific person's requirement; it needs to be analyzed and re-designed to cater to new requirements, which takes a considerable amount of time
Display data in tabular format under the graphs or dashboards	This cannot be done with the limitations and visualization issues, and there is no meaning in displaying data under a graph

However, some DMs are highly dependent on custom reports and need modifications to them with the aim of visualizing the data in a more meaningful manner. Such requirements are not addressed by the IT departments, hence, there is a conflict between the IT departments, and the DMs. Table 5.8 makes a comparison of the views of DMs versus the opinions of CEOs, CIOs, and the Heads of IT towards their DMs' complaints, requirements, and suggestions.

Some DMs consider only a few reports and graphs as useful for decision making. As observed during the interviews, DMs are used to existing reports and do not intend to use new reports or graphs developed to support the decision-making process. The root cause of this is that the perception created by training programs on BI tools and DDDM is not entirely a positive one. This has created a greater impact on the DMs' fear of DDDM and increased their unwillingness to learn DDDM. During the data collection interviews, a regional sales manager described the following:

"*Training is provided to us on how to read reports, but I believe there is more to be trained on than just reading reports.*"

Skepticism and curiosity on data, reports, and dashboards have a major impact on the DMs' adoption and practice of DDDM. As per the analysis, skepticism and curiosity were identified as major factors of resistance against DDDM. The underlying reasons for skepticism and curiosity are credibility and accuracy. During the analysis, almost all the interviewees highlighted that the credibility and accuracy of the data, reports, and dashboards are a major concern when DDDM is enforced. DMs are unsure of the correctness of the reports provided, which has to lead them to consider intuition-based decision making over DDDM. The Head of IT from a private bank mention that he experienced a situation where:

"*I had discussions with many managers who claimed that they are not willing to use BI tools and reports due to bad experiences, which is a perception that is hard to change.*"

This is more of a concern for the senior managers than the younger managers. It was identified that many decision-makers tend to perform manual calculations to check the reports' accuracy and verify them.

DMs complain that the reports and dashboard consist of assumptions in visualization and that assumptions lead to inaccurate interpretations of the reports. Alternatively, as per the IT leadership in banks, some reports and dashboards are visualized by mentioning the assumption which communicates a clear visualization. Even though the assumptions are being communicated to the DMs, the understandability of the stated assumption is also low.

Issues with data visualization, limitations of the BI tools, and the inability to generate customized reports are a few major issues identified during the study, which are more related to the technical and implementation issues of BI tools. During an interview, one of the DM's pointed out that:

"*The visualizations are not clear and identifying a difference between two data points are difficult for me, so this report is not useful at all.*"

Alternatively, another DM pointed out that:

"*The graph's Y axis is being scaled, but in my case, the scaling is not useful; it is useful for the managers who have a higher number of transactions.*"

These issues make DMs ignore visualization interpretations and compel them to make decisions based on intuition.

As per the data analysis, it can be concluded that a DM's data literacy level is a major factor that impacts their adoption and practice of DDDM. Moreover, DMs' competencies, socio-demographic characteristics, and personal characteristics have a direct influence on DDDM too. Even though the above factors are direct influencing factors, individualistic culture also has a significant impact on the adoption of DDDM. The individualistic culture and behavior of a DM has influenced DMs positively as well as negatively. As per the data analysis, it is being discovered that a few factors related to the individual culture of a DM have a direct impact on embracing DDDM. Overall, there seems to be a clear relationship between the above four main factors as well.

During the study, factors such as organizational culture, competition among banks, networks of professionals, age, gender, and organizational behavior were identified to have a lesser impact on DDDM, compared to the factors and dimensions discussed in the earlier sections. Below are some lesser impacting factors that were identified during the literature review, but during interviews and data analysis it was observed that these factors do not have a significant impact on a DM's ability to use DDDM. Hence, these factors will not be considered. Table 5.9 elaborates the open coding for these factors. A further analysis of factor selection is illustrated in Appendix C.

5.2.5. Individual and team culture of DDDM

A DM's individualistic culture is an influencing factor in his/her intention to perform DDDM. As per the observations made during the interviews, each person is from a different culture and this has a direct impact on adopting or practicing DDDM. Some banks do have a team culture where the team has a willingness to perform DDDM, but different branches of the same bank may have different cultures. A clear conclusion to be made here is that individual and team culture are factors which change from person to person, as well as among teams in different branches of the same bank.

During this study, it was identified that when a bank has younger DMs who are willing to perform DDDM and senior managers with a STEM and/or good statistical backgrounds, it creates a more positive culture on performing and adopting DDDM. In this regard, a CIO from a private bank mentioned:

"*Most of the times when we impose new technology like BI tools, the problems are with experienced old-school managers, but younger managers are more eager to adopt new technology.*"

Table 5: 9 Open coding for the least impacting factors.

Factor	Open Coding
Organization culture	• No considerable influence • Many organizations have a hierarchy culture and a few organizations have a flat culture • Overall, organization culture is more open to international and private banks
Competition among banks	• Competition is only among the business and not how the decisions are made • DMs do not see a connection between competition and DDDM
Network of professionals	• Professional network has no influence on DDDM • Increase the interest of DDDM
Age and gender	• Does not have a direct impact on the decision making • A small percentage of responders see gender as an influencing factor
Organizational behavior	• Organizational behavior is not considered in a DM's ability of decision making

5.3. Summary

The author conducted face to face interviews of six (6) banks and eighteen (18) DMs. Once the first interview was completed, keywords and sentences were extracted as open coding and memos were written based on these. The constant comparative analysis was used for the second interview onwards and the author was required to edit, add, and remove a set of questions and change the sequence of the interview before going into the next meeting. Comments from previous interviews were used to get more details from respondents. Axial coding was generated based on the open coding collected from the data gathered, and finally, the main categories (selected coding) were derived after analyzing the axial coding. To check and confirm these axial coding and final categories, a scale from zero to three was used. The researcher had to go through the gathered data and the banks were asked to identify whether they agreed with these categories. The categories that got more than 50% as agreed and neutral were identified as factors to be considered.

While conducting the interviews, the researcher made observations and based on the data analysis, several key insights were also identified. Some of the key findings include:

- As a DM's experience grows, they tend to make decisions based on their intuition and overrule the DDDM process in the bank.
- Many managers make sure that their intuition-based decision is supported and explained using data or tend to use data to defend the intuition-based decision when it fails.
- The lack of quality and clarity of visualization have a negative influence on DMs that result in them resisting to use reports and dashboards for decision making. This has also led to DMs requesting for self-service BI tools.
- Issues with visualizations have resulted in abandoning some of the reports.
- DMs with a STEM and statistical education are more comfortable in adopting and practicing DDDM compared to other DMs.
- Younger DMs can be easily influenced to adopt and practice DDDM compared to more experienced DMs.
- Some DMs intentionally overrule the DDDM and make decisions based on intuition due to unfavorable experiences faced while practicing DDDM.
- Lack of familiarizing themselves with system-generated reports, dashboards and data have lead DMs to make decisions based on intuition.
- Self-service BI tools could lead to more issues and failure, as the report or the graph will not be tested for accuracy, which might mislead DMs in decision making. This is a result of uncertainty towards the accuracy of data.

These findings and observations are further described and discussed, and recommendations are provided in the following chapter.

6. RECOMMENDATIONS AND CONCLUSION

This chapter summarizes the key findings, recommendations, and conclusions of the research. Section 6.1 presents the conclusions from the research. Section 6.2 lists the observations made during the research, findings from the data analysis, and recommendations for higher management in banks. Section 6.3 lists the limitations of this research while the future work is proposed in Section 6.4.

6.1. Conclusions

Modern day banks are under intense competition and a dynamic business environment. Every bank aims to gain a competitive advantage over its competitors, to be successful in the market. However, to be successful in such dynamic and cutthroat markets, the need to make good strategic, operational, and branch-level decisions becomes key. Banks have identified that it is important to use data for decision making, as it is proven that Data Driven Decision Making (DDDM) can produce competitive advantages. However, Decision Makers (DMs) in banks still struggle to adopt and perform DDDM, which has been a major issue for banks and a challenge for their IT departments to enforce BI tools' reports and dashboards for DDDM.

This study identified several challenges that DMs face when performing DDDM through a careful investigation of six (6) selected banks in Sri Lanka, which included local commercial banks, state banks, and international banks. Researcher interviewed branch level manager, regional level managers, and CIO/CTO or Head of ITs. During the investigation, the author identified that the DMs' competencies, socio-demographic characteristics, personal characteristics, and data literacy levels have a direct impact on the adoption of DDDM. Moreover, external factors such as organizational behavior and culture were found to have a moderate impact on the DMs' willingness to utilize DDDM.

A DM's competencies can be categorized under experience and perception. Furthermore, a DM's experiences can be grouped into several dimensions such as domination of intuition, justifying experience-based decisions, ignoring data and reports due to experience, and the reduction in the need for data due to high experience levels.

It was discovered that when DMs gain more experience, the interest to practice DDDM is low and as such, many experienced DMs are resisting the use of data for decision-making. Many DMs have claimed to make successful decisions in the past without data. Moreover, having bad experiences while using data has also created a negative impression on the use of DDDM.

Even though intuition is still a dominating factor in decision-making, the uncertain business environment in Sri Lanka is forcing DMs to consider DDDM, where they rely on automated reports and dashboards to identify the current situation. However, this could be considered as only a basic level of DDDM. Nevertheless, intuition-based decision making is still dominating in the Sri Lankan banking industry, especially among most of the well-experienced DMs.

Justifying the accuracy of intuition-based decisions, supporting its quality, and obtaining acceptance through reference to data, are other practices of experienced DMs. This was performed by many DMs to ensure that the data will support their intuition-based decision making, as well as act as a backup to justify their decisions to the higher management in case it goes wrong. While the former can be considered acceptable as the data is at least checked to ensure the accuracy of decisions, the latter gives the impression that DDDM is not useful and would lead to failure.

During the study, the researcher identified a set of DMs who are eager to use DDDM. These DMs have unique characteristics such as willingness to take risks, elaborate decisions to higher management by providing evidence from data, trying to achieve a competitive advantage from data.

However, it was identified that the ego factor of personal experience versus computers, and the confidence on making decisions based on intuition rather than using DDDM, are the key underlying factors where intuition-based decision making overrules DDDM. Hence, the challenge for banks is to gain the trust and increase the confidence of DMs to use DDDM in their day-to-day practice.

Apart from the experience of a DM, their perception of DDDM is also another key aspect. This perception includes a lack of trust and expectations from customized reports and data. Another key observation is that most of the DMs tend to perform manual calculations on the values/figures provided by the system generated reports to ensure that they are getting correct values. This shows a major lack of trust in the data, reports, and dashboards. After performing manual calculations for a while, DMs begin to gain trust on data and reports, but still, do not have the confidence to drive decisions based on the data. The recommendation for banks is to ensure that DMs gain the confidence that pure data can drive successful decision making.

The socio-demographic characteristics of a DM is a combination of a different set of dimensions such as the knowledge of the banking domain, academic and professional qualifications of DMs, exposure due to working for different banks, and experience with working in different geographical locations. During the study, it was identified that mapping data to a business problem is a major struggle DMs face when considering DDDM. However, having an in-depth knowledge and exposure to different levels of banking can provide a strong background for DMs to map data to business problems. Alternatively, academic, professional, and domain-related qualifications have a positive impact on adopting and practicing DDDM. Moreover, another interesting finding is that the DMs with an STEM and statistical background are more comfortable in DDDM in comparison to other DMs, where they practice DDDM more frequently.

The geographical location of a branch has a significant impact on whether the DMs practice DDDM. As per the analysis, it was identified that DMs away from the commercial capital tend to use more DDDM with the aim of achieving KPIs. However, DMs in the commercial capital constantly achieve KPIs more easily, hence the need for data is considered low. This indicates that when DMs exhaust all other options to improve their KPIs, they rely on data to gain insights and make decisions. Moreover, branches in the commercial capital seem to be having lower KPIs, so DMs are comfortable in relying only on intuition to reach their targets. This is perhaps an indication that the banks' higher management have not investigated data to identify those who have achieved their KPIs, and where they need to raise the bar.

While a DM's competencies and socio-demographic factors have a significant influence on adopting DDDM in Sri Lankan banks, his/her personal characteristics have a similar impact too. DMs' personal characteristics are categorized into their risk-taking attitude, decision-making style (i.e., cognitive style), moral and individual perception on DDDM, and the willingness to change their cognitive style. An interesting finding is that most of the experienced DMs are not willing to take risks as they have had bad experiences in the past. On the contrary, many inexperienced DMs are willing to take a risk with the aim of achieving their KPIs, but they expect support from data analysis and forecasting reports to mitigate these risks and ensure that the decision is supported by data analysis. As per the researcher's observations, each DM has a unique style of decision making which is known as cognitive style. However, banks require DMs to change their cognitive style to adopt DDDM and address the underlying issues such as uncertainty, lack of trust, lack of knowledge, and experience.

Data literacy of DMs is considered as a major factor in this study, where it was observed as a major struggle. Data literacy is broken down into four main categories, namely data knowledge, data assimilation, data interpretation, and skepticism and curiosity. The study identified an important finding that DMs have a knowledge gap which creates a major resistance towards the acceptance of DDDM. A knowledge gap occurs due to the inability to understand the data in a business context, not having basic knowledge of statistics, and the lack of understanding of domain-related data. Data assimilation is a key skill that a DM needs to perform DDDM, where data assimilation is about familiarizing themselves with the data presented. It was identified that most of the decision makers are not aware of where the data is available, what data is available in which report, and how to find the required data. These issues lead DMs to request new reports and use self-service BI tools for creating custom reports. However, according to the Heads of IT, CTOs, and CIOs of banks, this is not a positive move, as they argue that the use of self-service BI tools has the potential risk of making false conclusions and wrong decisions due to the possible inaccuracy and errors in such custom reports. Alternatively, some DMs argue that the existing reports do not cater to their data needs and that customized reports could give them a unique advantage to achieve their KPIs. Some DMs complain that not providing self-service BI tools leads to intuition-based decision making, as DMs are unable to find data to support or oppose their innovative ideas. The first problem of lack of awareness could be addressed through better user-training on BI tools and what resources they provide. Alternatively, this also indicates that the higher management does not trust the data on the system and fear that custom reports could be wrong as the underlying data may be inaccurate. Moreover, they seem to not trust their subordinates' competencies to use self-service BI tools. Therefore, the management prefers to restrict the options and double check every report and dashboard produced by the BI tools before releasing to DMs. Alternatively, it also indicates that BI tools are not mature enough to ensure that only the appropriate graphs and report can be generated based on the role of DMs and the business domain. For instance, it is very easy to generate a wrong graph if some incorrect numeric values are fed into the system.

Another key observation related to data visualization and interpretations was that many DMs were only concerned about the shape of the provided graphs rather than the numerical values they reflect. The reason for this is that the DMs are so used to these graphs over time and the metrics remain the same. Due to poor quality visualizations, DMs are not willing to use newer reports and prefer to make their own calculations. DMs are more in favor of having data represented in a tabular format over graphs or charts, and even prefer to see tabular data below the graphs and charts. This could be due to that fact that they are not well trained in visual analytics and their interpretations.

As identified in this study, a DM's personal and socio-demographic characteristics have a direct relationship to their ability and intention to use DDDM. The lack of trust and uncertainty on DDDM, differences between the younger versus experienced DMs' risk-taking attitudes, educational backgrounds (especially STEM education), the need of self-service BI tools, and the conflict among DMs and Heads of IT, are the unique findings for this study compared to related work in this field of research.

6.2. Observations, Findings, and Recommendations

During the data collection and analysis, a series of observations were made, and recommendations were derived based on those findings. Table 6.1, 6.2, and 6.3 summarize the observations, findings, and recommendations, respectively.

Table 6: 1 Observations made during the study.

Uncertainty and Lack of Trust	•Even though intuition dominates them, DMs often require support and backup from data to defend their intuition-based decisions when it fails. •DMs have a habit of justifying intuition-based decisions by conducting a cross-reference with data, reports, and dashboards. •Lack of data knowledge and trust on existing system-generated reports leads to the request for customized reports.
Need of Self-Service BI Tools	•DM are eager to use self-service BI to create custom reports to make decisions. •Even though DMs are eager to use self-service BI tools, higher management is not in favor of providing self-service BI tools to DMs. •DMs complain that not providing self-service BI tools lead to intuition-based decision making over DDDM. •Higher manaement is not in favor of providing self-service BI Tools for DMs to perform DDDM with self-created reports due to concerns on accuracy and incorrect decisions.
DMs Personal and Working Environment	•DMs away from the financial capital are not satisfied with the forecasting reports provided. •Each DM has a unique style of decision making, which is a blend of intuition and DDDM in many occasions. •DMs with a STEM and statistical background are more comfortable in using DDDM. •Because DMs are not familiar with reports and dashboards, they request for customized reports and data though they may already existing in the system.
Risk Taking Attitude	•Even though their intuition dominates them, DMs tend to get support and backup from data to defend intuition-based decisions when they fail. •DMs are not willing to take risks due to bad experiences in the past. However, DMs with less experience are more eager to take risks.

Table 6: 2 Findings from the study.

Data Vizualization Issues	• Lack of quality and clarity of visualization have a negative influence on DMs, where they resist using reports and dashboards for decision making. This leads DMs to request self-service BI tools. • Some graphs and charts are not used at all due to poor visualization.
Personal Characteristics of DMs	• DMs with a STEM and statistical education background are more comfortable in the adoption and practice of DDDM compared to other DMs. • Younger DMs can be easily influenced to adopt and practice DDDM compared to more experienced DMs. • DMs intentionally overrule DDDM and make decisions with intuition due to adverse experiences gained while practicing DDDM.
Domain-Knowledge Related Issues	• Lack of familiarity of system provided reports, dashboards, and data lead to intuition-based decisions. • Self-service BI tools will lead to more issues and errors, as the report/graph will not be tested for accuracy, which might mislead DMs in decision making. • There is a lack of trust in the accuracy of data in the system among all levels of DMs.
Uncertainty and Lack of Trust in DMs	• Uncertainty, lack of trust, knowledge, and experience in DDDM create a resistance towards a DM's willingness to change their cognitive style. • Lack of ability in understanding the data from a business perspective, domain-related data, and not having basic knowledge on statistics are underlying factors for a data knowledge gap among DMs.
Risk Taking Attitude of DMs	• Experienced DMs are not willing to take risks (implemeting a decison made based on data, strategic decisons which can lead to monetory loss and penalties). • Younger DMs with less experience are willing to take risks, but they expect data to support and mitigate the risk.

Table 6: 3 Deriving Recommendations Based on Observations and Finings.

Findings and Observations	**Derived Recommendation**
Training and Development	
• Even though intuition dominates them, DMs often require support and backup from data to defend their intuition-based decisions when it fails. • DMs have a habit of justifying intuition-based decisions by conducting a cross-reference with data, reports, and dashboards. • Lack of data knowledge and trust on existing system-generated reports leads to the request for customized reports • DMs away from the financial capital are not satisfied with the forecasting reports provided. • Each DM has a unique style of decision making, which is a blend of intuition and DDDM in many occasions. • DMs with a STEM and statistical background are more comfortable in using DDDM.	• Make DMs aware of what tools, reports, and data are already available. • Provide training and conduct practical sessions with the aim of reducing the data literacy gap. • Focus on training the younger DMs on DDDM. • Train DMs on basic statistics and how to map data to the business domain. • Encourage DMs to gain domain-related data knowledge through professional qualifications.
Trust and confidence of DDDM	
• Uncertainty, lack of trust, knowledge, and experience in DDDM create a resistance towards a DM's willingness to change their cognitive style. • Lack of ability in understanding the data from a business perspective, domain-related data, and not having basic knowledge of statistics are underlying factors for a data knowledge gap among DMs. • Even though their intuition dominates them, DMs tend to get support and backup from data to defend intuition-based decisions when they fail. • DMs are not willing to take risks due to bad experiences in the past. However, DMs with less experience are more eager to take risks. • Higher management is not in favor of providing self-service BI Tools for DMs to perform DDDM with self-created reports due to concerns about accuracy and incorrect decisions.	• Gain DMs trust through accurate data, reports, and graphs. • Improve quality and clarity of visualizations. • Provide self-service BI tools and some custom reports as they may have innovative ideas that require data to support. • Improve the confidence of DMs that DDDM can drive decisions to success. • Provide support for DMs to make decisions based on data and provide them a platform to test DDDM against their intuition.
Process Changes	
• Younger DMs can be easily influenced to adopt and practice DDDM compared to more experienced DMs. • DMs intentionally overrule DDDM and make decisions with intuition due to adverse experiences gained while practicing DDDM. • DMs complain that not providing self-service BI tools lead to intuition-based decision making over DDDM. • Higher management is not in favor of providing self-service BI Tools for DMs to perform DDDM with self-created reports due to concerns about accuracy and incorrect decisions.	• Use well-experienced DMs who have the intention and ability to perform DDDM as change champions to enforce DDDM. • Recognize successful cases of DDDM. • Encourage risk-taking based on DDDM. • Revise KPIs to see whether they are pushing DMs to look beyond trivial information.

Table 6: 4 Recommendations from the study.

Training and Development	Trust and Confidence on DDDM	Process Changes
• Make DMs aware of what tools, reports, and data are already available. • Provide trainings and conduct practical sessions with the aim of reducing the data literacy gap. • Focus on training the younger DMs on DDDM. • Train DMs on basic statistics and how to map data to the business domain. • Encourage DMs to gain domain-related data knowledge through professional qualifications.	• Gain DMs trust through accurate data, reports and graphs. • Improve quality and clarity of visualizations. • Provide self-service BI tools and some custom reports as they may have innovative ideas that require data to support. • Improve the confidence of DMs that DDDM can drive decisions to success. • Provide support for DMs to make decisions based on data and provide them a platform to test DDDM against their intuition.	• Use well-experienced DMs who have the intention and ability to perform DDDM as change champions to enforce DDDM. • Recognize successful cases of DDDM. • Encourage risk taking based on DDDM. • Revise KPIs to see whether they are pushing DMs to look beyond trivial information.

6.3. Framework to develop DDDM ability and practice DDDM

Based on the observations and findings, the author proposes the framework illustrated in Figure 6.1 to develop DDDM skills among DMs, influence practicing DDDM among DMs, and to provide organizations with the benefits of DDDM. The proposed framework consists of three stages related to adopting, practicing, and influencing DMs towards DDDM. The first stage, namely initiation, focuses on the prerequisites for DDDM such as providing DMs with the required knowledge about data sources, tools, and how to perform DDDM. Moreover, all the required processes in bank needs to be implemented to use data as a source for DM. Furthermore, a conducive, low-stake environment for DDDM needs to be promoted to gain trust and confidence. The practice stage is an icebreaker for DMs, where experienced DMs who are willing to adopt DDDM approach, as well as DMs with a STEM or statistical background, will influence the DMs who are resisting and/or struggling to practice DDDM. This could provide the required level of influence and confidence from fellow managers to move away from their comfort zone of intuition-based decision-making and to make sure they are aware and using DDDM to gain tangible benefits. When DDDM results in even small but visible benefits DMs should be recognized and rewarded. While root cause analysis is needed in cases of failure, it should be carried out with the objective of providing support than criticism. The stage three, i.e., maturity of the framework, is about the continuous practice of DDDM by the DMs. As more DMs adopt and practice DDDM, KPIs need to refine to raise the bar without overstressing the DMs.

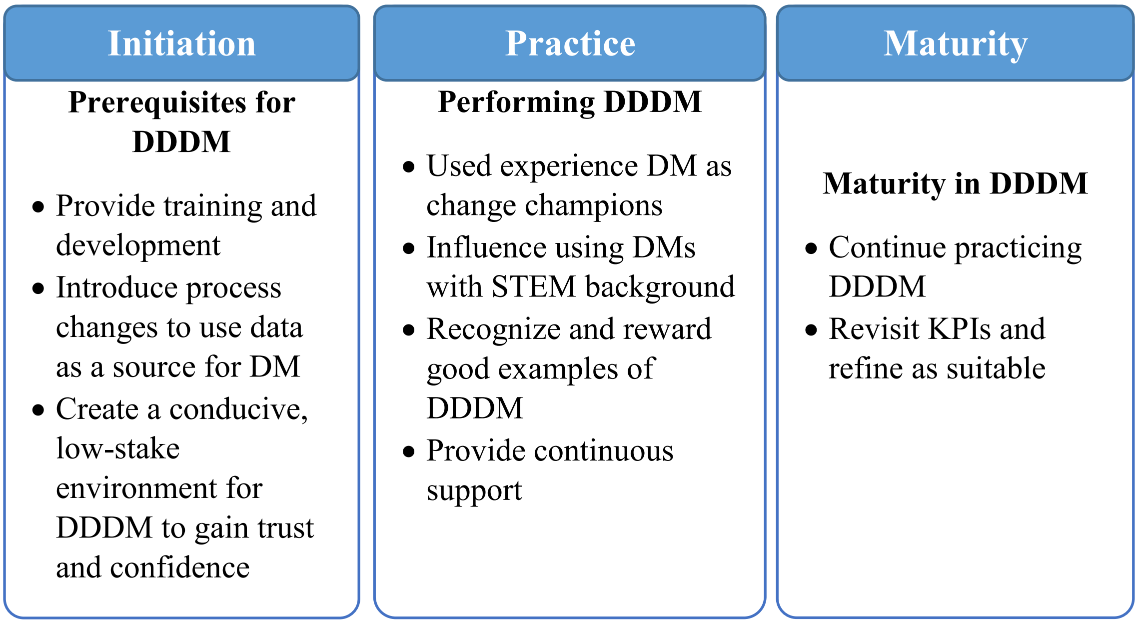

Figure 6:1 proposed framework to adopt, practice, and influence DDDM.

6.4. Research Limitations

The following limitations can be identified pertaining to this research. This study only focusses on the banking industry in Sri Lanka, which consists of a mix of private local, state, and international banks. It does not include all 25 licensed commercial banks in Sri Lanka and some banks are not known to use BI tools. Therefore, some of the conclusions from this study may not be fully generalized to other banks or banks outside Sri Lanka. BI tools are implemented in banks only recently; hence, most of the DMs and managers had limited exposure to DDDM using BI tools. The study only focused on operational and mid-level DMs, and how their struggles are seen and addressed by the higher management. This study did not address DMs from all the departments in a bank such as human resources, strategic level management, other employees who use reports on a daily basis or administration, but these other departments could have different perspectives on DDDM. Moreover this research did not consider the leader in the banks during this study, and will remains as a future work on interviewing the leaders. Measuring the DDDM ability of a DM is a difficult task, so DDDM abilities are not measured during this study; only the struggles of DMs on adopting and practicing DDDM has been considered.

6.5. Future Work

Extensive use of DDDM can provide banks with a significant competitive advantage over its competitors. This study clearly shows that DMs, CTOs, CIOs, and Heads of IT have higher expectations from DDDM. This study has identified the struggles that DMs face while adopting and practicing DDDM. The author has given only a few recommendations to overcome these challenges, some of which were derived from the interviews itself while others were derived based on the author's views and related work. Therefore, it would be useful to explore what other actions could be adopted to address the struggles faced by DMs.

Furthermore, the researcher was unable to identify a suitable methodology to measure the DMs' DDDM abilities and their levels of data literacy. Developing a methodology to measure the DMs' data literacy is an essential tool to identify their levels of maturity and recommend a suitable professional development plan accordingly. Moreover, to make it widely useful, it would help if the tool can be derived in a way that would be independent of the business domain.

Several limitations were found relating to the accuracy of data, the accuracy of reports and graphs, risks of generating wrong report/graphs in self-service BI tools, as well as visualization issues. This indicates that BI tools still have a long way to go before these issues can be addressed. Hence, further research on the non-technical aspects of BI tools is of importance too.

Furthermore, the author was unable to identify the percentage of DDDM practice in banks, and the popularity of DDDM among DMs. A study that extended its focus to research these variables could help in finding a strategy to promote DDDM among DMs in banks.

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APPENDIX A: QUESTIONNAIRE INSTRUMENT

Interview question for regional manager/ branch managers

Could you please explain your role?

- Focus on day to day activities & responsibilities

Could you please explain those roles & activities ones that involve the use of reports, graphs, data, as well as experience and even intuition?

- Try to identify where they are using data as well as could use data
- What is your most preferred method of making the decisions?
- If so how often you use data in decision making

Could you please explain your biggest achievements in your current role?

- Any what you're your awareness about data and/or experience contributed to such success?

What sort of a role your education play in use, analysis, and decision making based on reports, graphs, data, etc. (especially for your best achievements)

- Focus should be on educational background, any professional qualifications related to banking, what are the locations worked.

What sort of a role your experience with the bank play in use, analysis, and decision making based on reports, graphs, data, etc.

- Years of experience, years of service in the banking industry, year of experience in the current position, did you start your carrier as a banker? Have you worked in different banks?
- Have your approach to DM changed with experience

Do you use data as a fact for making your decisions?

- If so why, if not why?
- How comfortable or at ease are you in making decisions by analyzing and interpreting a graph or table of data provided by the system?

- What is your opinion on the data visualization such as interpretation of graphs and charts?

Do bank's system and your team provide you forecast and reports to easy your decision making?

- How could your current system provide you meaningful data to make your decision easier and a concrete decision?

What should/could improve to enhance the quality of decision making & reaching KPIs?

Interview Questions for CTO/ CIO or Head of IT

Could you please explain your role?

- Focus on day to day activities & responsibilities

Could you please explain those roles & activities ones that involve the use of reports, graphs, data, as well as experience and even intuition?

- Try to identify where they are using data as well as could use data
- What is your most preferred method of making the decisions?
- If so how often you use data in decision making

What sort of a role your education play in use, analysis, and decision making based on reports, graphs, data, etc. (especially for your best achievements)

- Focus should be on educational background, any professional qualifications related to banking, what are the locations worked.

What sort of a role team's experience with the bank play in use, analysis, and decision making based on reports, graphs, data, etc.

- Years of experience, years of service in the banking industry, year of experience in the current position, did you start your carrier as a banker? Have you worked in different banks?

Does your company use data as a fact for making decisions?

- If so why, if not why?
- What seems to be more common?
- Is there a specific process of decision making which involves data and reports?
- How comfortable or at ease is your team in making decisions by analyzing and interpreting a graph or table of data provided by the system?
- What is your opinion on the data visualization such as interpretation of graphs and charts?

How much of your team's gut feeling or intuition with experience seems to be involved in making decisions?

- Have you come across any situations even though analytics and reports are provided still the managers make a decision based on their intuition/gut feeling? Any specific reasons for this?

What level of risk is the bank consider as acceptable when making decisions to achieve the target or set KPI's?

Do bank's system and your team provide forecast and reports to easy team's decision making?

- How could your current system provide you meaningful data to make your decision easier and a concrete decision?
- What is your opinion on the enforcing data-driven decision making in the bank?

What should/could improve to enhance the quality of decision making of your team & reaching KPIs?

- Training
- Analytics and BI tools in your bank
- Competitions

What is the most common decision-making approach used in the bank is it data-driven or intuition-based decision making of the manager?

APPENDIX B: QUESTIONNAIRE INSTRUMENT – REVISED

Interview question for regional manager/ branch managers

Could you please explain your role?

- Focus on day to day activities & responsibilities

Could you please explain those roles & activities ones that involve the use of reports, graphs, data, as well as experience and even intuition?

- Try to identify where they are using data as well as could use data
- What is your most preferred method of making the decisions?
- If so how often you use data in decision making

Could you please explain your biggest achievements in your current role?

- Any what you're your awareness about data and/or experience contributed to such success?

What sort of a role your education play in use, analysis, and decision making based on reports, graphs, data, etc. (especially for your best achievements)

- Focus should be on educational background, any professional qualifications related to banking, what are the locations worked.

What sort of a role your experience with the bank play in use, analysis, and decision making based on reports, graphs, data, etc.

- Years of experience, years of service in the banking industry, year of experience in the current position, did you start your carrier as a banker? Have you worked in different banks?
- Have your approach to DM changed with experience

Do you use data as a fact for making your decisions?

- If so why, if not why?
- How comfortable or at ease are you in making decisions by analyzing and interpreting a graph or table of data provided by the system?

- What is your opinion on the data visualization such as interpretation of graphs and charts?

Do bank's system and your team provide you forecast and reports to ease your decision making?

- How could your current system provide you meaningful data to make your decision easier and a concrete decision?

What should/could improve to enhance the quality of decision making & reaching KPIs?

How much of your gut feeling or intuition with experience is involved in making the decisions?

What level of risk are you willing to take when making decisions to achieve the target or set KPI's?

APPENDIX C: SELECTION OF FACTORS

0 - Not Applicable 1 - Disagree **2** - Neutral 3 – Agree

The equation used to calculate the percentage is as follows:

Total Percentage = (*No of agreed or neutral organization* / *Total no of organizations*) × 100

The percentage value above 50 is only considered as factors for the study analysis.

Factors	Decision makers from the selected six banks in Sri Lanka																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	%
Personal characteristics of DMs																			
Need for achievement	3	3	3	2	1	3	2	3	1	3	2	3	3	2	3	3	3	3	89
Risk taking attitude	3	2	2	1	3	2	2	1	2	3	2	1	3	1	3	1	1	3	67
Cognitive style	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	100
Moral and individual perception	3	3	1	3	1	3	1	3	1	3	1	3	3	1	3	1	1	3	56
Willingness to change	1	2	1	1	3	2	2	3	3	2	3	2	3	2	3	1	1	1	67
Individual culture	1	1	1	1	1	1	1	3	3	2	3	3	3	1	0	3	0	0	39
DMs competencies to practice DDDM																			
Years of experience	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	100
Competition	1	1	2	3	0	2	0	3	2	2	0	1	1	0	3	3	0	0	44
Creation of networks	2	1	0	1	0	1	1	1	3	0	1	0	0	3	0	3	0	3	28
Perception of DM on DDDM	3	3	3	3	2	3	2	2	3	3	2	3	2	3	3	3	3	3	100
Trust on DDDM	3	3	3	3	2	3	2	3	3	2	2	2	3	3	3	3	3	1	94
Expectation on customized reports	3	3	0	3	0	3	0	3	3	0	3	3	3	2	0	0	3	2	67
DMs Socio - Demographic characteristics																			
Age	0	0	1	0	0	1	1	2	2	1	1	2	0	0	0	2	3	3	33
Gender	0	0	1	2	3	3	3	3	0	1	2	0	1	2	1	0	1	2	44
Academic qualification	3	3	2	0	2	3	1	3	3	2	3	3	3	3	3	3	3	3	89
Professional qualification	3	2	2	1	3	0	2	3	2	1	1	3	2	3	0	2	2	1	67
Different working environment	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	100
exposure on working in Different banks	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	100
DMs Data literacy characteristics																			
Data knowledge	2	2	2	1	2	3	2	3	2	3	3	2	3	2	2	3	3	2	94
Data assimilation	0	0	1	3	3	2	2	3	3	3	2	3	2	3	2	3	3	3	83
Data interpretation	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	100
Data skepticism and curiosity	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	100
External factors influencing DMs DDDM																			
Organizational behavior	0	0	0	2	1	3	1	3	3	0	0	1	0	1	2	2	0	0	33
data availability	2	1	1	2	2	0	1	2	2	1	0	1	1	2	2	1	1	1	39
organization culture	2	1	0	0	0	2	1	1	0	0	1	2	2	1	0	0	1	2	28

APPENDIX D: MEMO – SUPPORTIVE STATEMENTS FOR KEY FINDINGS

DMs competencies

A relationship between experience and intuition-based decision-making is being discovered as an insight. While a decision maker's experience grows they intend to make decisions based on the intuition by overruling the DDDM process in the bank. However, the most interesting finding is many managers' needs to make sure that the intuition-based decision will be supported and explained using data or required data to defend the intuition-based decision when decisions fail.

Interviewees had a positive impression on DDDM approach, however intuition has overruled the DDDM approach due to factors such as, uncertainty, lack of trust in the system reports and dashboards, lack of knowledge in system reports and not willing to change the decision-making style hence DM's are not willing to make decisions beyond the comfort zone

DMs socio-demographic characteristics

Knowledge and exposure in banking domain have a significant influence in DDDM approach whereas with the vast knowledge and exposure the decision maker pretend to make more intuition-based decisions rather than DDDM approach. Moreover, the opinion of many DM's is the geographical location is key for choosing the decision-making approach, nevertheless achieving KPI's out of the commercial capital is challenging.

Academic, professional and domain-specific qualifications have a significant impact on a DM's approach in decision making, a decision maker with an SMTE background are more influenced from their educational background to move towards DDDM rather than intuition-based decision making

DMs Personal characteristics

DM's cognitive style is a major factor on influencing a decision maker to adopt or practice DDDM, according to the analysis DM's are unable to move from a specific cognitive style to a different cognitive style. Gut feeling based decision making, influenced by the senior management, a unique blend of DDDM and intuition-based decision making. As per the analysis younger managers can be influenced more to change the cognitive style hence the younger DM's requires more knowledge and support from data or higher management to make successful decisions.

The uncertainty of DM's, due to lack of trust on DDDM intuition-based decision making overrules and lack of experience and knowledge in DDDM. Banks should focus on these dimensions to enforce DDDM on decision makers.

DMs Data literacy

DM's understand the data banking perspective; however, as per the interview data analysis, it is defined most of the DM's doesn't have a clear idea or a knowledge on the data available in the bank which is a major drawback in enforcing DDDM to bank's strategic and operational decision making.

Many banks encourage the DM's to gain banking domain related knowledge by doing professional banking related qualifications. CTO/ CIO or Head of IT's opinion is to conduct training and hands-on training sessions to transfer the data knowledge to breach the gap of data knowledge of the DM's.

DM's are not comfortable with the data and the reports presented to the DM's for decision making which lead them to request for customized reports. As per the discussions with the CTO/ CIO or the Head of IT's most of the change or system upgrade request they receive from the DMs are related to customizing the reports or creating a new report even though the existing reports can provide the required information.

Lack of quality in data visualization is another major finding from the data analysis which requires a consideration from the IT departments. Many DMs complain about the quality of the visualization as an example, DMs need to clearly identify the interest rate fluctuation however due to the unclear visualization from the BI tools has dissatisfied the DMs.

Skepticism and curiosity have identified as the major factor for resistance by the DMs in adopting and practicing DDDM. The major underlying reasons for skepticism and curiosity are credibility and truthfulness. During the analysis almost all the interviewees' highlighted that credibility and truthfulness of the data, reports, and dashboards is a major concern when DDDM is enforced for decision making.