UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

THE ROLE OF MOTIVATION IN REGULATING THE EXTENT TO WHICH DATA VISUALISATION LITERACY INFLUENCES BUSINESS INTELLIGENCE AND ANALYTICS USE IN ORGANISATIONS

by
Boithatelo Josephine Malibeng
u19149982

Submitted in partial fulfilment of the requirements for the degree
M Com

in the

FACULTY OF ECONOMIC AND MANAGEMENT SCIENCES

at the

UNIVERSITY OF PRETORIA

Study leader:
Prof. Mariè Hattingh

Date of submission
16/11/2022

Declaration regarding Plagiarism

The Department of Informatics emphasises integrity and ethical behaviour with regard to the preparation of all written assignments.

Although the lecturer will provide you with information regarding reference techniques, as well as ways to avoid plagiarism, you also have a responsibility to fulfil in this regard. Should you at any time feel unsure about the requirements, you must consult the lecturer concerned before submitting an assignment.

You are guilty of plagiarism when you extract information from a book, article, web page or any other information source without acknowledging the source and pretend that it is your own work. This doesn't only apply to cases where you quote verbatim, but also when you present someone else's work in a somewhat amended (paraphrased) format or when you use someone else's arguments or ideas without the necessary acknowledgement. You are also guilty of plagiarism if you copy and paste information directly from an electronic source (e.g., a web site, e-mail message, electronic journal article, or CD ROM), even if you acknowledge the source.

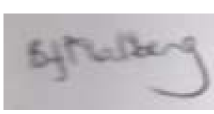
You are not allowed to submit another student's previous work as your own. You are furthermore not allowed to let anyone copy or use your work with the intention of presenting it as his/her own.

Students who are guilty of plagiarism will forfeit all credits for the work concerned. In addition, the matter will be referred to the Committee for Discipline (Students) for a ruling. Plagiarism is considered a serious violation of the University's regulations and may lead to your suspension from the University. The University's policy regarding plagiarism is available on the Internet at *http://upetd.up.ac.za/authors/create/plagiarism/students.htm*.

I (full names & surname):	Boithatelo Josephine Malibeng
Student number:	u19149982

Declare the following:

1. I understand what plagiarism entails and am aware of the University's policy in this regard.
2. I declare that this assignment is my own, original work. Where someone else's work was used (whether from a printed source, the Internet or any other source) due acknowledgement was given and reference was made according to departmental requirements.
3. I did not copy and paste any information directly from an electronic source (e.g., a web page, electronic journal article or CD ROM) into this document.
4. I did not make use of another student's previous work and submitted it as my own.
5. I did not allow and will not allow anyone to copy my work with the intention of presenting it as his/her own work.



Signature

16/11/2022
Date

ACKNOWLEDGEMENTS

This is a bittersweet moment as I write this message to close this chapter of my 2 years journey. First and foremost, thanks and praises to God almighty for all the blessings throughout my research journey and for making all these possible.

I would like to express my sincere gratitude to my research supervisor Prof Marie Hattingh for her continuous support and invaluable guidance throughout this research. I feel privileged to have worked under your guidance, you made this journey doable. Special thanks to Andries Masenge for your tremendous support in crunching that data, I really feel like a real statistician. I would not have completed this research without all the respondents who contributed to this research, many special thanks.

A big special thanks to my great friends OB, Cathy, Makoti, and Phumlani for taking a huge initiative in making sure my survey gets distributed, friends like these are really rare, thank you! thank you! A very special thanks to ALL my friends and family for their unwavering support throughout this journey. Many thanks to my mom for all her prayers, this is all possible because of your continuous prayers. This is a special dedication to my nephews and niece (MJ, Amo, and Khaly), my cheerleaders, make sure you go to school 😊.

TABLE OF CONTENTS

APPENDICES

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

GLOSSARY OF TERMS

Abbreviation/ Acronym	Term
BA	Business Analytics
BDA	Big Data Analytics
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
BI-aa-S	Business Intelligence as a Service

BIS	Business Intelligence Systems
CB-SEM	Covariance Based Structural Equation Modelling
CET	Cognitive Evaluation Theory
CFI	Comparative Fit Index
CFA	Confirmatory Factor Analysis
DD	Data Democratisation
DV	Dashboard and Visualisation
DVL	Data Visualisation Literacy
IDT	Innovation Diffusion Theory
IT	Information Technology
ITSE	IT Self-Efficacy
IS	Information Systems
IwIT	innovation with IT
KR-20	Kuder Richardson
LSp	Literacy Score Percentage
MPCU	The Model of PC usage
MM	Motivation Model
PE	Perceived Enjoyment
PIIT	Personal Innovativeness in IT
PLS-SEM	Partial Least Squares-Structural Equation Modelling
PU	Perceived Usefulness
QAR	Query Analysis Reporting
OLAP	Online Analytical Processing
RMSEA	Root Mean Square Error of Approximation
SCT	Social Cognitive Theory
SDT	Self-Determination Theory
SEM	Structural Equation Modelling
SRMR	Standardised Root Mean Square Residual
SSBI	Self Service Business Intelligence
TAM	Technology Acceptance Model
TLI	Tucker-Lewis Index
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action

TOE	Technology Organisation Environment Framework
UTAUT	Unified Theory of Acceptance and Use of Technology
VLAT	Visualisation Literacy Assessment Test

THE ROLE OF MOTIVATION IN REGULATING THE EXTENT TO WHICH DATA VISUALISATION LITERACY INFLUENCES BUSINESS INTELLIGENCE AND ANALYTICS USE IN ORGANISATIONS

ABSTRACT

The ability to read and interpret visualised data is a critical skill to have in this information age where business intelligence and analytics (BI&A) systems are increasingly used to support decision-making. Data visualisation literacy is seen as the foundation of analytics. Moreover, there is great hype about data-driven analytical culture and data democratisation, where users are encouraged to have wide access to data and fully use BI&A to reap the benefits. Motivation is a stimulant to the richer use of any information system (IS), yet literature provides a limited understanding of the evaluation of data visualisation literacy and the effect of motivation in the BI&A context. Thus, this study aims to explain the role of motivation in regulating the extent to which data visualisation literacy influences BI&A's exploitative and explorative use in organisations. Data visualisation literacy is measured using six data visualisations that focus on the five cognitive basic intelligent analytical tasks that assess the user's ability to read and interpret visualised data. Two types of motivations are assessed using perceived enjoyment as an intrinsic motivator and perceived usefulness as an extrinsic motivator. The model is tested using quantitative data collected from 111 users, applying Structural Equation Modelling (SEM). The results indicate that intrinsic motivation exerts a positive effect on BI&A exploitative and explorative use while extrinsic motivation has a positive effect on BI&A exploitative use but weakens innovation with a negative effect on explorative use. The results further show an indirect relationship between data visualisation literacy with BI&A use

through motivation. In addition, exploitation leads to creativity with exploitation positively being associated with exploration.

Keywords: Data visualisation literacy, Business intelligence and analytics, Exploitative use, Explorative use, Intrinsic motivation, Perceived enjoyment, Extrinsic motivation, Perceived usefulness

Chapter 1

INTRODUCTION AND BACKGROUND TO STUDY

1.1 BACKGROUND INFORMATION

The ever-increasing volumes of digital data from internal transactional systems and external sources have changed the art of decision-making and problem-solving in organisations. Decisions and actions are supported by data (data acts as evidence); this has resulted in organisations investing in Business Intelligence and Analytical (BI&A) tools to visualise data and generate insights for the creation of innovations (products, services and procedures) and sharing of knowledge for quality business decisions (Awan *et al.,* 2021; Božič & Dimovski, 2019b; Ghasemaghaei *et al*., 2018; Olszak, 2016). BI&A refers to technologies and processes that enable the collection of data from heterogeneous sources, the transformation of data into information and the analysis of information into knowledge to support user data-driven strategic, tactical and operational decisions (Donohoe & Costello, 2020; Işık *et al.*, 2013; Kiani Mavi & Standing, 2018). Business intelligence provides end-users with easy access to organisational data, allowing them to quickly extract valuable insights and discover complex patterns through data visualisation (Božič & Dimovski, 2019b; Kiani Mavi & Standing, 2018; Ruhode & Mansell, 2019). Visualisation enables the use of the human visual system to extract information from data or to determine if further exploration is necessary (Tegarden, 1999). Data visualisation simplifies the analysis and exploration of large datasets as it can elucidate patterns that are typically obscured and reduce cognitive overload, as a result, users make better decisions (George *et al.,* 2020; Loos *et al.*, 2019; Moore, 2017).

Users are the primary enablers in the Business Intelligence (BI) value chain because they are responsible for translating insights into meaningful actions that improve organisational efficiency and effectiveness while also assisting an organisation in gaining a competitive advantage (Ghasemaghaei *et al.*, 2018). For an organisation to realise its return on information technology investment, users need to use the deployed information system (Rezvani *et al.*, 2017). Users can use the BI &A systems in a standardised routine way to complete work-related tasks or apply the system innovatively to support their tasks (Božič & Dimovski, 2019b; Li *et al.*, 2013). For data from BI&A platforms to be transformed into useful information and finally into actionable intelligent knowledge, human interpretation of data has to happen. This requires data visual literate individuals as the majority of data in BI&A platforms is visualised (Frank *et al*., 2016; Pangrazio & Sefton-Green, 2020; van Geel *et al*., 2017). Moreover, analytics and big data analysis are seen as the next frontier in the information revolution by organisations, and there is a growing demand for the right skills to make sense of data (Namvar et al., 2021). Data visualisation literacy is important as more individuals are using data to support their communications, and decision-making (Lee *et al.,* 2019). Data visualisation literacy is defined as the ability to read, identify patterns, interpret and understand the meaning of graphically represented data to obtain information (Börner *et al*., 2019; Lee *et al.,* 2016; Loos *et al*., 2019). The person reading visualised data needs to have skills which will affect how they read data visualisation (Donohoe & Costello, 2020). Data that is understood and is in a familiar format may deem to be more accessible and usable than more powerful data that is in a less familiar format (Frank *et al.,* 2016).

Data visualisation literacy will be the most sought-out skill of the 21st century and data visualisation will be blooming as organisations, countries and people fully take advantage of their data, as they believe data literacy unlocks the value of open data and leads to economic growth (Gray *et al*., 2018; Loos *et al*., 2019; McDowall *et al.,* 2020). The benefit of improved decision-making provided by BI&A tools may be hindered if users don’t have the necessary skills needed to read and interpret the data, thus, data visualisation literacy may be viewed as the foundation of analytics that promotes data use (Ghasemaghaei *et al.*, 2018; Loos *et al*., 2019; McDowall *et al.,* 2020). Data literacy cultivates people's data awareness which leads to data as an information resource being effectively used (Gray *et al.*, 2018). Motivation can be seen as a stimulant that promotes different forms of data use by data visualisation-literate users in organisations (Gray *et al.,* 2018; Li *et al*., 2013). Lack of motivation may result in resistance to use an Information System (IS) or discontinued use of the IS even though the users have the necessary skills (Rezvani *et al.,* 2017). Users will be motivated to use their skills if they believe their skills will lead to good performance and rewards. Rewards can be intrinsic or extrinsic (Chang *et al.,* 2015). To maximise the business value of analytics, organisations need a workforce that is motivated and can use, analyse, and communicate using data when managing business operations. Literacy and motivation play an integral part in the use of any information system (Mudzana & Maharaj, 2015; Rezvani et al., 2017).

1.2 PROBLEM STATEMENT

Despite the growth in the Business Intelligence (BI) market and the business value it brings to the decision-making in organisations, numerous organisations fail to realise BI&A's full potential due to ineffective and low extended use (Ain *et al*., 2019; Lautenbach *et al.*, 2017). More than 50% of BI projects fail (Ain *et al.*, 2019; Lautenbach *et al.,* 2017). Individual challenges highlighted to contribute to failure include (i) suboptimal BIS usage, (ii) lack of data analysis skills, (iii) lack of understanding of how to use the available data and act on the discovered insight, and these challenges are linked to literacy (Ain *et al*., 2019; Boyton *et al*., 2015). Also, Ghasemaghaei *et al*. (2018) argue that the high failure rate could be because the majority of organisations prioritise the technical data aspect of BI (e.g. data extraction and quality). The necessary human factors needed to generate insights are neglected. Adequate competencies needed for the appropriate use of data is another investment organisations need to consider (Klee *et al.,* 2021; Perdana *et al.*, 2022)

Moreover, the introduction of self-service BI, real-time, interactive data visualisation, and the current shift from reporting-centric BI to a more analytic-centric BI impel a need to focus on user data visualisation literacy, as there are more opportunities for data misrepresentations and misinterpretations for visually presented data, which can affect the quality of data-driven products and services (Günther *et al*., 2017; Sutherland & Ridgway, 2017; Torres *et al.*, 2018). Lennerholt *et al.* (2020), emphasised the importance of educating BI users on how to use self-service BI as well as interpret and analyse data for decision-making. Users now have to be data-aware as they no longer rely on analysts to share the knowledge of what the data means. Besides, data has become an organisation's economic asset and the users' ability to leverage value from the use of BI&A has become a differentiating factor of top-performing organisations as it enables fast identification of threats or opportunities and guides future strategies and daily operations (Ghasemaghaei *et al*., 2018; Sharma *et al.,* 2014). Moreover, knowing how to analyse and communicate with data has become an important competency in society (D'Ignazio, 2017; Perdana *et al.*, 2022). When designing BI&A tools it is important to evaluate users' ability to read graphs and charts to improve the effectiveness of these tools (Boy *et al*., 2014). If the user finds it difficult to comprehend the information presented to them, they will have to spend more time trying to analyse and interpret the information (Lennerholt *et al*., 2020). Thus, the benefit of time-saving provided by BI will be nullified. Although effective BI&A use is a major challenge in the implementation of BI, human competencies have been significantly overlooked in BI&A use studies (Ain *et al.*, 2019; Ruhode & Mansell, 2019).

More focus in the literature has been given to the technological and organisational aspects of BI, and the factors influencing BI&A use have mainly been studied from an organisational context (Ain *et al*., 2019; Božič & Dimovski, 2019b; Işık *et al*., 2013; Lautenbach *et al.*, 2017; Torres *et al*., 2018). BI end-users are an important accessory in operationalising BI in organisations, and knowing the individual factors that influence BI&A usage contributes to the effective deployment of IT resources (Peters *et al*., 2016; Ruhode & Mansell, 2019). People skills are a crucial component that must be considered while developing a complete BI strategy (Brooks *et al.,* 2015). Data visualisation literacy skills must be measured to understand the organisational capability and realise the limitations to developing the individual ability to use the information for decision-making (Donohoe & Costello, 2020). The value of an Information system relies on the people using it, and it is people who make BI&A work in organisations (Ruhode & Mansell, 2019; Seddon *et al.*, 2017). Regardless of how good the IT is, if the people are not motivated to use the system and have insufficient knowledge regarding the use of the system efficiently, organisations are unlikely to reap benefits from their investment (Seddon *et al*., 2017). It is common for demotivated users to discontinue the use of IT systems and revert to using shadow systems (unauthorised systems) (Rezvani *et al.,* 2017). Organisations need to find ways to encourage the use of BI&A systems. Additionally, there is growth for data-supported actions as more data is being generated (Akhtar *et al.,* 2019; McDowall *et al.,* 2020), and there is a need to investigate individual factors that motivate richer forms of BI use.

1.3 RESEARCH QUESTIONS

The primary research questions the study seeks to address are:

- What is the influence of data visualisation literacy on business intelligence and analytics use in organisations?
- What is the role of motivation in regulating the extent to which data visualisation literacy influences business intelligence and analytics use in organisations?

Secondary-question:

- Which type of motivation has the most positive impact on regulating the relationship between data visualisation literacy and BI&A use?

1.4 RESEARCH OBJECTIVES

The primary research objectives of the study are :

- To investigate the influence of data visualisation literacy on business intelligence and analytics use in organisations, where user literacy has been overlooked in the implementation of BI&A in organisations yet data visualisation literacy is the foundation of analytics.
- To investigate the influence that motivation and data visualisation literacy have on business intelligence and analytics use in organisations. Motivation is relatively understudied in the BI&A context and there is a need to comprehensively look at internal or external factors that can stimulate various forms of BI&A use.

Secondary-Objectives:

- To examine which type of motivation has the most positive impact in regulating the relationship between data visualisation literacy and BI&A use.

1.5 PURPOSE OF THE STUDY

The main purpose of this study is to develop and validate an empirical model to explain the effects of extrinsic and intrinsic motivation in regulating the influence of data visualisation literacy on BI&A use while making a distinction between exploitative and explorative BI&A use. This will aid in a better understanding of user BI usage behaviours patterns focusing on the role of motivation and data visualisation literacy. It also serves to understand the effects of intrinsic and extrinsic motivations in promoting BI&A usage. Motivation has been highlighted to be an important stimulant of IS use.

1.6 CONTRIBUTION

The study expands the current knowledge in BI&A by introducing motivation in the BI context to confirm or challenge the role it plays in BI&A use. Two types of use are distinguished in the BI&A context. The study further provides several contributions for both academic scholars and practitioners. Scholars who are interested in individual-level business intelligence and analytics competencies can be interested in this paper. Academics interested in IS user usage behaviours and IS success can benefit from this paper since the system use construct is widely used in evaluating IS adoption success. The results obtained may be useful for theorists, as well as for managers, business analysts and IT specialists, in dealing with the planning and implementation of BI systems in different organisations and to determine individual factors they need to be aware of for a successful implementation. In addition, It gives managers insight into how they can use intrinsic and extrinsic motivation to encourage employees to use information technology. It can act as a guide used by BI developers in determining the level of their user data visualisation literacy, resulting in BI developers developing fun, interactive, easy-to-use dashboards or data visuals that cater to the level of their user data visualisation literacy. It can also assist in the development of data visualisation literacy resources for education.

1.7 ASSUMPTIONS

The participants of this study belong to organisations that have implemented BI and are users of BI platforms or have used BI platforms. Users for this study belong to various management levels in the organisations, this was based on the fact that BI can be used to support strategic, tactical and operational decisions. There is an assumption that organisations have readily available quality data, as data is the prerequisite of analytics, one cannot be analytical without data (Seddon *et al.*, 2017). Decision-makers can cast aside potential insights if they are produced from questionable data (Torres & Sidorova, 2019). It is assumed that organisation BI maturity doesn't influence how users feel about BI&A.

1.8 DELINEATIONS AND LIMITATIONS

Finding a sufficient targeted sample size might be challenging as it entails the researcher finding organisations that have implemented BI and there is no public database for that. To improve sample size, a snowball sampling technique will be used which entails the recruitment of subsequent respondents by the initial seed respondents (Saunders *et al.*, 2012). The study doesn't consider the BI maturity level of the organisations to which the users belong, and the organisation's BI maturity level might influence the way users use BI. The increased BI maturity results in greater extended use of BI&A by individuals in the organisation (Lautenbach *et al*., 2017).

1.9 BRIEF CHAPTER OVERVIEW

Chapter 1 provided the background, problem statement, research purpose and assumptions of the proposed study. The remainder of the thesis paper is structured as follows:

Chapter 2 covers a literature review related to data visualisation literacy, BI&A use and motivation. Data literacy will be broadly discussed and this will lead to narrowing down to data visualisation literacy. IS use in organisations will be discussed and then narrow down to BI&A use in the organisation.

Chapter 3 motivation and use behaviours will be discussed leading to the formulation of hypotheses and proposed conceptual model.

Chapter 4 delivers the research design to address the research question outlining the research approach, research philosophy, research strategy, research instrument, data collection, and any ethical considerations.

Chapter 5 covers data analysis which consists of the demographical profile of respondents, data visualisation literacy analysis and hypotheses testing, statistical results of the sampled data, and a summary of the key findings of the study.

Chapter 6 concludes with a discussion of the practical implications of the study, research limitations and recommendations for future research.

Chapter 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter reviews the related works on business intelligence and analytics, analytics use, motivation and literacy. Business intelligence and analytics will be defined and facilitators of BI&A in organisations elaborated. Data literacy and data visualisation literacy, and the initiatives that promote literacy will be discussed.

2.2 BUSINESS INTELLIGENCE

The ultimate goal of BI is to transform raw data from heterogeneous sources into information, and information into knowledge to support timely data-driven decision-making in organisations (Shollo & Galliers, 2016). BI integrates historical and current data across different data sources, stores it in an atomic warehouse and provides a platform to easily access information and reveal insights (Kiani Mavi & Standing, 2018). Data sources could be a mix of internal data sources, data from competitors, customers, and the macroeconomic environment (Sparks & McCann, 2015). Thus, Işık *et al.* (2013) argued that interoperability and integration of BI with other systems, appropriate user access to BI, and the flexibility of BI are factors that positively contribute to the success of BI in organisations. Implementation of BIS contributes to faster access to information, easier querying of data, and interactive analysis (Larson & Chang, 2016). BI allows users to drill up, down and through data, allowing for cross-analysis or detailed analysis of data, thereby, stimulating discussions on the given analysis. This debate results in a better understanding of the organisational market or a problem (Shollo & Galliers, 2016). BI balances subjectivity and objectivity by using data to support subjective insights and tactic knowledge or arguments (Kiani Mavi & Standing, 2018).

Proactive BI processes include real-time data warehousing, automatic detection of anomalies and exceptions, automated alerts, automatic learning of data patterns and seamless refinement of business processes (Weng et al., 2016). Traditionally BI relied massively on relational or multidimensional structured and numerical structured data collected from internal legacy systems, but this has changed with advancements in technology (Lennerholt *et al*., 2020). Traditional BI involves BI developers serving users for their reporting needs, but modern BI changed all that by introducing various capabilities such as mobile BI, self-service BI, automated updates and exception reports (Işık *et al.*, 2013; Lennerholt *et al.,* 2020). The introduction of web technology and virtual worlds, as well as new data sources such as social media, sensory data, open data, and online groups, has resulted in BI technological advancement (Günther *et al.,* 2017). Also, more tools are available for text and data mining unstructured data (Günther *et al*., 2017; Işık *et al.,* 2013; Lennerholt *et al*., 2020). This evolution of BI resulted in various ways of defining BI. Some authors refer to BI as technology, management process, service, product, or a combination of all the prior mentioned approaches (Lennerholt *et al.,* 2020; Sharma *et al.,* 2014; Shollo & Galliers, 2016; Torres *et al.,* 2018; Weng *et al.,* 2016).

2.2.1 Technological Approach to BI

The Technology approach refers to the set of tools, technologies and software products that enable data extraction, transformation, storage and analysis of information to improve decision-making (Ghazanfari *et al.*, 2011; Weng *et al.,* 2016). BI process driven by technologies consists of three layers, namely data collection and storage, data processing, data analysis and reporting (Weng *et al.,* 2016). Primarily, BI technologies encompass software solutions made available via the use of hardware technologies and the platform that facilitates data flow (George *et al.,* 2020). There are two subsets of BI&A tools, namely data management and data analytics. Data management tools refer to tools used for data acquisition, recording, storage, extraction, cleaning, integration, aggregation and management of structured and unstructured data. Data analytics tools refer to tools that support data transformation and analysis, visualisation, interpretation and predictive analysis (George *et al.,* 2020). The most prevalent BI technologies include data warehouses or data lakes, Online Analytical Processing (OLAP), Extract-Transformation-Load (ETL) tools, balanced scorecards, statistical tools, analytic and reporting tools, machine learning tools and dashboards (George *et al*., 2020; Olszak, 2016; Weng *et al.,* 2016). These technologies are anchors in the provision of other forms of BI.

2.2.2 Managerial Process Approach to BI

The management process BI approach involves a process of collecting, integrating and analysis of data from a variety of sources to generate intelligent knowledge to reveal strategic insights for management decision-making (Sangari & Razmi, 2015; Weng *et al.,* 2016). BI is seen as a management philosophy or a trigger that supports management strategic activities such as organisational transformation in the areas of change management, customer relationship management, business continuity and the introduction of new business models (Olszak, 2016; Sangari & Razmi, 2015).

2.2.3 BI-as-a-Product

BI-as-a-product refers to the relevant information and knowledge gained from the collected data about the business environment, industry trends and economic issues (Ghazanfari *et al.,* 2011; Sangari & Razmi, 2015). BI-as-a-product is a transformed output of the core BI&A system in the forms of daily, monthly and yearly reports, dashboards and alerts intended for decision-making (George *et al.*, 2020). Based on the frequency and granularity of data, BI-as-a-product is further classified into strategic, tactical and operational BI. Strategic BI consists of highly aggregated data developed for executives to support long-term goals and monitoring of organisations' objectives. Tactical BI is created for business and data analysts whose daily job is to analyse data for short-term business decisions. Operational BI consists of detailed reports designed for functional units to respond faster to operational events and optimise ongoing business processes (Ahmad *et al.,* 2016; Mudzana & Maharaj, 2017). The use of BI-as-a-product is influenced by intra- and inter-organisational cultural components like analytical decision-making culture, beliefs, values, norms, and practices (Popovič *et al.*, 2012; Sangari & Razmi, 2015).

2.2.4 BI-as-a-Service

BI-as-a-service (BI-aa-S) is a cloud-based application that delivers business analytics for data analysis, including visual displays of the results with minimal software and hardware cost, due to the on-demand access to software and hardware resources (Chang, 2014; Olszak, 2016). The benefits of cloud-based service delivery of IS include reduced costs, easy scalability, flexibility, organisational agility, fast adaptation to market changes and accelerated speed to access the markets (Camargo-Perez *et al.,* 2019; Olszak, 2016). Small and middle-sized organisations can take advantage of BI-aa-S and implement BI at a low cost. BI-aa-S is portable, resulting in advancing mobile BI use. Mobile BI delivers BI&A through mobile devices such as smartphones and tablets to promote self-service BI (Peters *et al.*, 2016).

2.2.5 Self-service BI (SSBI)

The massive dynamic business data that is currently being generated requires more end-users to use BI, which leads to high requests for reports to BI developers. To alleviate BI developers on this bottleneck, organisations are investing more in self-service BI to provide fast, easy-to-access reports (Lennerholt *et al*., 2020). The main objective of SSBI is to enable end-users to proactively analyse their multifaceted data without involving BI developers, eliminating the risk of guessing or using obsolete data during the decision-making process (Alpar & Schulz, 2016; Lennerholt *et al*., 2020). The interactive models available in SSBI enable users to build dynamic reports with ease, and users can seamlessly switch through data sources without noticing (Alpar & Schulz, 2016). Once data has been collected there is need to transform it into knowledge through analytics.

2.3 BUSINESS ANALYTICS

Business Analytics (BA) is an element of BI that deals with data processing centred around applying analytical techniques to turn information into intelligent knowledge to improve business decision-making and sharing of insights about the market and competition (Božič & Dimovski, 2019b; Torres *et al*., 2018). Analytics is an application of mathematical and statistical techniques to data to perform analytical tasks (Lautenbach *et al.,* 2017). Analytical tasks include deriving trends, historical and current comparison of data and prediction of future events that provide economic and societal benefit by facilitating better decision-making and more informed planning (Lee *et al*., 2019; Namvar *et al*., 2021). In today's dynamic and uncertain market, the application of analytics assists organisations in solving business challenges and improving operational processes (Namvar *et al.,* 2021). Business analytics entails users leveraging data to support business activities, the organisation's strategic and tactical goals, and informed decision outcomes for organisations to gain a competitive advantage or performance improvement (Ahmad *et al.*, 2016). Business analytics technologies enable organisations to exploit big data to produce innovative insights for product and service development (Günther *et al*., 2017).

Visual analytics of descriptive data is still a popular type of analytics, but predictive and prescriptive analytics is on the rise with the introduction of big data and machine learning (Awan *et al.,* 2021; Larson & Chang, 2016). Analytics is considered a foundation of innovative products, services, refinement and optimisation of business operations and business opportunities (Günther *et al.,* 2017). BA has recently been extended to Big-Data Analytics (BDA), as data volume, variety, and velocity have changed (Akhtar et al., 2019; Camargo-Perez *et al.*, 2019). Strong BDA capabilities are a result of flexible infrastructure, proper management of data analytics capabilities and personnel expertise (Awan *et al.,* 2021). Organisational BDA capabilities enhance data-driven insights (Awan *et al.,* 2021). The usefulness of BA lies in its output (i.e. insights), which varies based on the granularity and richness of the data. Insights mean one gains a deeper understanding of something through the use of BI capabilities (Seddon *et al.,* 2017). Analytics assists users by supplying information on decision-making scenarios; this information, together with human perception, assists users in a better understanding of their business environment (Namvar *et al*., 2021).

There are two approaches to using analytics and studying data in organisations: inductive and deductive (Namvar *et al*., 2021). In the inductive technique, data analysts encourage a bottom-up strategy to pursue business possibilities by creating insights without any specified business understanding or problem (Namvar *et al*., 2021). The inductive technique can lead to new insights when previously unrecognised patterns are identified, allowing an organisation to be proactive (Günther *et al*., 2017). The deductive strategy is more of a reactive approach; there is a business problem that data analysts seek to solve using data (Namvar *et al.*, 2021). The deductive technique is more frequent than the inductive opportunity-oriented approach, yet these two approaches are interconnected and should complement one another (Günther *et al*., 2017). The level of leeway given to analysts and the attitude of those analysing data affect the degree to which inductive and deductive techniques are balanced (Günther *et al.,* 2017; Sharma *et al.,* 2014).

2.4 BUSINESS INTELLIGENCE AND ANALYTICS

BI&A involves technologies, techniques, applications, methods and processes that analyse organisational data to help an organisation better understand its operations, and environment, as well as aid in timely quality business decisions (Kiani Mavi & Standing, 2018; Shollo & Galliers, 2016; Torres *et al*., 2018). Quality decision-making refers to the ability to make correct decisions as a result of valuable insights generated from various data sources (Awan *et al.,* 2021). Quality decisions lead to the improvement of business processes and the identification of business opportunities (Awan *et al*., 2021; Olszak, 2016). Primarily investment in BI&A was to support decision-making in organisations, but in recent years BI&A has been considered to support organisational learning, agility, improvement of operational business processes efficiency and strengthening of organisational intelligence, resulting in gaining a competitive advantage (Božič & Dimovski, 2019a; Sangari & Razmi, 2015). BI&A system is more than just technological innovation; it is a new way of executing and managing business operations and decision-making processes, and facilitating the transition to a fact-based decision culture (Fink *et al.,* 2017). BI&A enables organisations to process large amounts of internal and external data that humans had difficulty comprehending to facilitate knowledge creation and knowledge sharing (Božič & Dimovski, 2019b; Ghazanfari *et al.,* 2011). BI&A simplified knowledge creation in organisations by expanding human mental capacity in processing summarised data with fewer errors (Božič & Dimovski, 2019a).

Knowledge sharing increases an organisation's ability to generate new ideas and develop new business opportunities (Lin, 2007). BI&A techniques and outputs include data and text mining, forecasting, predictive analytics, data visualisation, machine learning, alerts, reports and graph analysis (Ahmad *et al.*, 2016; Božič & Dimovski, 2019b; Lautenbach *et al.,* 2017). BI&A involves using various technologies to aggregate inbound and outbound data into meaningful actionable knowledge (de Jager & Brown, 2016). BI&A aids in the exchange of knowledge among different departments (Olszak, 2016). BI&A provides information content and access quality to the right people at the right time by provision of insights about the current operations, analysis of historical data and predictions of the future based on previous trends (de Jager & Brown, 2016; Ghazanfari et al., 2011; Işık et al., 2013). The valuable insights are a result of end-user meaningful translation of BI&A insights into intelligent knowledge, which is then acted upon by business units facilitated by technology, human and the relationship between business units (Božič & Dimovski, 2019a).

2.4.1 Technology assets as a facilitator of BI&A

Technology enables the storage, analysis and sharing of knowledge in the BI&A value chain (Božič & Dimovski, 2019a). Technological capabilities are the necessary foundation for BI&A to be successful (Işık *et al.*, 2013). BI&A starts from the collection of data and data integration of data using technologies that support data extraction, storage and transformation (Larson & Chang, 2016). Data-related technology capabilities like IT infrastructure, data repositories, communication technologies, technical platforms and BI tools for integrating, cleansing, and transforming data for BI&A consumption are seen as critical in enabling BI&A utilisation (Lautenbach *et al.*, 2017). Technology enables organisations to organise, process, store and recover information that has been acquired (Božič & Dimovski, 2019a). BI technology facilitates the dissemination of information across different business divisions and the provision of knowledge in an appropriate format that enables knowledge to be universally accepted and used as evidence to support new knowledge claims (Božič & Dimovski, 2019a; Shollo & Galliers, 2016).

2.4.2 Relationship assets as a facilitator of BI&A

Relationship assets include inter-departmental relationships, external networks, departmental cross-collaboration and management sponsorship (Božič & Dimovski, 2019a). To make sense of previously unknown patterns, there has to be collaboration and interdepartmental dialogue in an organisation, as BI&A stimulates multiple problem articulations, interpretations and perspectives (Shollo & Galliers, 2016). BI&A insights emerge from an active collaboration process between analysts and business managers who use data and analytic tools to discover new knowledge (Sharma *et al.*, 2014). Intra-organisational learning and knowledge consolidation can occur when knowledge is transferred between business divisions via collaboration, strengthening both the recipients' and organisations' knowledge base (Božič & Dimovski, 2019a). Collaboration has the potential to provide novel insights. Günther *et al.* (2017) emphasised the importance of multidisciplinary team collaboration, which leads to shared knowledge between teams in realising the value of data.

Another important collaboration is between data analysts and end-users, as data analysts are seen as shapers of how end-users make sense of the information provided; their relationship has the potential to result in innovative data visualisations, improved end-user knowledge of the available data and what data can do for the organisation and the integration of disparate data sources in novel ways (Namvar *et al.,* 2021). Data Analysts do trustworthiness analysis to guarantee that end-users have trust in BI&A output, as well as appropriateness analysis to ensure that BI&A solutions are suited for pursuing business opportunities or addressing business challenges (Namvar *et al.*, 2021; Sharma *et al.*, 2014). Analysts and end-users require regular interaction and communication for better data sense-giving and sense-making (Namvar *et al.*, 2021).

2.4.3 Humans assets as a facilitator of BI&A

Human assets are employee business knowledge, technical skills, and job experience (Božič & Dimovski, 2019a). Quality information provided by BI technology does not guarantee better decision-making that leads to better performance. Human assets are the main contributor to turning intelligent knowledge into valuable actions through data selection and articulation processes, resulting in improved performance (Ain *et al.,* 2019; Shollo & Galliers, 2016). Articulation is the process of communicating one's beliefs, opinions, and ideas in a logical clear manner. Data selection is the process of filtering specific data elements (data fields, dimensions, and measures) from a collection of collected and integrated data to investigate a phenomenon or measure various indicators (Shollo & Galliers, 2016). The results of data selection are the development of new distinctions and an articulation process is used to try to comprehend the distinctions. Data is analysed at several levels, resulting in the emergence of new insights (Shollo & Galliers, 2016). Although, more emphasise has been on technology and less on the human process of making sense of data and insights (Lennerholt *et al.*, 2020; Shollo & Galliers, 2016). Human information processing capability is a critical determinant that influences the extent to which BI is effectively used in an organisation (Işık *et al*., 2013). Human intellectual knowledge adds meaning to the data for it to be informative (Shollo & Galliers, 2016).

Human asset processing and interpretation of data can be influenced by time constraints and scepticism with the underlying data, team compositions, visualisation outputs, relational versus analytic, evidence-based attitude, historical insights processing, users' analytical abilities, experiences, and trust in data-driven decision-making (Günther *et al.,* 2017; Namvar *et al.*, 2021). To address these challenges more investment is made in artificial intelligence and machine learning algorithms (Awan *et al.*, 2021). However, human intelligence will still be required to solve new unforeseen environmental conditions or problems (Shollo & Galliers, 2016). In the BI&A process, human actors collect, analyse, discuss, and make decisions based on data-driven insights, as well as act and engage based on those insights (Günther *et al*., 2017). The human intellect differs for each individual (Manninen *et al.*, 2020). Thus, the same data can mean different things to different people and yield different results. Humans formulate new hypotheses that might arise from intuition or prior experiences, based on the available selected data (Lennerholt *et al.,* 2020). Analytics should be complemented by human experience, common sense and contextual knowledge as these elements cannot be captured by data (Günther *et al.,* 2017). BI&A human element is associated with the process and activities of sense-making, value creation and decision-making (Günther *et al.*, 2017; Namvar *et al*., 2021).

2.5 BI&A MODULES SUPPORTING DATA EXPLORATION

The most popular BI&A modules which are sources of insight for users in descending order of popularity are ad-hoc queries, fixed reports, data visualisation and dashboards, and OLAP (Seddon *et al*., 2017). Ad-hoc queries involve users requesting or creating reports when the need arises. The reports can be created by the BI developers or end-users can create their reports through the drag-and-drop BI feature in self-service BI (Popovič *et al.,* 2012). Fixed reports are standard reports consisting of key performance indicators, usually used for monitoring purposes. The reports are usually automated and emailed to the subscribed user (Seddon *et al*., 2017). BI&A data visualisation is a graphical representation of data (Djerdjouri, 2020). End-users can create these visual elements using an interface provided by the BI visualisation tool (Djerdjouri, 2020). In the data science process, visualisation tools are used to study raw data to facilitate exploratory data analysis (Larson & Chang, 2016). Each data visualisation needs to provide the most suitable presentation of data for users to obtain the right information and make informed decisions while minimising misinterpretation of data (Donohoe & Costello, 2020). Visualisations are intended to entice the reader with their aesthetic appeal before providing an analysis of the data underpinning the visualisation (Wolff *et al.*, 2016). One of the features that arouse the users' interest in BI is appealing data visualisation (Peters *et al.,* 2016).

A dashboard is a tool for visualising a collection of organisational graphical data indicators (Olszak, 2016). Dashboards allow the setting up of key performance indicators to highlight important metrics, as well as monitoring of strategic organisational objectives (Mudzana & Maharaj, 2017). Dashboards are usually web-based and consist of a collection of data visuals that provide easy data access to anyone with appropriate permissions (Djerdjouri, 2020). OLAP is a multidimensional summary view of organisational data. OLAP is used to explore important data characteristics using interactive reports generated by users' predefined data dimensions. It allows users to answer what, what if, why and when questions with data (Olszak, 2016). OLAP allows users to produce a variety of reports or visualisations and analyses of large amounts of data (Irtaimeh *et al.*, 2016). The way the users perceive data visuals and use these tools is affected by their education, personal experience, usefulness, skill, cognitive biases and organisational BI&A maturity (Donohoe & Costello, 2020).

2.6 BI&A MATURITY

Maturity refers to a "state of being complete, perfect or ready" (Olszak, 2016, p. 113). BI maturity refers to the state of BI development in an organisation to determine where an organisation stands in terms of BI use, identify gaps and guide BI&A improvements (George *et al.*, 2020; Lautenbach *et al*., 2017; Olszak, 2016). BI&A maturity is evaluated through technology infrastructure maturity (e.g. data integration), business and technical processes and capabilities maturity, business-technical alignment, and people or workforce analytical capabilities complemented by BI&A critical success factors *(*Brooks *et al.,* 2015; Popovič *et al.,* 2012). A BI&A readiness needs to deepen an understanding of data governance, policies, culture and business processes (Brooks *et al.*, 2015). The transition from one maturity level to the next necessitates an evolutionary transformation path from the initial to the target stage to be followed and BI&A capabilities to be improved. The following BI&A aspects should also evolve for an organisation to properly mature in BI&A: data quality, BI&A system-generated information and knowledge, user competency, information technology and business intelligence specialist competency, technologies for data management and analytical tasks, data transformation processes and activities, technology infrastructure, organisational environment, and strategic alignment (George *et al.,* 2020). The evolutionary process is guided by the maturity models.

Business intelligence maturity models have been developed that take into consideration an organisation's technological capacity and data requirements to make meaningful business decisions (Brooks *et al.*, 2015). Maturity models assist organisations in evaluating and measuring their maturity level, highlighting areas for improvement as well as areas of strength (Gudfinnsson *et al.*, 2015; Lautenbach *et al*., 2017). BI maturity models describe stages of BI progression within an organisation and serve as a solid foundation for long-term BI development so that organisations evolve to the next level (Lautenbach *et al.,* 2017; Olszak, 2016). Organisations can use a combination of maturity models to gain a comprehensive view of their BI maturity, as each model focuses on different aspects of BI&A (Lautenbach *et al.,* 2017; Shaaban *et al.,* 2012). Brooks *et al.* (2015) proposed using a design science approach to develop a domain-specific BI maturity model, as they argued that a maturity model should cover key process areas and critical success factors specific to a business domain. The framework consisted of six activity steps, namely: (i) Problem identification and motivation for BI maturity (ii) Definition of the objectives of the solution (iii) Design and development of an iterative domain-specific maturity model (iv) Demonstration and evaluation of the new maturity model (v) development of a maturity validation assessment tool to further evaluate the new maturity model (vi) Documenting the design and publication of the results (Brooks *et al*., 2015).

This framework will contribute to developing domain-specific dimensions that may be used to assess the level of maturity. Organisations with lower levels of BI maturity are not getting the most value from their collected data and are failing to reach their strategic goals (George *et al.,* 2020); whereas organisations with higher levels of maturity are further along on their BI journey, BI&A is extensively used and those organisations are reaping more benefits from the use of BI (Lautenbach *et al.*, 2017; Olszak, 2016). Less mature BI&A systems produce information and knowledge that is typically used to address specific departmental structured and operational decisions or tasks, whereas a more mature BI&A system supports multiple business departments' day-to-day decisions, predictive decisions to focus more on the future, and prescriptive decisions that cut across departments (George *et al.,* 2020).

The level of maturity of BI in organisations affects the type of questions the organisations seek to answer. Questions can shift from what happened to what will happen, affecting exploration and exploitative use of BI&A (Işık *et al*., 2013). Moreover, low-maturity organisations have limited ability to gather, aggregate, and exchange information, but high-maturity organisations can collect massive volumes of unstructured and structured data in real-time and disseminate it across the organisation (George *et al.,* 2020). Higher levels of BI&A systems maturity enable dynamic data interpretation in the BI&A system, as well as user control and manipulation of data using drill-down and what-if scenario techniques (George *et al*., 2020).

2.7 INFORMATION SYSTEMS DIMENSIONS OF USE

In IS literature, use has been evaluated in various ways namely, actual usage, frequency of use, intensity of use, intention of use, duration of use, purpose of use and appropriateness of use (Grublješič & Jaklič, 2015; Thatcher *et al.,* 2018; Torres & Sidorova, 2019). Table 1 shows studies that contributed to usage literature and their key findings. For an organisation to fully gain the benefits of an adopted IS, Kim and Gupta (2014) identified three ways users may actively use IS to its maximum potential beyond the intended usage in the infusion model: extended use, integrative use, and emergent use. Extended use refers to using system features to support the completion of tasks. Integrative use refers to using the system to strengthen task linkages. Emergent use refers to discovering innovative new ways to use the system to support work-related tasks (Kim & Gupta, 2014). Emergent use could be another form of adaptive system usage. Adaptive system use refers to how a user changes what and how the system in use features are used (Sun, 2012). Features in use are system features known to the user and are ready to be used to complete the user's tasks. These features can be selected voluntarily by the users or are mandatory due to the task being executed (Sun, 2012). Thatcher *et al.* (2018) however, highlighted two ways a user can generally use IT systems: actively and automatically. Active system usage means a user consciously considers how to use the system and if required modifies how to use the system.

Automatic or habitual system use entails users who use the system without cognitive assessment or decision-making (Thatcher *et al.*, 2018). Individuals' habits will be reinforced if users do not face conditions that cause them to substantially stimulate their cognition (Jasperson *et al.*, 2005). Active users are often aware of the system features relevant to a given task, and as a result, they might discover novel ways to use certain information technology. Thus, deep structure usage and trying to innovate are used to represent active usage, where they are defined similarly to extended and emergent use respectively (Thatcher *et al.*, 2018). In deep structure, the user identifies a class of relevant features to support the completion of a task, while trying to innovate puts a user's abilities to the test to innovate (Thatcher *et al.*, 2018). Koo *et al*. (2015) also indicated that individual-level actual use can be described in two ways exploitative use and exploratory use, where exploitative use can be mapped to extended use, while exploratory use can be mapped with emergent use.

Exploitation is linked with users doing a routine execution of a job that leads to the refinement of products or services as well as the extension of current capabilities and skills, which may result in operational efficiency. Burton-Jones and Grange (2013) defined effective use as some form of exploitation use. Effective use refers to using a system in a way that increases goal achievement, which can be either individual, group or organisational (Burton-Jones & Grange, 2013). Users can improve their system's effective use through adaptation and learning actions. Adaptation actions are activities taken by users to change system representation through the use of surface or physical structures (e.g. changing data around the system or sending change requests to the developers to change the application directly). Learning actions are actions taken by users to learn the represented system domain or learn to leverage from the represented systems; this could be done by experimenting with system features, reading material from the internet, asking a colleague, or training (Burton-Jones & Grange, 2013).

Various drivers promote effective use namely, perceived usefulness, ease of use, customisation, habit, trust, environmental uncertainty, intra-group, quality of use before training, revised perception after training, and user's interaction with the system (Burton-Jones & Grange, 2013). Exploitative involves building on existing creations, resulting in incremental upgrades to existing products that serve current customers and markets, while exploration creates new streams of knowledge by recombining existing knowledge across technological or organisational boundaries (Božič & Dimovski, 2019b; Fink *et al*., 2017). Exploitation activities promote exploratory tasks like experimentation, change, and innovation (Fink *et al*., 2017). Exploration focuses on sensing, discovery, risk-taking, system feature experimentation, flexibility, scanning slowly to answer questions in novel ways, and testing current conventions, which may result in breakthrough ideas or radical innovations (Božič & Dimovski, 2019b; Fink *et al.*, 2017; Koo *et al*., 2015). Explorative use involves the three elements: the user, the task and the information systems as this usage behaviour includes the user actively engaging in exploring the efficacy of the IS to accomplish a new task or using it in a new context (Saeed & Abdinnour, 2013). Explorative users can discover new methods to use the IT system to complete tasks in ways that were not feasible or recognised before (Kim & Gupta, 2014).

Intention to explore has been used to explain users' intentions to learn new ways of applying the IS to perform their tasks (Saeed & Abdinnour, 2013). Individual users, peers, experts, and managers are agents for modifying technology usage structures by initiating interventions in the form of task structures, work processes, and social structures (Jasperson *et al.*, 2005). These interventions force individuals to use previously under-used system features or use previously used features at higher levels of use to discover new applications for existing features or a need to include new features in the IT application (Jasperson *et al.,* 2005). Organisations can stimulate innovation and exploitation use of data by opening up data to their employees (Günther *et al.*, 2017). Soleas (2021) highlighted past relevant experience, successes, validation of past behaviours, training and practice in a creative environment, and a supportive stable work environment are factors that promote motivation to innovate.

Past experiences, background, and stimuli (i.e. beliefs that are shaped based on direct experience with the target system) can adjust users' perception and use of the IS (Venkatesh, 2000). Individuals who are proficient in using a certain IS perceive the system as easy to use and are explorative in using the system. Individual competency, on the other hand, has been overlooked, while designing system features and only Human Interaction with Computer (HCI) has been prioritised when it comes to increasing system use (Torres & Sidorova, 2019; Venkatesh, 2000). Users' familiarity with the information system acts as their knowledge base, assisting them in identifying new ways of applying the IS (Weng *et al*., 2016).

Table 1: Usage Dimensions Literature Review

Prior Studies	Founding Theory	Focus Area	Variables	Dimension of use	Findings
(Mun et al., 2006)	TAM,TPB, IDT	Personal Digital Assistant	• Personal Innovativeness in IT • Results Demostrability • Image • Subjective Norm • Perceived usefulness • Perceived ease of use • Perceived behavioural control	• Behavioural use intention	Perceived usefulness was shown to have the most significant effect on the intention to use technology, whereas perceived ease of use had no significant relationship with behavioural intention. Subjective norms and perceived behavioural control influence users' intention and usage of technology directly and indirectly through their association with perceived usefulness. Results Demonstrability, image, and personal innovativeness in IT all have an indirect impact on behavioural intention to use

					technology via perceived usefulness.
(Gefen et al., 2003)	TAM	E-Commerce	• Trust • Perceived ease of use • Perceived usefulness • Calculative based • Institution-based structural assurances • Institution-base situational normality • Knowledge-based familiarity	• Intended use	Users' trust in the e-vendor and the technology used impact their decision to use the technology. The antecedents of trust include (i) the user's belief that the vendor has nothing to gain by deceiving (Calculative-based beliefs) (ii) The belief that safety precautions are integrated into the system (structural assurances) (iii) possessing typicality or adhering to a norm (situational normality) (iv) the interface is simple and easy to use. Trust increases the perceived usefulness of the website. Users' familiarity and situational normality have a substantial impact on the websites' perceived ease of use of the website. Perceived ease of use and perceived usefulness significantly influence users' use of the online platform.
(Kim & Gupta, 2014)	Psychological Empowerment Theory	Customer Relationship Manageme	• Perceived Fit • Job Autonomy • Climate for Achievement	• Extended use • Integrative use • Emergent use	User empowerment has a significant positive effect on all IS infusion usage

		nt (CRM) System	• Competence of user • Impact of system usage • Meaning of system usage • Self-determination of user • Perceived usefulness • Facilitating conditions • Perceived ease of use • Social Influence		subtypes namely, integrative use, extended use, and emergent use. User empowerment results in proactivity and innovation. Perceived fit, job autonomy, and climate for achievement are the antecedents of user empowerment. Integrative use has a significant effect on emergent use, whereas extended use does not affect emergent use.
(Lautenbach et al., 2017)	Technology Organisation Environment (TOE) Framework	Business Intelligence and Analytics	• Data-related Infrastructure capabilities • Data Management challenges • Top management support • Talent Management challenges • External Market Influence • Regulatory Compliance	• Usage Extent	Data-related infrastructure capabilities, top management support, and external market significantly influence the extent BI&A is used in the organisation. However, Talent management challenges, such as the acquisition of BI/analytics talent, costly training of internal staff, and identifying skilled personnel do not have a statistical influence on the extent of BI&A use in organisations.
(Sun, 2012)	-	Microsoft Office	• Novel Situations • Discrepancies • Deliberate Initiatives • Facilitating Conditions	• Adaptive system use	Novel situations and discrepancies are antecedents of adaptive system use, whereas deliberate initiative indirectly influences adaptive

			• Personal Innovativeness in IT		system use via discrepancies, implying that suggestions from others on how to use system features are insufficient to motivate one to change the way they use the system, discrepancies perceptions must be created to encourage adaptive system use. PIIT positively moderates the relationship between novel situations and adaptive system use, also PIIT moderates the negative relationship between discrepancies and adaptive system use.
(Sparks & McCann, 2015)	DeLone and McLean	Business Intelligence system	• Data Integration • Analytical capabilities • BIS Maturity • Information Content quality • Information Access Quality • Analytical Decision-Making Culture	• Use of Information from BIS in the Business Processes	When antecedents of use of information from BIS in the management decision-making model are integrated with BI antecedents for organisational performance model, analytical decision-making culture, information content quality, and information access quality all significantly influence the use of information

					from BI&A in the business process. However, when the two models were assessed individually, information access quality did not affect the use of BIS information in business processes.
(Yildiz Durak, 2019)	UTAUT	Online Social Networking Sites	• Performance Expectancy • Effort Expectancy • Social Influence • Behavioural Intention • Gender • Branch • Usage Status • Technology Literacy • Academic self-efficacy • Self-directed Learning Readiness • Motivation • Satisfaction	• Actual use	The social influence had the most significant on teachers' decision to use social media, indicating that social settings such as peers, friends, and colleagues play an important role in users' technological acceptance and use. Performance and effort expectations both have a significant influence on behavioural intention. Academic self-efficacy, Self-directed Learning, and motivation are all moderators of behavioural intention. Technology literacy had a positive effect on performance expectations. Gender, branch, and satisfaction usage status had no statistical significance on behavioural intention.

(Wang et al., 2013)	Information System Continuance	BI system and ERP system	• Perceived usefulness (PU) • Satisfaction • Personal IT Innovative (PIIT) • IT Self-efficacy(ITSE)	• Innovative use with IT	Perceived usefulness positively influences innovative use with IT (IwIT) for both ERP and BI system users. ITSE positively moderates the relationship between perceived usefulness and IwIT, while it negatively moderates the relationship between satisfaction and IwIT. PIIT positively moderated the relationship between PU and IwIT among BI technology users and positively moderated the influence of satisfaction on IwIT among ERP system users.
(Peters et al., 2016)	IS success	Mobile BI	• Accessibility • Attractiveness • Ease of use • Flexibility • Engagement	• Frequency of use	System quality (i.e., attractiveness, perceived ease of use, accessibility, and flexibility) has a substantial impact on mobile BI use through user engagement, and flexibility has a direct impact on system usage. Attractiveness, perceived ease of use, and accessibility are related to the user experience, whereas flexibility is related to the BI system. System

					capabilities related to user experience should lead to user engagement in order to positively influence m-BI use.
(Koo et al., 2015)	IS continuance model	smartphones	• Perceived usefulness • User competence (finess breadth of knowledge, depth of knowledge) • User satisfaction • Perceived ease of use	• Exploitative use • Explorative use	Perceived usefulness and user competence are strong predictors of exploitative and explorative use behaviours. Perceived ease of use moderates exploitative use but not explorative use. Exploratory use is stimulated by exploitative use.
(Thatcher et al., 2018)		Microsoft excel	• IT mindfulness (Alertness to distinction, Awareness of multiple perspectives, openness to novelty, orientation to the present) • Perceived ease of use • Perceived usefulness • Self-efficacy	• Continuance intention • Deep structure usage • Trying to innovate	IT mindfulness has a significant impact on deep structure usage and trying to innovate, but not on continuance intentions. IT-mindful users are smart enough to stop using technology if it no longer meets their needs or if other alternative new technologies exist that could help them support their tasks.

2.8 BI COMPONENTS AS EXPLOITATIVE AND EXPLORATIVE STIMULI

Lee and Widener (2016) highlighted the two fundamental BI systems components which support different forms of use and trigger different forms of learning because of how they are used: Query Analysis Reporting (QAR) system and Dashboard and Visualisation (DV) system. QAR is a performance management reporting solution that enables businesses to extract comprehensive information from budget or planning data (Lee & Widener, 2016). QAR is mostly employed at the operational level and the manner in which data is presented frames the user to make exploitative use of BI&A (Lee & Widener, 2016). Operational BI capabilities promote exploitative use (Fink *et al*., 2017). At the operational level, BI is used to improve business process efficiency, and for process management operations decision-making. The decision-making process is designed to solve day-to-day organisational challenges, and decisions are either incremental or aligned to standard operating procedures (Fink *et al.,* 2017). QAR consequently promotes exploitative learning (Lee & Widener, 2016).

DV is a business analytics tool that allows users to access organisational data and produce various balanced scorecards or analyses of specific key performance indicators (Lee & Widener, 2016). Larson and Chang (2016) argued that the use of advanced analytical technology elevates BIS from a low-value operation to a strategic tool. DV is mostly used at the strategic management level. Strategic BI capabilities trigger exploratory use (Lee & Widener, 2016). Strategic decisions are complex and open-minded, intending to address long-term objectives (Fink et al., 2017). In DV key metrics are presented in an open-minded frame allowing users to make unconstrained judgements, hence supporting the explorative use of BI&A (Lee & Widener, 2016). BI&A use represents the extent and manner in which users exploitatively and exploratively use the capability of the BI&A system to achieve their goals (Fink *et al*., 2017; Peters *et al*., 2016).

2.9 FACTORS INFLUENCING BI&A USE IN ORGANISATIONS

BI&A usage and acceptance have been popularly explained on an individual level through Technology Acceptance Model (TAM) while Technology-Organisation-Environment (TOE) framework is being used in explaining BI&A use on an organisational level (Grublješič & Jaklič, 2015; Lautenbach *et al*., 2017). The emphasis of TAM is on the individual level, with a primary focus on the end-user perception of the technology (Aggarwal *et al*., 2015; Venkatesh, 2000). TOE focuses on the organisational level, with a primary emphasis on technology (technology capabilities), organisational characteristics (characteristics of the organisation and the available resources) and the environment (the industry's market structure, technology support infrastructure, and the regulatory environment) (Baker, 2012; Lautenbach *et al.,* 2017). These determinants are broadly categorised into individual, technological, organisational, and micro-environmental factors (Grublješič & Jaklič, 2015). The same dimensions are used to explain BI&A's use in management decision-making in organisations. However individual factors are further subdivided into behavioural beliefs and attitudes, and individual effort perceptions, while organisational factors are further subdivided into facilitating conditions and social influence (Ruhode & Mansell, 2019). Table 2 shows a summary of the factors that influence BI&A use in organisations. In BI&A context technological factors can be categorised further into infrastructure capabilities and data quality and data management factors (Lautenbach *et al*., 2017).

Lautenbach *et al.* (2017) argued that data-related infrastructure capabilities, management support and external market pressures positively influence the extent to which BI&A is used in organisations. Solid data-related infrastructure transforms data for consumption by BI&A and is an enabler for BI&A usage. Organisations in a highly competitive industry are more likely to use their BI&A strategically to stay ahead of the competition. Hence, competitive pressures are a significant driver for BI&A use (Lautenbach *et al.,* 2017). Moreover, strong executive support and users' trust in the BI are factors that aid organisations stay at the high BI maturity level (Olszak, 2016). The lack of user knowledge about the capabilities of BI can result in low BI usage (Sparks & McCann, 2015).

The organisational factors that affect BI&A use include management leadership and support, a corporate culture that enables effective management of resources, and clearly articulated BI strategy and objectives (Olszak, 2016; Sparks & McCann, 2015). Management support for BI&A is viewed not just as an organisational factor influencing use, but also as a critical factor for successful BI&A implementation (Yeoh & Popovič, 2016). Top management promotes the use of BI&A by leading the change process, securing essential financial and human resources, and facilitating collaboration amongst business divisions (Lautenbach *et al.*, 2017). Organisational analytical culture is another factor that influences the intensity, extent and embeddedness of BI&A in management decision-making (Grublješič & Jaklič, 2015). Additionally, antecedents of system use include system quality, information quality, and service quality (Torres & Sidorova, 2019). Service quality relates to the competency and expertise of users of BI&A. Information quality refers to the meaningful, accurate and comprehensive information output of BI&A (Torres & Sidorova, 2019).

Larson and Chang (2016) classified information quality into two categories: information content quality and information access quality. System quality refers to the BI&A solution that effectively integrates data from heterogeneous sources, is flexible to adjust to new organisational demands and is versatile in addressing users' data needs (Torres & Sidorova, 2019). System quality can be evaluated from both the system designer's perspective and the end-user perspective (Peters *et al*., 2016). Designers' perspectives are related to a collection of preset standard features that are thought to be important to all users (Jasperson *et al*., 2005). The system quality from the user perspective signifies a user-friendly system that is easy to use, properly documented, has a quick turn-around time and employs modern technology (Peters *et al*., 2016; Torres & Sidorova, 2019). These system characteristics influence individual beliefs and attitudes towards system use (Peters *et al*., 2016; Ruhode & Mansell, 2019). The trust users have in the BI and BI organisational capabilities, individual skills needed to effectively use BI&A, the BI maturity level and alignment between tools, tasks and people influence the extent to which BI&A is used in organisations (Günther *et al*., 2017; Olszak, 2016).

Table 2: Factors Influencing BI&A Use (Lautenbach et al., 2017; Peters *et al.,* 2016; Ruhode & Mansell, 2019; Sparks & McCann, 2015)

Individual		Technological		Organisational			Macro-environment
Individual Characteristics	**Individual behavioural beliefs and attitudes**	**Infrastructure Capabilities**	**Data quality and data management**	**Organisational characteristics**	**Facilitating factors**	**Social Influence**	-
Age	Relative advantage	System compatibility	Information content quality	Management support for BI&A	Technical support for BI&A issues	Reporting evidence visibility	External market influence (competitive pressures)
Computer Literacy	Trust in the information	Task-technology fit	Information relevance	Customer orientated organisation	Managing analytical people	Promotion of BI&A	Business Sector
Education	Job relevance	System quality	-	user participation in BI&A project implementation	-	-	-
Prior experience	Perceived ease of use	System complexity	-	development approach to BI&A implementation	-	-	-
Computer self-efficacy	Indididual engagement	System accessibility	-	analytical decision-making culture	-	-	-
Computer anxiety	user experience	System triability	-	Organisational culture	-	-	-
Personal innovativeness	-	System user interface/ attractiveness	-	Organisational resources that support BI&A	-	-	-
Readiness for change	-	System flexibility	-	Change Management	-	-	-
-	-		-	size	-	-	-
-	-		-	Organisation investment in user training	-	-	-

2.10 BUSINESS INTELLIGENCE AND ANALYTICS USE

Generally, BI&A use is an enabler of descriptive (focuses on what happened or what is currently happening), diagnostic (explains why it happened), predictive (focuses on predicting what will happen in the future), and prescriptive (determines if specific interventions will lead to certain outcomes, i.e. how can it happen) analytics to gain competitive advantage (Ruhode & Mansell, 2019). Different users can use the same system but achieve different results depending on their intentions of use, the organisation's strategic goals or key aspects of their organisational performance (Günther *et al.*, 2017; Torres & Sidorova, 2019). The use of BI&A leads to economic, individual and societal social value (Günther *et al.*, 2017). Economic value usually consists of monetary benefits such as increased profit, business growth, and competitive advantage. On an individual level, social value comprises of improving people's social well-being through education, healthcare, and public safety and security, whereas societal economic advantages include job growth, increased productivity, and consumer surplus (Günther *et al*., 2017). Profit-making organisations invest in the BI&A system in the quest to achieve a competitive advantage, while non-profit organisations believe BI&A can aid them to achieve their business goals efficiently by leading them to the optimal allocation of resources (Seddon *et al*., 2017).

Organisations use BI&A for routine and non-routine analysis of structured and unstructured data from various sources to reveal insights that inform business decisions' performance (Seddon *et al.,* 2017; Sharma *et al.,* 2014). Decisions subsequently lead to value-creating intelligent actions, which lead to improved organisational, environmental, operational, financial, and new business development performance (Akhtar *et al.,* 2019; Seddon *et al.*, 2017; Sharma *et al*., 2014; Torres *et al.,* 2018; Wolff *et al.,* 2016). Management can instantly know what is happening at the operational level or receive real-time alerts for risk identification for them to act accordingly (Akhtar *et al*., 2019).

The use of the BI&A system at the strategic level enhances strategic alertness, and strategic response capacity, while its use at the operational level leads to the operation or episodical alertness and operation or episodical response (Sangari & Razmi, 2015). BI&A insights can be consumed by humans for decision-making or be triggers of events for other automated systems (e.g. adjusting prices in real-time due to high demand) (Akhtar *et al*., 2019; Torres & Sidorova, 2019). The organisational decision-making process is a key part of how efficient insights are converted into decisions (Sharma *et al.*, 2014). Users use BI&A with the intent to use data for rational problem-solving, and their main goal is to produce insights or intelligent knowledge discovery from the available data (Russell *et al.,* 2010; Seddon *et al*., 2017).

Knowledge is the most important strategic organisational resource which is difficult to imitate, thus leading to sustainable competitive advantage (Awan *et al*., 2021). Users can act upon questionable statistical patterns based on historical data (Djerdjouri, 2020). BI&A helps end-users better understand their internal and external working environments through the exploration and interpretation of data (Torres *et al*., 2018; Weng *et al.*, 2016). End-users can monitor ongoing day-to-day operations and assess the business environment by uncovering hidden patterns, correlations, relationships and anomalies, identifying risks or opportunities, business process management and competitor analysis, and facilitating data sharing (Ahmad *et al.,* 2016; Djerdjouri, 2020). Users are empowered to make decisions using timely, useful information through the BI&A system (Djerdjouri, 2020). End-users take actions suited to improve service quality, make effective investment decisions and proactively take actions against competitors (Akhtar *et al*., 2019). BI&A predictive analysis feature can help determine persuadable clients, and through the BI segmentation feature, organisations can develop targeted campaigns and identify customer profiles (Djerdjouri, 2020; Sparks & McCann, 2015).

The use of BI&A promotes technical as well as administrative creativity and leads to market development, high-quality products or services, and growth (Irtaimeh *et al.,* 2016). Administrative creativity refers to changes in organisational structures, operational activities, and the development of new strategies or control systems (Irtaimeh *et al.*, 2016). Technical creativity refers to technical or industrial steps that contribute to the creation of exploitative and explorative innovations (Awan *et al.*, 2021; Božič & Dimovski, 2019b; Irtaimeh *et al.*, 2016; Weng *et al*., 2016). BI&A acts as a catalyst for the improvement and creation of products and services innovations, therefore increasing the organisation's competitiveness (Sharma *et al*., 2014). Organisations can proactively identify customer motives, habits, needs and wants based on the data characteristics and take appropriate actions (Akhtar *et al*., 2019; Sparks & McCann, 2015). Organisations can understand their current capabilities and accumulate knowledge of future market trends through the use of the BI&A system (Olszak, 2016; Weng *et al.*, 2016). Integration of data from various sources enables organisations to perform basket analysis to detect a combination of products that are regularly bought by customers (Akhtar *et al.*, 2019). BI&A enhance organisational agility (Weng *et al.*, 2016).

There are two organisational agility types: market capitalising and operational adjustments, which can be evaluated in terms of detection, response to opportunities and threats, and adaptation to emerging opportunities in global markets (Chen & Siau, 2020; Cheng *et al.*, 2020). Organisations can predict changes in demands or an increase in competitors' market share and respond quickly to service improvements or customer demands, leading to quality services (Işık *et al*., 2013; Weng *et al*., 2016). The quality of service can lead to the acquisition of new customers (Weng *et al*., 2016). Generally, the effective use of BI&A leads to improved organisational performance, improved business process performance and internal process efficiency, customer intelligence and supplier relationship benefits (Akhtar *et al*., 2019; Božič & Dimovski, 2019b; Djerdjouri, 2020; Sparks & McCann, 2015). There are various factors such as analytical culture, individual power to make decisions, data analytical capability and the use of information, and management commitment to BI that can significantly influence how BI&A is used and the perceived value it brings to the organisation (Božič & Dimovski, 2019a; Günther *et al*., 2017). Analytical culture refers to organisational norms, beliefs, and behavioural patterns that result in systematic methods of collecting, acquiring, integrating, and evaluating data and making it available to the relevant person (Namvar *et al.*, 2021). BI&A use is a highly human-centred approach and requires humans with the necessary skills (Torres & Sidorova, 2019).

2.11 DATA LITERACY

There are three main fields of study that contributed to the data literacy discipline, namely, education, library and information science, and information systems (Akhtar et al., 2019; Cech et al., 2018; Frank et al., 2016; Ghasemaghaei et al., 2018; Koltay, 2015; McDowall et al., 2020; van Geel et al., 2017; Wolff et al., 2016). Literacy refers to “the ability to read and write” (Lee *et al.*, 2016, p. 552). Data literacy for education is defined as pre or in-service teachers' capacity to collect, analyse and use data effectively to inform and improve their teaching practice (McDowall *et al.,* 2020). Data literacy in education helps teachers use data to inform and evaluate their teaching practice and assess students’ learning needs to improve student outcomes (McDowall *et al.,* 2020). Interpreting and understanding student assessment data is a key component of data literacy in education (McDowall et al., 2020; van Geel et al., 2017). Educators need to be able to transform data into actionable knowledge, so an array of skills such as data analysis, data summarization, and data synthesising and prioritisation are assumed to be important for the effective use of data in education (van Geel et al., 2017). Data literacy for information science is the ability to understand, reason, collect, interpret and visualise quantitative and qualitative data (Koltay, 2015; Wolff *et al.*, 2016).

Data literacy for data science is an enabler for data use and interpretation that aids in extracting economic, technological, and social value from data (Gray *et al*., 2018). Different approaches to efficient use of data and data-based reasoning are essential components of data literacy (Koltay, 2015; McDowall *et al.*, 2020). To be data literate in the field of IS one has to possess a combination of competencies including statistics, information literacy and technical skills (Gray *et al*., 2018). In collaboration with Gray et al. (2018), van Geel et al. (2017) stated that numeracy (ability to understand and process numerical data), statistics literacy and data analysis skills are necessary for the efficient interpretation and use of data. Data literacy is regarded as a life skill, as it enables individuals to use data for everyday thinking and reasoning to solve real-life problems (Wolff *et al*., 2016). There is a need for communicators, readers, creators and scientists to be data literate so that they can use data intelligently to solve real-world problems (Wolff *et al.*, 2016). Educators, data creators, data publishers, tool developers, tool and data visualisation designers, tutorial authors, government, organisations and artists are information providers who play an important role in fostering and enhancing data literacy (D'Ignazio, 2017).

To be data literate one has to identify the context in which data is used, data sources and format, graphically present quantitative data, analyse and have meaningful conversations about data, and have know-how in handling data (Koltay, 2015; Wolff *et al.*, 2016). Data illiterate users are at risk of attempting to solve problems through data analysis although the root of the problem cannot be solved with the existing data or miss the opportunity to support their arguments with data (Wolff *et al.*, 2016). Additionally, individuals have to be able to locate the appropriate sources for the required information, determine and use suitable research methods or analysis techniques, and apply data analysis results for learning, decision making or problem-solving (Koltay, 2015). McDowall et al. (2020) developed a data literacy framework for teachers that informs data use for teaching. The framework consists of five domains, namely, (i) identification of problems and framing of questions, (ii) data use, (iii) transformation of data into information, (iv) transformation of information into decisions, and (v) evaluation of outcomes. In this framework data use is identified as the heart of the process that informs teaching practice. Based on McDowall et al. (2020) and Seddon et al. (2017) data literacy framework for BI&A users is conceptualised in Figure 1. In the BI&A users' data literacy framework, the first step of identifying the problem and framing questions is eliminated because of the two approaches to analysing data (inductive and deductive).

Data quality (which is completeness, integrity, accuracy, reliability and validity) and data authenticity are the driving force for data literacy (Koltay, 2015). There are several competencies users need to possess to learn from data, namely, interpret, critique complex data and data visualisation, identify problems that could be solved using data, and solving problems with data (Koltay, 2015; Wolff *et al*., 2016). Data literacy competencies components include; data discovery and acquisition, data management, data conversion and interoperability, metadata, data curation and re-use, data preservation, data analysis, data visualisation, ethical use of data, and citation of data (Koltay, 2015). Analysing data requires one to have basic skills drawn from multi-disciplinary domains, namely operational management, computing, mathematics and statistics, to effectively obtain valuable insights (Akhtar et al., 2019). These skills can be assessed based on cognitive tasks using domain-based literacies (Locoro *et al*., 2021). Cech et al. (2018) distinguished four forms of data analysis: non-empirical, summary, correlational, and causal. The non-empirical employs human judgement or observations to make decisions, and it can be unreliable and may lead to bias. In summary, correlation and causal analyses are the most reliable forms of data analysis; they use quantitative data to perform descriptive statistics like means and standard deviations or investigate statistical relationships between variables (Cech *et al.*, 2018). In transforming information into knowledge, users may need to employ the four analysis techniques to make a meaningful decision.

The ability to collaborate and work in teams, the familiarity with digital technological data sources, statistical quantitative research, and the general knowledge of metadata standards aid in developing individual data literacy (Koltay, 2015). Organisations are establishing data university programs to improve employees' data literacy. Born-digital organisations develop custom training programs and promote peer-to-peer training, while traditional organisations often use external training materials for data literacy initiatives, with data awareness as the starting point (Lefebvre *et al.,* 2021). Schools are the foundation for creating a data-literate society (McDowall *et al.,* 2020; Wolff *et al*., 2016). D'Ignazio (2017) advocated for five creative data literacy tactics for empowering non-technical learners to "speak data"; namely (i) carefully selecting a data source that is relevant to the community that will be learning to work with data for data visualisation workshops or demo applications (ii) Allowing learners to write data biographies before attempting to do data analysis so that they understand how data was collected, its purpose, how is it used and the known limitations (iii) Take learners through the process of working with raw data, data creation, collection, categorisation processes. (iv) Build learner-centred tools that are simple, focused, guided, inviting/appealing, and expandable. (v) Designing data visualisation output that is community-centred (that caters to individuals' level of expertise).

Wolff et al. (2016) proposed that the most effective approach to transferring data literacy skills would be to teach data literacy as a cross-curricular subject, incorporating it into subjects like science and mathematics using complex datasets and visualisation. McDowall et al. (2020) however, argue that an experiential learning environment is good for promoting data literacy, especially now that on-the-job users need to be data-literate. A work environment that exhibits or offers opportunities for users to use data enhances users' data literacy (McDowall *et al*., 2020). There are various initiatives, tools, and resources that promote data literacy competency, namely, online data literacy projects for geospatial data analysis and digital data storyboards, sets of games and videos that teach children to conduct survey research and successfully use data, online labs that provide a variety of datasets for data manipulation and analysis (Wolff *et al.*, 2016). There are various online open and subscription data banks such as the UNdata, the world bank and data planet which one can use. Game-based training is the use of interactive games for educational or skill development purposes (Sanchez *et al.*, 2022). The game-based environment consists of tasks that immerse users in the activity, and users have complete control over the outcomes. Game-based training has been used across various contexts to enhance adults' and children's training experiences (Sanchez *et al.,* 2022). Some organisations established analytics competence centres to assist in better using the vast amounts of data they collect, standardising BI processes, improving communication between BI developers and business users, and improving the company's analytical capabilities, as well as providing guidance to other teams or departments struggling with analytics skills shortages (Günther *et al.,* 2017).

Using a step-by-step instructional interventions programme (experiential) to teach data literacy, yielded fruitful results (McDowall *et al.*, 2020). Participants reported an increase in understanding and comfort with data, improved analytical abilities and a better awareness of how data can inform their teaching practice (McDowall *et al.*, 2020). Yildiz Durak (2019) advocated for a self-directed learning approach which is regarded to promote innovativeness. Self-directed learning is a way of learning that allows individuals to select the best learning techniques and methodologies for themselves to realise their learning objectives (Yildiz Durak, 2019). Self-directed learning individuals tend to try out new things regularly to overcome complex challenges, handle change, and build novel learning methods (Yildiz Durak, 2019). In all the disciplines that contributed to data literacy literature, data literacy cannot be described without taking into account the concept of data use. Data literate individuals understand data and comprehend visually presented data, effectively argue with data and are numerically literate. For students to be regarded as data literate they had to understand effective data visualisation design principles, gather and interpret datasets in order to create informative visuals from them, use digital tools to organise and present qualitative and quantitative data, incorporate effective visual designs and data visualisation into practice (Donohoe & Costello, 2020). Users need to know how to access, and synthesise past knowledge, present data from various sources and apply the knowledge to problem-solving or decision-making (Koltay, 2015). To promote access the process of data democratisation has to happen (Lefebvre & Legner, 2022).

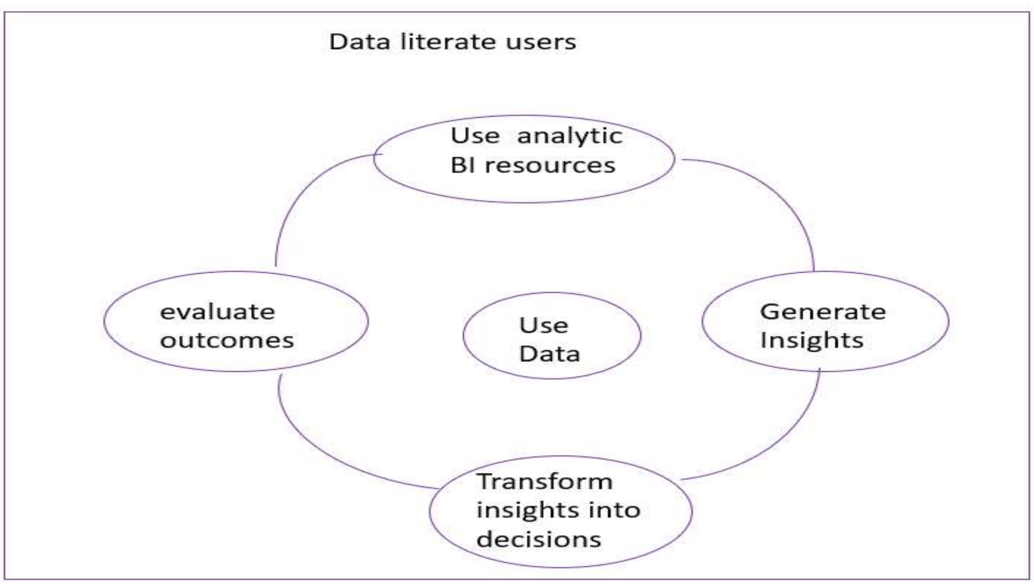


Figure 1: Data Literacy for Business Intelligence End-users Based on (McDowall *et al.*, 2020; Seddon *et al.*, 2017)

2.12 DATA DEMOCRATISATION (DD)

DD is a process of empowering users by opening organisational data for access to applicable users for data exploration and sharing while still considering legal confidentiality and data security (Lefebvre *et al.*, 2021). The prerequisite to granting users access to this data is data literacy to avoid misinterpretation. DD relies heavily on the development of autonomy and trust of end-users to apply data in their working area (Lefebvre & Legner, 2022). Lefebvre *et al*. (2021) also highlighted data and analytics competency as an important dimension of DD. DD is characterised by broad data access, self-service analytics tools, development of data and analytics skills, collaboration and knowledge sharing and promotion of data use (Lefebvre *et al*., 2021). Data democratisation is an important factor in executing data-driven strategies. In data-driven organisations, data use is marketed across the workforce and integrated into organisational business processes. DD initiatives can either grant data access in a controlled manner to promote the value of data and break data silos while emphasising data quality and data governance or they can address the gap between data specialists and end-users (Lefebvre *et al*., 2021). Lefebvre and Legner (2022) Three communities of practice support data democratisation namely, developing users' skills around tools and analytical methods, addressing data objects and data domain, deploying general practices and spreading data awareness (Lefebvre & Legner, 2022). Having access and literacy will enable the user to answer data questions (Donohoe & Costello, 2020; Lefebvre *et al.,* 2021).

2.13 DATA QUESTIONS

Visualised data can be used to solve exploratory, confirmatory and production tasks (Tegarden, 1999). Confirmatory tasks are fairly stable and predictable; users are normally attempting to confirm or refute a hypothesis. Production tasks are based on reports and users are using visualised reports to monitor or check an already existing validated hypothesis. Exploratory activities are dynamic, and users are typically looking for structure or patterns that may be learned from the visualisation, or they are seeking to build or test hypotheses about the underlying data (Tegarden, 1999). There are three categories of questions that may be answered using data: composition questions, distribution questions and comparisons questions (Hunter-Thomson, 2018). Composition questions seek to understand or explain the proportion of data for each subgroup component and how the components make up the whole (Hunter-Thomson, 2018). Composition visuals include pie charts, and treemaps (Galesic & Garcia-Retamero, 2011; Lee *et al*., 2016). Distribution questions explain how different data points are related to one another by displaying the entire array of values and their intervals. In a distribution chart, values are usually ordered from smallest to largest (Hunter-Thomson, 2018). Distribution charts include histograms and box plots (Galesic & Garcia-Retamero, 2011; Hunter-Thomson, 2018).

Comparison questions can either investigate the similarities between two or more groups or investigate the correlation between the two or more groups. Comparison graphs include column charts, bar charts, line graphs, incident maps and magnitude maps (Hunter-Thomson, 2018; Lee *et al.*, 2016). Each question determines what kind of data and how much data is needed to effectively answer the question (Hunter-Thomson, 2018). Composition questions need data on the entire group and on each subgroup, a distribution question requires the group's entire range, and a comparison question requires sufficient data for each variable to make a meaningful comparison.

In science, graphs, charts and maps are used to organise, visually represent data and make sense of data. A key step in preparing individuals to successfully interpret and analyse data is to educate them on how to create graphs in a way that will allow them to make sense of the data as well as explain the choice of chosen visuals, which can differ depending on the type of data collected or type of question being asked (Hunter-Thomson, 2018). Data can be communicated more effectively through visual representation than through words or statistics, and users can better comprehend and recall the content provided (Szabo *et al.,* 2019). Visual recollection appears to be better than verbal recall (Tegarden, 1999). As the amount of available data grows, people use data visualisations to explore data, extract useful insights, and answer data questions (Lee *et al.*, 2016).

2.14 DATA VISUALISATION

Data visualisation has become a preferred mode of communicating data since emerging technologies greatly emphasised visual information; besides organisations make grand arguments about using data-driven visualisation when evaluating operations and in decision-making (Donohoe & Costello, 2020; Moore, 2017; Szabo *et al.*, 2019). Data visualisation is used in various fields such as medicine, engineering, statistics, government, business and sports to highlight key information (Giner, 2011; Loos *et al.*, 2019; Szabo *et al.,* 2019). Data visualisation refers to the graphical representation of aggregate data to explore, synthesise, display and communicate large datasets (Galesic & Garcia-Retamero, 2011; Szabo *et al.,* 2019). Visual encoding maps data to graphical representation (Saket *et al*., 2018). Visualisation technologies improve users' capability to process unidimensional or multidimensional data (Tegarden, 1999). Visualisation assists subject matter experts in overcoming regression bias in their predictions (Dimara *et al*., 2016).

One of the first data visualisations was in 1700 by William Playfair, it was a line graph that represents exports and imports between Denmark and Norway see Figure 7 (Giner, 2011). The graph clearly showed a point of balance of trade (where imports equal exports). Charles Minard in the 19^{th} century created the best and now famous map of Napoleon's troops' tragic deaths during the Russian invasion in 1812 (Figure 8). The width of the cream bar represented troop size, and it steadily narrowed to signify troops dying as they reached Moscow (Tegarden, 1999). Visualisations seek to improve understanding of underlying data through the use of visual perception for fast pattern detection and recognition (Saket *et al.,* 2018). Data visualisation makes datasets visible and actionable by aiding with simple communication of more complex data stories; organisations become aware of what is stored in their data systems (Camba *et al*., 2022; Johansson & Stenlund, 2021).

Statistical analysis (e.g rank), temporal analysis (variation of a variable over time), geospatial analysis (location-based analysis), topical analysis (key words detection), and relational analysis (examines the relationship between) are general types of analysis that are used to reprocess or model data before being visualised (Börner *et al*., 2019). Data visualisation aggregates large datasets to communicate key insights, helping users to comprehend the nature of relationships or heterogeneity in the data (Szabo et al., 2019). Human capability input channels are greater when visual abilities are used. Visualisation technologies can be categorised into scientific visualisation, data or information visualisation and virtual reality (Tegarden, 1999). Scientific visualisation refers transformation of data through scientific or engineering calculations into images. Data visualisation transforms non-spatial or behavioural data into visuals that convey an analogy or metaphor for a problem (Tegarden, 1999). Loos et al. (2019) proposed using data visualisation in structural engineering to quickly compare multiple models and gain insights into models' structural behaviours and efficiencies during the design process as parameters are changed.

Virtual reality is a 3D simulated computer-generated environment that is rendered in real-time as per user behaviour (Tegarden, 1999). In data visualisation, individuals take longer to perform tasks for 3D charts and accuracy perception is lower (Saket *et al*., 2018).In designing effective data visuals and interactive visuals developers must follow the user interface guidelines: (i) Developers must be aware of the diversity of potential users (people learn, think and solve problems differently) and the task the visual is to support. This can be accomplished by performing task analysis, observation techniques, interviews, and scenario-based design techniques. (ii) Follow the eight heuristic user interface design principles: user interface should be consistent (e.g. similar visuals should be presented similarly across the platform), allow the use of shortcuts, the system should provide meaningful feedback, dialogues should be informative, cater for user error handling, allow an easy way for the user to undo their actions, be aware of the short-term memory constraints (iii) The system should prevent errors by grouping commands that require a sequence (Tegarden, 1999).

Properties of effective data visualisation include (i) simple clear display of data by avoiding unnecessary aggregations of data (allow users to do their aggregations for deeper insight), 3-D representations, chart junk and pie charts abound (ii) Avoid unnecessary decorations (iii) Avoiding distorting data by choosing the right visual that represent the data and avoid trancing of the axis values (iv) Compress as much information as you can into a visualisation while emphasising the most crucial aspects rather than presenting many numbers in a small space (avoid cluttering), cluttered data visualisation can hinder proper data interpretation (Lee *et al.*, 2015) (v) Visually represented data should be closely integrated with the statistical and verbal description of the underlying dataset (vi) Graphics should encourage the user to make comparisons between different data variables, thus introducing storyboards of insights can effectively communicate the connection between data variables or visuals (vii) In interactive visuals provide a view of data at the different level of details (viii) Ensure that the user is focused on the visual's content rather than the picture itself (Giner, 2011; Szabo *et al.*, 2019; Tegarden, 1999). Visually representing data simplifies understanding and aids in information retention (Giner, 2011).

The usability of data visualisation principles includes the correct type of graphic, correct range or scale, correct use of the semantic variables and correct labelling of the displayed information (Camba *et al.*, 2022). Moreover, graphic display design should be guided by these principles (i) the mind is not a camera (i.e do not overload the decision-maker with separate bits of information in one visual) (ii) the mind judges a book by its cover (create graphics that may be naturally linked with real-world entities or with which users are familiar). In an organisation, the first step is to examine the organisational charting methodologies. Information presented in a user-preferred format is better accepted and used in decision-making (Peters *et al.*, 2016). (iii) the spirit is willing, but the mind is weak (only a limited amount of information can be retained in short-term memory) (Tegarden, 1999). Additionally, the visualised data should be coherent with the large datasets when users are interpreting the data. Data represented at several levels of detail should start from a broad overview to a more detailed fine structure. The graph should be chosen with a clear purpose or objective whether it is to describe, explore, or tabulate (Moore, 2017; Szabo *et al.,* 2019). The cognitive fit theory states that the greater the fit between the problem given and the problem-solving process, the more successful the problem solution (Tegarden, 1999).

The primary components of a visual are size (height, length, width) and location (x-axis, y-axis, z-axis), whereas the secondary components are animation and colour (Tegarden, 1999). Size, colour, position, shape and pattern are visualisation properties that help organisations to faster detect trends, uncover anomalies within large datasets and identify correlations between data variables more easily (Hunter-Thomson, 2018). The underlying presented data may represent either concrete objects (e.g patients, cars) or abstract objects (profits, costs) (Tegarden, 1999). Different forms of visualisations such as tables, bar charts, pie charts and line charts may be used to present various types of data (Tegarden, 1999). A bar plot is suitable for representing categorical data by highlighting a single key point when comparing proportions. Stacked bar plots can be difficult to interpret because of the difficulty in comparing the size of categories across bars. Various stimuli can contribute to the difficulty of a data visual: number of graphically encoded elements, variation of data, layout and level of distractions (Boy *et al.,* 2014).

A histogram is suitable for displaying categorised continuous data. A histogram is useful for understanding the skewness of the data and in determining outliers. A line chart is suitable for representing ordinal data over a time series; it can be used in comparing trends over time. A Scatter plot is used for representing continuous data; it is used to determine the relationship between two variables (Hunter-Thomson, 2018). Pie/donut charts are suitable for presenting categorical data; they are used for comparing proportions. Pie charts can be difficult to interpret as individuals are poor at judging angles. Moreover, for donut charts, angles have been removed which can make them even more challenging to interpret.

Heatmap can be suitable for presenting continuous, ordinal or binary data. Heatmaps are used to understand levels of the factor on a map or over any two variables. Treemaps are suitable for representing categorical data (Szabo *et al.*, 2019). Treemaps are useful for showing the hierarchical composition of a whole where there are various categories (Lee *et al.*, 2016).

Scatter plots are useful in comparing two magnitudes (Giner, 2011). Sparklines are small, high-resolution word-sized graphics used to represent complementary information (Giner, 2011). Bar charts and pie charts are significantly faster and more accurate for finding clusters in the data but users prefer using bar charts over pie charts (Saket *et al., 2*018). This could be because Saket et al. (2018) looked at clusters as just subpopulations of the entire group. Lee et al. (2016) however, argued that finding clusters of tasks can be appropriately determined by using a scatter plot and bubble chart. A line chart performs better in finding correlations on the bases of speed, accuracy and user preferences than a scatter plot. Scatter plots have high accuracy, speed and user preference for finding anomalies. Line charts should be avoided for retrieving precise data value points as there is a low performance in terms of accuracy and speed. Table and pie charts should be avoided for performing correlations as they are less accurate, slower and less preferred by users (Saket *et al.,* 2018). Data visualisation techniques are useful for data exploration and communication (Moore, 2017). However, Darrell Huff also highlighted how graphical data representation can be manipulated to support ones conflicting interests and this can only be spotted by data visualisation literate users (Giner, 2011).

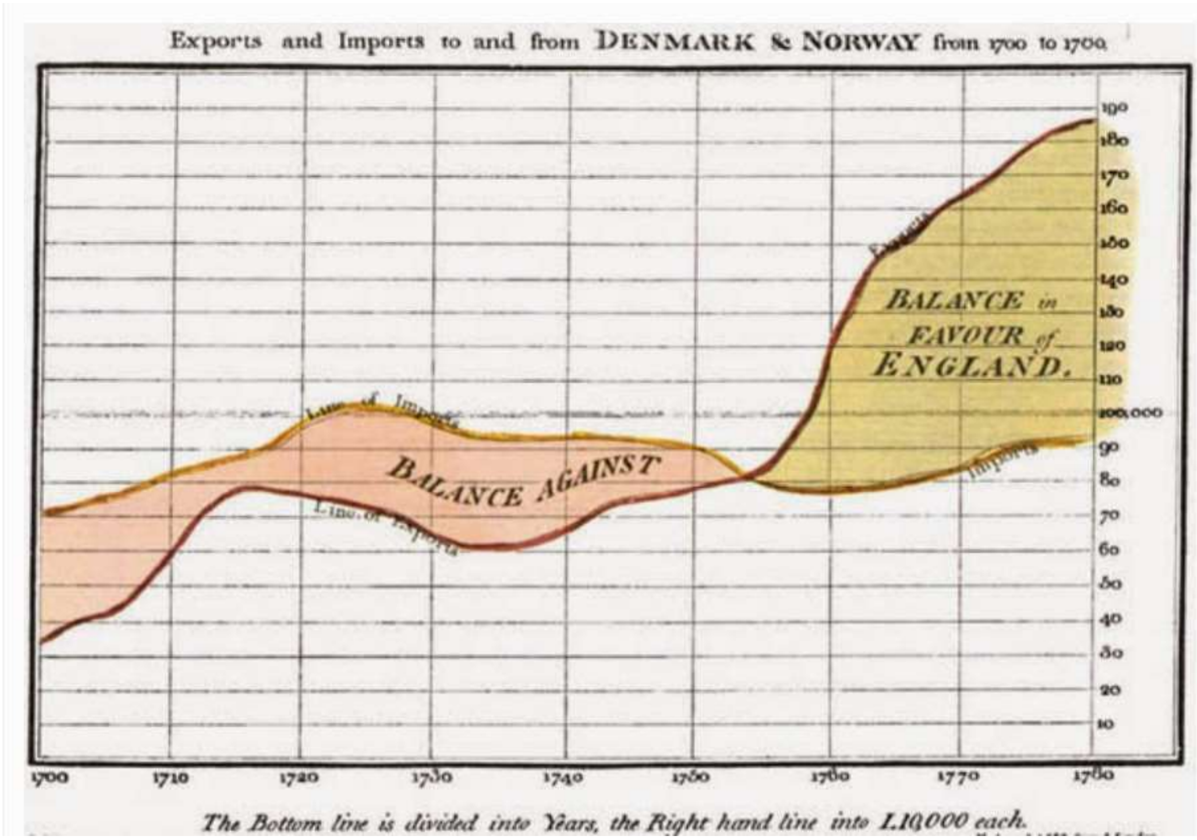


Figure 2: William Playfair's First Data Visualisation by Giner (2011)

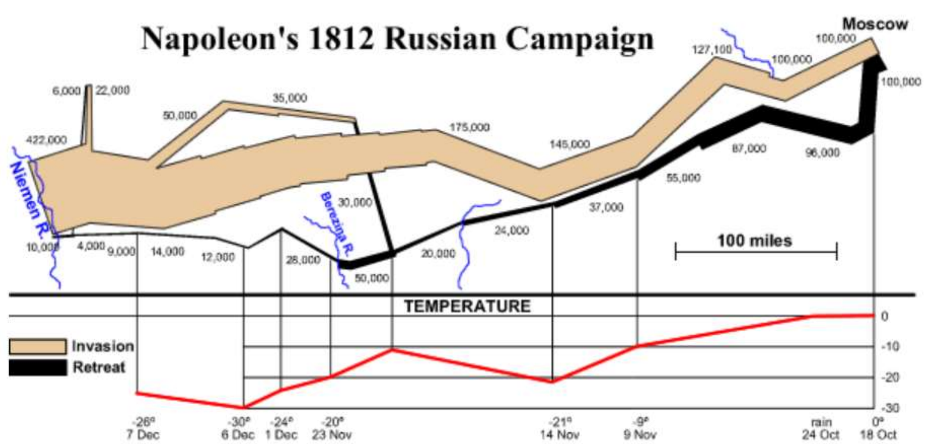


Figure 3: Charles Minard Napoleon Troops Moscow Invasion in 1812 (Giner, 2011)

2.15 DATA VISUALISATION LITERACY

Data Visualisation Literacy (DVL) has mostly been studied in the context of education, and information science (librarian science) concepts like “graphicacy” (Wainer, 1980), visual literacy (Avgerinou & Ericson, 1997), visualisation literacy (Boy *et al.*, 2014) and visual information literacy (Locoro *et al*., 2021) have been used to describe it. Graphicacy is the ability to read graphs and other two-dimensional formats (Wainer, 1980). Visual literacy refers to vision competencies that enable individuals to discriminate and interpret natural or man-made visual tasks, images and symbols (Avgerinou & Ericson, 1997). Visualisation literacy refers to the ability to confidently use well-established data visuals to answer queries presented in the data domain (Boy *et al*., 2014). Visual information literacy refers to the ability to encode and decode information from data graphics (Locoro *et al.*, 2021).

The scope of these definitions is different but the concepts relate to the ability to read and interpret different forms of visuals. Visualisation literacy is equally crucial in data representation as in reading and comprehending text (Lee *et al.*, 2016). A visual can be understood on three different levels by the users: elementary, intermediate and comprehensive. Elementary-level users can do a simple information extraction from the data visual. The intermediate-level users can detect trends and relationships. At the comprehensive level, a user can compare the whole data structure using inferences based on data and background knowledge (Boy *et al*., 2014).

Similarly, Lee et al. (2016) emphasised those three visual comprehension levels; data visualisation literate users should be able to read graphical data, read between the graphical data and finally read beyond the visualised data. Reading the data and reading between the data are basic analytical tasks (reporting) while reading beyond the data is classified as advanced analytics because one is predicting as one manipulates and computes new elements from a visual (Lee *et al.,* 2016; Lefebvre *et al*., 2021). Individual ability to create and read data visuals has become an important part of data literacy as individuals can easily comprehend data if it is presented with appropriate visuals (Donohoe & Costello, 2020; Hunter-Thomson, 2018).

When users' expectations are supported by a particular graph, graph comprehension improves. However, when expectations are challenged, users are prone to making errors in visual interpretation (Lee *et al.,* 2015). Visuals allow faster comprehension and selection of relevant patterns in data compared to text due to the visual analogical nature (Locoro *et al.,* 2021). Familiarity with dataset context is one of the main factors influencing visualisation comprehension (Lee *et al*., 2016). Thus, if visualisation is to be successful, data visual developers must pay attention to the work performed by decision-makers. The most effective organisational approach to supporting data visualisation literacy is to expose users to dynamic interactive visuals and give relevant users access to reach and interact with data (Bendoly, 2016). Sutherland and Ridgway (2017) emphasised the importance of including statistical literacy in data visualisation literacy initiatives to reduce data misrepresentation and misinterpretation.

Data visualisation literacy necessitates familiarity with current visualisation tools, awareness of potentially misleading aspects of displays caused by visual illusions, and a willingness to learn about new features (Sutherland & Ridgway, 2017). There are several models for assessing data visualisation literacy based on: (i) data graphics syntactic and their involvement with tasks evaluation (Wainer, 1980) (ii) the ability to answer questions with related data graphics (Lee *et al.*, 2016), and (iii) evaluation of cognitive tasks to be carried out with and through data graphics (Boy *et al.*, 2014). Boy *et al.* (2014) created visualisation literacy tests to assess the individual ability to use the most popular charts (line, bar, scatterplots). Item Response Theory (IRT) was adopted in developing the instrument and assessing users' level of visualisation literacy (Boy *et al.,* 2014). The assessment was on six visual intelligence tasks: maximum, minimum, variation, intersection, average and comparison (Boy *et al.*, 2014). Lee et al. (2016) also developed the Visualisation Literacy Assessment Test (VLAT) which consists of 12 data visualisations types (Line chart, bar chart, stacked bar chart, 100 per cent Stacked bar chart, Pie chart, Histogram, Scatterplot, Bubble chart, Area chart, Stacked Area chart, Choropleth Map and Treemap). These charts can be seen on various reports and dashboards from BI&A tools.

Possible tasks were associated with each type of visualisation (retrieve the value, find extremum, determine the range, characterise distribution, find anomalies, find clusters, find correlation/ trends, make comparisons) based on the quantitative dataset (quantitative datasets can be in the forms of tabular data, multidimensional table, geometric and network datasets types). Table 3 shows Vlat visuals together with the essential tasks associated with each visual and graph comprehension framework level. Correlation tasks are linked to predictions, an additional prediction task has been added to the charts that can effectively perform correlation (Lee *et al.*, 2016). Retrieve value task individuals can identify data points values of attributes. Finding extremum individuals can find extreme values (minimum, maximum) of a data attribute. Determine the range individuals can find a span of values within the dataset. Characterise distribution individuals identify attributes that meet certain criteria or conditions. Finding anomalies individuals identify any anomalies within the dataset based on a given relationship or expectation. Finding correlation/ trends for a given set of two data variables an individual identifies if there is a relationship, while in a trend analysis an individual identifies a pattern in a time series dataset. Finding clusters individuals identify groups that have similar data attribute values (Lee *et al.,* 2016; Lee *et al*., 2019). Boy *et al*. (2014) grouped tasks related to finding anomalies, trends and clusters into determining variation and introduced finding average and intersection as additional graphical analytical tasks.

Making comparisons individual identifies similarities or differences between two or more data attribute values (Lee *et al*., 2016). The task of locating data attribute extrema applies to all data visual types on the VLAT, although the effectiveness of each visual type varies across tasks (e.g pie charts are fast and more accurate than bar charts for proportional comparison tasks, tables are more effective in retrieving exact values than bar charts) and might not be appropriate for other tasks (Lee *et al.*, 2016; Saket *et al*., 2018). The visuals can represent absolute, relative, derived and approximate values of the underlying dataset. Education and training have been used to promote and improve the data visualisation literacy of users (Lee *et al.,* 2019). The ability to identify misleading data visualisations is a critical component of data visualisation literacy (Camba *et al.,* 2022).

Ways in which data visualisation developers can deceive users are by using some design deceptive tactics like truncating y-axes and not displaying data values or fading out or excluding the baseline, using illustrations where numerical accuracy is expected, using cherry-picking data points, spacing inconsistency along an x-axis, using 3-D effects, comparing two different data types in the same graph and using slated visual titles (Lauer & O'Brien, 2020). It is therefore critical to include data visualisation deceptive techniques in teaching data visualisation literacy. There are misrepresentations and error checklists that users need to be aware of when dealing with data visualisation and sense-making of data namely, (i) is all data included in the visualisation or have some filters been applied, (ii) Is the data correctly identified in the visual? (iii) is the type of visual used compatible with the query being answered (Camba *et al.,* 2022).

Table 3: VLAT Data Visuals and Associated Essential Tasks (Lee et al., 2016)

	Graph Compehension Framework	Read data		Read Between the data						Read Beyond data
	Data visualisation Task	**Retrieve value**	**Find extremum**	**Determine Range**	**Characterize Distribution**	**Find Anomalies**	**Find Clusters**	**Find Correlations/ Trends**	**Make Comparisons**	**Make predictions**
data Visualisation Types	Line Chart	✓	✓	✓				✓	✓	✓
	Bar Chart	✓	✓	✓					✓	
	Stacked Bar Chart	✓	✓						✓	
	100% stacked Bar Chart	✓	✓						✓	
	Pie Chart	✓	✓						✓	
	Histogram	✓	✓						✓	
	Scatterplot	✓	✓	✓		✓	✓	✓	✓	✓
	Area Chart	✓	✓	✓				✓		✓
	Stacked Area chart	✓	✓					✓	✓	✓
	Bubble Chart	✓	✓	✓		✓	✓	✓	✓	✓
	Choropleth map	✓	✓						✓	
	Treemap		✓						✓	

2.16 DATA VISUALISATION SENSE-MAKING

Data visualisation sensemaking refers to the process of understanding and interpreting visualised data and making decisions on the next learning actions (Jivet *et al.*, 2020). Thus, data visualisation literacy helps individuals make sense of data. The conversion of insights into intelligent knowledge is influenced by end-users sensemaking (Namvar *et al.,* 2021). Four tasks make up the process of sensemaking namely information gathering, representation of information in a schema to aid analysis, the development of insights and the creation of knowledge (Pirolli & Card, 2005).

Information processing in sense-making is a result of a bottom-up approach (from data to theory) or a top-down approach (from theory to data). The bottom-up approach consists of searching and filtering data, reading and extracting information, schematising, building a case/ theory, and telling a story by publishing the theory. Thus visual format and visual characteristics influence the bottom-up approach (Lee *et al.,* 2015; Pirolli & Card, 2005). The top-down process consists of a re-evaluation of theory, the search for information for support, the search for evidence, the search for relations from raw data and the search for information from raw data (Pirolli & Card, 2005). Individuals engage in different sensemaking techniques depending on the visualisation format (Lee *et al.,* 2015). Prior visual knowledge and knowledge about the subject influence the top-down process (Lee et *al.,* 2015). Sense-making improves the effective use of data for intelligent actions. When users grasp BI&A

capabilities and make decisions based on BI&A reports and insights, value is created (Namvar *et al.*, 2021). The design decision of how data is presented influences users' responses and sense-making (Jivet *et al.,* 2020).

Visual designers anticipate how each user will interpret the visualised data and that all users will gain a shared understanding of the provided insights. Individuals prefer certain visuals because they are easy to understand, provide information breakdown, show trends or facilitate comparison, appearance and accuracy (Jivet *et al.,* 2020). Latent factors of sense-making of the visualised data include transparency of designs, reference frames and support for action (Jivet *et al.*, 2020). Transparency of design entails including explanatory information that can help users understand the information displayed and how certain indicators were calculated in the design. Transparency can promote users' trust in the data. Reference frames refer to the creation of anchor points for data comparison.

The comparison standards users can use as anchors include average, maximum and minimum. Support for action refers to recommendations that support taking a certain action (Jivet *et al.,* 2020). Users go through the five stages as well as perform some miscellaneous activities in sense-making of unfamiliar data visual: encountering the visualisation, constructing a frame object and content, exploring the visualisation, questioning the frame and floundering visualisation (Lee *et al.*, 2015). Data visualisation aids sense-making in data exploration activities (Namvar *et al.*, 2021). Prior knowledge and interest in the subject matter, gathering of visualisation textual information (e.g title), and already constructed alternative frames about the possible explanation of the visual aid a novice user in making sense of an unfamiliar visualisation (Lee *et al.*, 2015).

2.17 DATA VISUALISATION LITERACY AND BUSINESS INTELLIGENCE AND ANALYTICS USE

BI&A identifies patterns in data by visualising them, allowing organisations to scan and absorb information to predict opportunities and reduce risks (Awan *et al.,* 2021). Thus, user data visualisation literacy in the BI context plays a critical part in transforming data into knowledge to inform intelligent actions in organisations (Djerdjouri, 2020; Lee *et al.,* 2019). When one talks about the analysis of quantitative data, data visualisation automatically comes to mind. It is important to teach end-users how to read charts and graphics to obtain insights, and how to use the information/insights provided by charts and graphics to make critical decisions or take action, as part of a data visualisation literacy initiative in the BI context (D'Ignazio, 2017). Data literate users need to be motivated to use BI&A to solve business problems and support their business arguments with data because accurate timely data analysis and transparency of the analysis strengthen the persuasive power of BI&A (McDowall *et al.,* 2020; Seddon *et al*., 2017; Shollo & Galliers, 2016). Individual IT usage behaviour is influenced by social structures, both performance-related and personal. These social structures can act as incentives or disincentives (Jasperson *et al.*, 2005). Social learning theories emphasise the importance of motivation and social variables in human behaviour as motivation determines the direction, intensity and persistence of human behaviour (Fischer *et al.,* 2019; Schunk & DiBenedetto, 2020).

2.18 CHAPTER SUMMARY

This chapter reviewed literature associated with the topic of the study. A comprehensive look at the definition of BI is discussed where there is no universal definition of BI. The literature defines BI as a technology, management approach, product or service. Business analytics is then examined as an element of BI that is centred around deriving value out of BI for the benefit of organisations. Technology, relationships among business units, and employees (humans) are identified to be facilitators in operationalising BI&A in organisations. Data visualisation in the BI&A context is discussed, followed by analytical tasks that can be answered using data visualisation. Data visualisation literacy is then identified to be a foundation of analytics, that needs to be stimulated for the benefit of BI&A usage in organisations.

Chapter 3

RESEARCH MODEL AND HYPOTHESES

3.1 USER USAGE BEHAVIOUR

The benefits of IT investment begin to accrue through usage (Jasperson *et al.,* 2005). Organisations can obtain potential economic benefits by successfully encouraging and enabling users to efficiently use the IS to accomplish their tasks (Saeed & Abdinnour, 2013). Jasperson *et al.* (2005) highlighted the three elements that influence user usage behaviour: prior use, habit, and a feature-centric view of technology. Prior use refers to users' prior use experiences or history with the technology (Jasperson *et al*., 2005). According to Saeed and Abdinnour (2013), the position of a user's behaviour can be assessed using five variables: user-initiated learning, usefulness, ease of use, satisfaction and voluntariness of use.

Factors that have been used to factor in prior use include computer experience, computer skills, extent of prior technology use and prior use (Jasperson *et al.,* 2005; Venkatesh, 2000). Most studies ignore the prior use factor as they examine usage behaviour immediately after the adoption of the technology (Gefen *et al.,* 2003; Lautenbach *et al.*, 2017; Mun *et al.*, 2006; Sun, 2012; Thatcher *et al*., 2018). The degree to which an individual perceives an IS as an opportunity or a threat, as well as their usage behaviour, may lead to them classifying an IS as: a strategy for benefit maximisation, benefit satisfaction, disturbance management, and self-preservation (Saeed & Abdinnour, 2013).

Usage behaviour refers to the users' voluntary or mandatory interaction behaviours while choosing to use a certain system feature or voluntarily extending system features use to manage or accomplish their tasks with a deployed application (Jasperson *et al.,* 2005; Saeed & Abdinnour, 2013). A mandatory decision occurs when an organisation integrates an IT application within a working system, the user is forced to use it to fulfil job-related activities (Jasperson *et al.*, 2005). If the user's behaviour is based on user history (prior use), the user is more likely to use the application features that they have previously used, which could lead to habitual system usage. Habit refers to repetitive use behaviour that occurs without any cognitive processing (Jasperson *et al*., 2005). Automatic unplanned behaviour is the key to habit formation (Villalobos-Zúñiga & Cherubini, 2020). Feature-centric use of technology refers to using specific features of an IS as users' needs are likely to change over time (Jasperson *et al*., 2005). These specific features determine the potential usefulness of an IS and determine work outcomes. Both intention and future behaviour are well predicted by past behaviour (Jasperson *et al.*, 2005).

Jasperson *et al*. (2005) advocated for users' behaviour to be analysed over time and at a feature level of an application to enable individual learning of both IT applications and the work system so that direct intervention gaps can be implemented. Individuals' work environments change over time. As a result, organisations must examine user behaviour and develop training that adapts to the needs of users and take into account behavioural outcomes (Jasperson *et al.*, 2005). Individual usage behaviour literature has matured over the years, but the majority of the literature has studied it through the lens of the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behaviour (TPB), and Theory of Reasoned Action (TRA) (Kim & Gupta, 2014; Saeed & Abdinnour, 2013; Yildiz Durak, 2019). These theories aim to explain beliefs, attitudes, perceptions, intentions and actual system use at an individual level (Gefen *et al*., 2003; Ngee, 2020; Venkatesh, 2000; Venkatesh *et al.,* 2003).

3.1.1 Theory of Reasoned Actions (TRA)

TRA is the most popular psychological theory for predicting and explaining human behaviours and it is a foundation of other behavioural theories (Ngee, 2020). Following TRA, two factors determine the individual behavioural intention and prediction of how well the individual will perform the behaviour, namely, personal attitude and social subjective norms (Ngee, 2020; Vallerand *et al*., 1992). If the behaviour in question is entirely under volitional control, behavioural intention determines actual behaviour, although some behaviours may be affected by the availability of resources such as skills, money and time (Vallerand *et al.*, 1992). Individuals' attitudes are determined by their perceived evaluation outcomes and behavioural beliefs when performing the behaviour, whereas individuals' subjective norms are determined by individual social beliefs of what others think of their behaviour and motivation to comply (Vallerand *et al*., 1992). TRA predicts the attitudinal underpinnings of behaviours in a variety of contexts that drive system use (Kulviwat *et al.*, 2014; Mun *et al*., 2006).

3.1.2 Theory of Planned Behaviour (TPB)

TPB is an extension of TRA that was necessitated by the limitations of the original TRA model in dealing with behaviours over which people have insufficient volitional control (Ajzen, 1991). TPB is anchored on attitude, subjective norms and perceived behavioural control to explain and predict individual intention to perform a certain behaviour (Ajzen, 1991; Tucker *et al*., 2019). Subjective norms shape individual beliefs and attitudes about tasks regarded as important to them (Vilnai-Yavetz & Levina, 2018). Perceived behavioural control refers to an individual's perception of how easy or difficult it is to perform the desired behaviour successfully (Ajzen, 1991). Thus, perceived behavioural control is related to an individual's confidence in their ability (i.e self-efficacy). Task selection, preparation, effort, thoughts patterns, and emotional reactions can all be influenced by self-efficacy (Wang *et al*., 2013). Perceived behavioural control can predict behaviour intention or have a direct influence on the actual behaviour (Tucker *et al*., 2019). The attitude toward the behaviour refers to individual favourable or unfavourable emotions or appraisal of the behaviour in question (Ajzen, 1991). Subjective norm refers to "the perceived social pressure to perform or not to perform the behaviour" (Ajzen, 1991, p. 188). There is a bidirectional relationship between the three anchors of TPB. Intentions are assumed to be motivating factors that indicate people's willingness to try to perform the behaviour rather than how much effort they intend to put in (Ajzen, 1991; Tucker *et al.,* 2019). Intention and ability jointly influence behavioural achievement (Ajzen, 1991).

3.1.3 Technology Acceptance Model

Born from TRA, according to TAM, the external system features trigger individual cognitive responses which in turn influence their attitude towards using the technology which determines actual system use (Gefen *et al.,* 2003). The two cognitive reactions are perceived ease of use and perceived usefulness which are key constructs of the TAM model (Mun *et al.*, 2006). An individual's choice to carry out specific tasks is based on a consideration of effort and expected benefit. To understand conditions underpinning users' perception of technology use, TAM progressed into TAM 2, which now adds external factors influencing perceived usefulness (Venkatesh, 2000). Perceived usefulness was proven to be the strongest predictor of intention to use, thus prompting the exploration of perceived usefulness antecedents and overlooking the antecedents of perceived ease of use (Venkatesh, 2000; Venkatesh *et al*., 2003). The perceived usefulness antecedents include the image, subjective norms, job relevance and result demonstrability while voluntariness and experience are the moderators. Job relevance has output quality as a moderator. To address gaps identified in TAM2, there was the development of TAM3 which now included six antecedents of perceived ease of use, to provide an integrative explanation of technology adoption with a robust model (Dwivedi *et al*., 2019; Venkatesh & Bala, 2008).

The direct predictors of perceived ease of use include computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability. The predictors that shape users' perceptions were categorised into anchors and adjustment factors (Venkatesh & Bala, 2008). Computer anxiety, computer self-efficacy, perception of external controls, and computer playfulness are the initial drivers of perceived ease of use, indicating that users' perception of ease of use is anchored on external and internal controls related to general computer beliefs rather than the targeted system (Venkatesh, 2000). Adjustment factors namely, perceived enjoyment, and objective usability are triggered by the user’s direct experience with the technology (Venkatesh, 2000). This is in line with TPB where experience influences attitude (Tucker *et al.*, 2019). If users' experiences differ from what is expected from the anchors, adjustment factors come into play (Venkatesh, 2000). The anchors are related to the individual level of fear or emotions, the user’s intrinsic motivation and personal competence in using technology. In TAM3 experience is a moderator in the relationship between (i) computer anxiety and perceived ease of use (ii) perceived ease of use and perceived usefulness (iii) and perceived ease of use and behavioural intentions (Venkatesh & Bala, 2008). With the increased use of a system, computer playfulness is expected to diminish and perceived enjoyment to increase (Venkatesh, 2000).

3.1.4 The Unified Theory of Acceptance and Use of Technology

UTAUT is the result of the synthesis of the individual usefulness theories namely, TAM (perceived usefulness), Motivation Model (MM) (extrinsic motivation), The Model of PC Usage (MPCU) (job-fit), Innovation Diffusion Theory (IDT) (relative advantage), and Social Cognitive Theory (SCT) (outcome expectations) that contributed to the development of the concept of performance expectancy (Venkatesh *et al.,* 2003). The actual use of technology is influenced by users' behavioural intention, which in turn is determined by the direct effect of four major components of UTAUT, namely performance expectancy, effort expectancy, social influence, and facilitating conditions (Yildiz Durak, 2019). Performance expectancy refers to the extent to which individuals feel that using the system will assist them in improving work performance (Venkatesh *et al.,* 2003). Effort expectancy refers to the degree of ease associated with the use of the system (Venkatesh *et al.*, 2003, p. 450). A combination of constructs from TAM (perceived ease of use), MPCU (complexity), and IDT (ease of use) capture the concept of effort expectancies (Venkatesh *et al.*, 2003). Social influence refers to the extent to which an individual believes others will perceive them as important as a result of their use of technology (Venkatesh *et al.,* 2003).

Social influence is comparable to the social variables and image constructs used in TAM2, IDT, and TPB in that it indicates how other people's views might impact individual behaviour (Venkatesh *et al.,* 2003). Facilitating conditions refer to the degree to which an individual feels that a conducive technological and organisational environment exists that facilitates the use of information systems (Venkatesh *et al.,* 2003). UTAUT moderator variables like demographic factors, socio-economic factors, personal factors, educational level and competencies and personal innovativeness moderate the behaviour and intent of users in accepting and using technology (Yildiz Durak, 2019). According to UTAUT, the relationship between cognition and intention is moderated by individual demographic variables (Jasperson *et al.*, 2005). In UTAUT, the most essential factor explaining individual workplace usage behaviour is performance expectation (Yildiz Durak, 2019). Controllable variables resulting from user interaction with the system, such as motivation, must be considered, as these factors can adjust how users interact with the system (Venkatesh, 2000). Moreover, motivation has been crucial in the workplace's adoption of technology (Torres *et al.,* 2018). Knowing these factors can aid in system design interventions that promote use.

3.2 MOTIVATION

The concept of motivation encompasses what drives individuals to achieve their goals, what energises them, what sustains their behaviours as well as the reason why people think and act the way they do (i.e human behaviour) (Fernández-Avilés *et al*., 2020; Torres & Sidorova, 2015). More motivated individuals are more likely to re-engage in activity and invest more time and energy in it (Sanchez *et al.,* 2022). Motivation to use technology is influenced by management leadership style (Rezvani *et al.*, 2017), perceived task-technology fit (Higgins *et al.*, 2010), and appropriateness of technology to complete a task (Barr *et al*., 2022). There have been several psychological motivation theories developed for studying motivation in people. These theories can be broadly classified as motivational theories and behavioural change theories (Fernández-Avilés *et al.*, 2020). The motivation theories include expectancy-value theory, attribution theory, social cognitive theory, goal orientation theory and self-determination theory (Barr *et al*., 2022). The expectancy-value theory of achievement motivation states that motivation to choose a certain task and how well individuals will do on their upcoming chosen tasks, their persistence on those tasks and how well they perform on them are influenced by an individual's perception of their current competency (Wigfield & Eccles, 2000). Attribution theory states that a cause that explains a certain outcome or results qualifies the cause to be an attribution (motivator) to a certain behaviour (Barr *et al.,* 2022).

Vroom (1964) is the popular workplace motivational theory and a foundation for other motivational theories. Building on Vroom (1964) theory, Porter and Lawler (1968) introduced a concept of intrinsic and extrinsic work motivation. Porter and Lawler (1968) advocated for a work environment that would lead to individual intrinsic and extrinsic motivation and finally to job satisfaction and increased productivity (Gagné & Deci, 2005). The inclusion of intrinsic and extrinsic motivation sparked a debate about how tangible extrinsic rewards undermine intrinsic motivation while intangible extrinsic rewards enhance it (Gagné & Deci, 2005). This debate led to the conception of Cognitive Evaluation Theory (CET).

CET focuses on the effects of extrinsic motivators on intrinsic motivation. CET assumptions implied that intrinsic and extrinsic motivators cannot co-exist in a workplace. CET emphasises the importance of autonomy in intrinsic motivation. Autonomous motivation in the workplace is facilitated by a work environment in which jobs are interesting or challenging and allow freedom of choice (Gagné & Deci, 2005). Later, Ryan *et al.* (1985) represented a differentiated study of extrinsic motivation using the principles of internalisation. Ryan *et al. (*1985) critiqued CET assumptions that intrinsic and extrinsic motivation cannot co-exist in the workplace and that extrinsically motivated behaviour cannot be autonomous; this resulted in the development of Self-Determination Theory (SDT) (Gagné & Deci, 2005).

3.2.1 Self-Determination Theory

SDT is the most detailed framework that deals with the distinction or relationship between intrinsic and extrinsic motivation, which are the core elements of SDT (Fernández-Avilés *et al.,* 2020; Rezvani *et al.*, 2017). SDT indicates that motivational factors can either be deliberate, volitional and planned or non-conscious and unplanned (Villalobos-Zúñiga & Cherubini, 2020). According to SDT motivation, the quality of motivation guides and regulates human performance (Manninen *et al.*, 2020). Individuals that are intrinsically driven undertake autonomous activities towards the target activity. Intrinsic motivation is based on the notion that people have an inherent need for autonomy, competence, and relatedness (Rezvani *et al*., 2017). Autonomy refers to an individual's desire to self-organise their behaviour or the liberty to try out other various system features (Gagné & Deci, 2005; Rezvani *et al*., 2017). Competence indicates that individuals possess the skills required to be productive and expand their current capabilities (Gagné & Deci, 2005; Rezvani *et al.,* 2017). Competence is linked to task success and goal achievement (Torres & Sidorova, 2015). Relatedness refers to the feeling of affiliation and a sense of significance to others (Gagné & Deci, 2005; Rezvani *et al.,* 2017). According to SDT, if these three intrinsic motivation basic needs are fulfilled, self-determined actions for the targeted activity will be triggered (Villalobos-Zúñiga & Cherubini, 2020).

SDT categorises extrinsic motivation into external, introjected, identified and integrated motivation (Fischer *et al.,* 2019; Zou *et al*., 2020). In external regulation, an individual feels their behaviour is directly controlled through contingent rewards and threats (Deci *et al.,* 2017). In introjected regulation, individual behaviour is self-controlled by their self-esteem, ego, guilt and concern for recognition and status (Deci *et al*., 2017). Leaders play a critical role in the workplace in enhancing introjected motivation. In identification regulation, individuals are self-aware and have identified the importance of their role which controls their behaviour. In integration, individual behaviour is controlled by a need to integrate into the community (Deci *et al*., 2017; Gagné & Deci, 2005). Factors that may demotivate individuals include the difficulty in achieving the goal, the amount of time taken to complete a task, and the level of effort required to achieve the goal (Fernández-Avilés *et al.,* 2020). When an individual's motivation is low, it is more likely that an activity will be abandoned (Malhotra *et al.,* 2008). Effective motivational strategies can change certain human behaviours (Fernández-Avilés *et al.*, 2020). Motivation theories are extensively used to study IS acceptance and use (Chan, 2009; Davis & Wiedenbeck, 2001; Rezvani *et al*., 2017). The IS features, particularly those that enable efficiency, and flexibility foster intrinsic motivation, which in turn influences the cognitive, emotional, and attitudes of users (Torres & Sidorova, 2015). The primary difference between intrinsic and extrinsic motivations in SDT is intrinsically motivated individuals enjoy the process of performing a specific task, and extrinsically motivated individuals appreciate the outcome rather than the process (Li *et al*., 2013).

3.2.2 Intrinsic Motivation

Intrinsic motivation is a positive feeling an individual experiences in performing a task (Chan, 2009). Intrinsic motivation is mutable and is affected by training interventions (Sanchez *et al.*, 2022). People tend to engage voluntarily in an activity if they find it interesting (Gagné & Deci, 2005). The tendency to engage in activities of interest results in the encouragement of learning, growth, and capacity expansion (Chan, 2009). Elements of intrinsic motivation that impact satisfaction at work include self-fulfilment, achievements, hedonism, a sense of importance, and flow (which is a combination of perceived enjoyment, concentration, and curiosity) (Altin Gumussoy, 2016; Vilnai-Yavetz & Levina, 2018).

Individuals can self-report intrinsic motivation because intrinsic motives are more socially acceptable compared to extrinsic motivators (Vilnai-Yavetz & Levina, 2018). Intrinsic motivation magnifies technology's perceived ease of use in TAM and leads to creativity (Altin Gumussoy, 2016; Hannam & Narayan, 2015; Venkatesh, 2000). Hedonic motivation or enjoyment has been identified as an important factor in determining technology acceptance and use in the workplace (Vilnai-Yavetz & Levina, 2018). Hedonic motivation refers to the pleasure or fun one experiences in using technology (Baabdullah *et al.,* 2019).

Intrinsic motivation emanates from the relationship between the task or activity and its end goal (Fishbach & Woolley, 2022). Situational factors strengthen the association between the task and the end goal results; thus they are considered antecedents of intrinsic motivation (Fishbach & Woolley, 2022; Higgins *et al.*, 2010). Situational contexts can take many different forms, including pleasurable, serious, enjoyable, and important; and these situational surroundings encourage user interaction and help people become more intrinsically driven (Fishbach & Woolley, 2022). When situational factors fit people's orientation to the activity, the interest in doing the activity will increase whereas a nonfit situational factor will decrease interest (Higgins *et al.,* 2010). Hannam and Narayan (2015) emphasised a similar matter; individuals may be given identical tasks, but those who are intrinsically motivated see the tasks as being fairer than those who are uninterested in the task.

The regulatory fit theory also highlights, that individuals are motivated to participate in tasks when there is a fit between an individual's task orientation and the manner of activity pursuit, which is supported by surrounding situational factors (Higgins *et al.,* 2010). The perfect fit between an activity and a goal intrinsically motivates an individual (Fishbach & Woolley, 2022). Thus, strategies that promote engagement enhances intrinsic motivation. Higgins *et al*. (2010) reported a greater interest in the activity when individual orientation towards an activity was fun or enjoyable as opposed to when it was serious.

A unique association between an activity and a goal results in intrinsic motivation to pursue that activity because there is only one activity that achieves that specific goal. Adding additional goals that shift focus from the original goal, or adding a goal and then removing it, dilutes the unique goal activity association (Higgins *et al*., 2010). Having complementary additional goals increases motivation as they give individuals more reasons for performing an activity (Fishbach & Woolley, 2022). Repeatedly associating an activity with a goal strengthens their bond. Through repeated coupling, operant conditioning theory discovered that frequency of behaviour increases and user experience changes (positive behaviour reinforcement) when individuals and other animals learn that their behaviour leads to a reward (Fishbach & Woolley, 2022).

Rewarding an activity under one set of conditions increases the likelihood that the activity will be repeated later under similar conditions (Fishbach & Woolley, 2022). The joy of receiving the reward carries over to the behaviour that resulted in it; this is contrary to the self-determination theory which states that introducing monetary rewards for an activity undermines an individual’s sense of autonomy and in some cases leads to a negative effect (crowding-out) (Gagné & Deci, 2005; Rezvani *et al*., 2017; Vilnai-Yavetz & Levina, 2018). Shortening the period between the activity and goal achievement strengthens the association between an activity and its goal, thus intrinsically motivating (e.g. Pursuing an activity in which a goal is immediately attained feels more intrinsically motivating than pursuing an activity in which a goal will be attained later) (Higgins *et al*., 2010).

Providing user feedback and performance sharing with peers increases intrinsic motivation through competence and relatedness respectively (Barr *et al*., 2022; Villalobos-Zúñiga & Cherubini, 2020). Including a reminder application feature has been identified to result in intrinsic motivation through autonomy to trigger behaviour change as this design feature is often used by developers to compel users to use the application (Villalobos-Zúñiga & Cherubini, 2020). The positive feeling one gets from being intrinsically motivated leads to satisfaction (Chan, 2009; Torres & Sidorova, 2015). Four factors that evoke intrinsic motivation include challenge, curiosity, control and fantasy (Davis & Wiedenbeck, 2001).

Challenge also called competence occurs when the assigned tasks match the user's skills. The challenging task should be attainable, not too difficult or not too easy because the user will lose interest (Davis & Wiedenbeck, 2001). Intrinsic motivation compels individuals to be novel and accept challenges (Gagné & Deci, 2005). Individual Intrinsic motivation is a result of an individual ability to carry out an activity effectively (Davis & Wiedenbeck, 2001). Curiosity occurs when the task is complicated or the activity results are inconsistent with what the user expected. The inconsistency evokes cognitive curiosity and motivates the user to resolve inconsistencies through exploration (Davis & Wiedenbeck, 2001). Control enhances intrinsic motivation because users have power over the choice of actions. Fantasy evokes mental imagination and allows users to relate the new information to their existing knowledge (Davis & Wiedenbeck, 2001).

Autonomy is a significant intrinsic variable in the IS post-adoption phase as it decreases resistance and increases user satisfaction (Rezvani *et al.*, 2017). Intrinsic motivation is distinguished by a high regard for personal investment and engagement (Fischer *et al.*, 2019). In the IS discipline, the engagement concept was then introduced, which has some similarities to intrinsic motivation. Engagement is a condition of a user whose attention and interest are fully caught and retained by an intrinsically enjoyable experience (Davis & Wiedenbeck, 2001; Peters *et al.,* 2016). Constructs Peters *et al.* (2016) used to evaluate engagement include enjoyment, the discovery of knowledge, like, freedom and excitement. The attractiveness, system functionality and interesting interactive system features (e.g. drillable reports in BI&A context) can evoke user engagement, which can lead to a positive attitude and greater system use. The higher the level of user engagement, the higher the system's use (Peters *et al.,* 2016). In addition, trust significantly influences individuals' intrinsic and extrinsic motivation. Trust refers to the guarantee that the system is reliable (Altin Gumussoy, 2016). In the BI&A context, data quality plays an integral part in enhancing individual trust in the system (Peters *et al.*, 2016; Torres & Sidorova, 2019). In information systems literature, the intrinsic motivators of users are, perceived enjoyment and perceived ease of use which are regarded as the strong determinants of intention to use, while the extrinsic motivator dimension is perceived usefulness (Hwang, 2005; Li *et al.*, 2013; Rezvani *et al.*, 2017).

3.2.3 Extrinsic Motivation

Extrinsic motivation entails a strong desire to take action to get rewards or avoid punishment (Malhotra *et al.,* 2008). Extrinsic contingent rewards include financial incentives, career status, personal development, community contribution, perceived usefulness, giving encouragement or praise and social connections or recognition (Deci *et al.,* 2017; Malek *et al*., 2020). Contingent threats or rewards treatment includes threatening punishments, delegating a task, and giving criticism (Altin Gumussoy, 2016; Deci *et al*., 2017; Vilnai-Yavetz & Levina, 2018). Extrinsic deals with external regulation of individual behaviours (Gagné & Deci, 2005). Incentivisation can improve employee motivation, job satisfaction, performance, desired behavioural outcomes, and attitudes (Rezvani *et al.,* 2017).

Positive reinforcer incentives encourage effort, better compliance, and improved performance, but over time, contingent rewards and no-rewards groups frequently worsen performance since they are not focused on the task at hand (Altin Gumussoy, 2016). Explicit rewards undermine workers' confidence in their abilities or the value of the rewarded tasks resulting in them being classified as negative reinforcers (Altin Gumussoy, 2016; Deci *et al.*, 2017). Controlling workers' behaviour with contingent incentives and threats is often criticised as it is regarded as alienating and dehumanising (Deci *et al.,* 2017). Trust increases the extrinsic motivation of users in terms of the technical and non-technical benefits of using the system (Altin Gumussoy, 2016).

In the literature on work behaviour, it has been shown that extrinsic motivation has a substantial influence on worker participation (Lin, 2007). Extrinsic motivation is based on individuals feeling pressured to perform the activity, while intrinsic motivation is associated with the sense of freedom and relaxation in performing an activity (Li *et al.,* 2013). Extrinsically motivated behaviours are essentially motivated by the desire to gain organisational incentives or reciprocal benefits (Lin, 2007). Interventions intended to be extrinsic motivators might produce short-term behaviour change that lasts for the period of the intervention (Villalobos-Zúñiga & Cherubini, 2020).

3.2.4 Perceived Enjoyment as an Intrinsic Motivator in BI&A

Perceived enjoyment is the amount to which the action of using the BI&A system is perceived to be pleasurable in itself, independent of any expected performance benefits (Venkatesh, 2000). Perceived enjoyment excludes the pleasant feeling resulting from completing an activity because it focuses on the enjoyment of the process, not the outcome (Li *et al.*, 2013). Intrinsic motivation is evaluated by assessing individual experience and feelings while performing an activity; an individual is considered intrinsically motivated if they report positive feelings such as interest, excitement, curiosity, and enjoyment (Altin Gumussoy, 2016).

The enjoyment or satisfaction gained from performing an activity is a factor that strengthens intrinsic motivation. Thus, enjoyment is regarded as an effective intrinsic motivator as its basis is in the process (Li *et al.*, 2013). Moreover, Intrinsic motivators are associated with the inner psychological process of generating an individual's favourable sentiments such as enjoyment (Vilnai-Yavetz & Levina, 2018). Voluntary usage stimulates intrinsic motivation (Yildiz Durak, 2019). Intrinsic motivation is based on a desire to return to performing a task without being directed to do so, indicating an individual's values or interests (Sanchez *et al.*, 2022).

Perceived enjoyment impacts perceived ease of use of the IS; tasks perceived as unenjoyable are less likely to be completed (Rezvani *et al.,* 2017; Venkatesh, 2000). Software developers are striving to design entertaining interfaces that integrate social functions to please users. During the system design, development, and user training phases, practitioners can obtain a deeper knowledge of individual reports, comfort and interest in the IS (Venkatesh, 2000). The game-based training (playfulness) method improves intrinsic motivation and results in increased enjoyment and increased ease of use perception (Hwang, 2005; Sanchez *et al.*, 2022; Venkatesh, 2000).

Thus, some studies used computer playfulness rather than enjoyment to explain intrinsic motivation in IS (Venkatesh, 2000). Intrinsic motivators are internal and are likely to generate long-term positive results and user loyalty (Lin & Hwang, 2014). The inherent satisfaction or enjoyment that one feels while performing a task acts as an individual internal motivator towards a specific activity; thus, perceived enjoyment qualifies as an intrinsic motivator (Sanchez *et al.*, 2022). Using a BI&A system can be enjoyable to users if users find it meaningful, flexible, satisfying, and fulfilling (Li *et al*., 2013). Moreover, enjoyment is perceived to be a situational characteristic that can be adjusted through user interaction with the system (Venkatesh, 2000).

3.2.5 Perceived Usefulness as an Extrinsic Motivator in BI&A

Perceived usefulness (PU) refers to users' belief that using BI&A systems would improve their performance or productivity within an organisation, and it captures the usability of a BI&A system (Wang *et al*., 2013). In the technology acceptance model (TAM) theory, PU is a major factor in user desire to use new technologies. In the TAM model, PU is captured as an extrinsic motivator as its basis is the outcomes (Venkatesh, 2000). Extrinsic motivators are concerned with avoiding dissatisfaction and avoiding the loss of current motivation (Vilnai-Yavetz & Levina, 2018). Hwang (2014) highlighted that perceived usefulness is an extrinsic motivator which is influenced by Personal Innovativeness in IT (PIIT) and the relationship is moderated by user experience. PIIT refers to "individual willingness to try out new information technology" (Hwang, 2014, p. 228). PU has been used to study IS adoption, usage, IS continuance and behaviour intention to use IS (Koo *et al.,* 2015). Based on expectation confirmatory theory during the post-adoption phase, perceived usefulness is a result of users' expectations being confirmed, which leads to user satisfaction and continuance intention (Limayem *et al*., 2003). External stimuli such as tangible rewards and job performance, and recognition impact perceived usefulness (Malhotra *et al.,* 2008). Users use the IS if it improves their work performance and they perceive it useful hence the improved performance enables them to receive extrinsic rewards (Li *et al.,* 2013).

3.3 DATA VISUALISATION LITERACY AND EXPLOITATIVE AND EXPLORATIVE BI&A USE

Exploitative and explorative use describe IS usage behaviours. Exploitative use refers to using system features in a standard way to complete work tasks (Koo *et al.,* 2015; Li *et al.,* 2013). Exploitation involves the use of the BI&A system to execute structured, repeated activities to improve operational efficiency (Koo *et al*., 2015). Explorative use refers to the use of the BI&A system in an inventive or creative manner to assist work-related tasks in pursuit of new opportunities (Koo *et al*., 2015; Li *et al.*, 2013). The main difference between the two forms of use lies in how users use the IS (Li *et al.,* 2013). Being innovative can take various forms, such as integrating diverse ideas or challenging current methods of doing things (Wang *et al.,* 2013). User competence is the main determinant of exploitative and exploration use of IS usage (Koo *et al*., 2015). User competence in BI&A allows users to find and define new business opportunities through data collection and analysis (Torres *et al*., 2018). Moreover, one of the determinants of behavioural intention to use technology is one's ability to use technology (Yildiz Durak, 2019). Data visualisation literate users in the BI&A environment can use the established standard reports or dashboards created by BI developers daily to examine and monitor the indicators they are interested in and understand what is happening in the organisation at present. User repetitive or standardised use (users believe using the BI&A is normal and it is incorporated into their work activity) refers to exploitation. It is then hypothesised:

H1a: Data visualisation literacy has a positive effect on the exploitative use of the BI&A system

A higher degree of user competency allows a user to be more dedicated to achieving their goals and increases the user's commitment to exploring IT systems or full use of the IS features (Koo *et al.,* 2015). IT-Self-Efficacy (ITSE) is related to IT users' commitment, persistence, and information-seeking behaviour. ITSE refers to an individual's assessment of their capacity to use technology (Wang *et al*., 2013). Individuals' innovative use of new IS is encouraged by ITSE, and their familiarity with the current IS (Wang *et al*., 2013). Users who frequently use the reports and understand how to interpret the visualised data in BI&A systems can start exploring the data. Users can explore the BI&A system by creating their reports or extracting new variables (indicators) to compare with the variables from existing reports; use the drill down, drill through feature and interactive reports for more data exploration. This means users can creatively analyse the data in the BI&A system. The expertise of BI&A users enables users to identify and shape new business opportunities through data gathering and analysis (Torres *et al.,* 2018). Users may discover new ways to use certain features of an application as they acquire expertise with them, which may go beyond the implementers' intended application usage. Therefore, the following hypothesis:

H1b: Data visualisation literacy has a positive effect on the explorative use of the BI&A system

3.4 DATA VISUALISATION LITERACY AND PERCEIVED ENJOYMENT

Competence is linked to individual intrinsic motivation in the self-determination theory, as intrinsic motivation towards accomplishment is stimulated by individual competence, effectiveness and proficiency in the work environment (Gagné & Deci, 2005; Li *et al.,* 2013). Moreover, the need to be competent is strongly associated with emotional reactions such as joy, happiness and pride (Torres & Sidorova, 2015). Competence of BI&A users means being data visualisation literate and relates to the feeling of being effective at work (Fischer *et al.,* 2019). Faster goal achievement energises individuals and individuals are intrinsically motivated (Fishbach & Woolley, 2022). Thus, Data visualisation literate users will perform their data interpretation tasks faster which will result in enjoyment. A skilled individual will believe that the system is easy to use and enjoy using it. Thus the following hypothesis is proposed:

H2: Data visualisation literacy has a positive effect on BI&A system perceived enjoyment among users

3.5 DATA VISUALISATION LITERACY AND PERCEIVED USEFULNESS

The individual characteristics determinates that influence business intelligence usage by Ruhode and Mansell (2019) include education which is associated with perceived usefulness under behavioural beliefs and attitude factors. This indicates that a skilled individual will perceive an IS as useful because they can efficiently apply it. According to Lee *et al.* (2019) highly skilled graph readers can extract more elaborate valuable accurate information from graphs or charts, and rely more heavily on the graphically presented data than on their prior knowledge about the subject matter. Likewise, Perceived competence is positively associated with perceived usefulness (Mohammadi, 2015; Rezvani *et al.*, 2017). Data visualisation literate users will have the ability to read and use data from the BI&A system to achieve their work-related tasks. The sense of achievement resulting from analysing information and coming up with innovations will lead to the user perceiving BI&A as useful. The following hypothesis is then proposed:

H3: Data Visualisation literacy has a positive effect on BI&A system perceived usefulness among users

3.6 PERCEIVED ENJOYMENT AND EXPLOITATIVE AND EXPLORATIVE BI&A SYSTEM USE

One of the factors that evoke enjoyment as an intrinsic motivator includes curiosity. Curiosity, flexibility, enjoyment, and satisfaction when one performs an activity stimulate innovation (Hwang, 2005; Li *et al*., 2013). Perceived enjoyment is a major factor in the usage of technology by individuals. The pleasurable sensational usage experience successfully drives user interest, eases cognitive loads, encourages good usage attitudes and stimulates IS usage (Li *et al.,* 2013). A high level of enjoyment will lead to users voluntarily spending more time using the system (Venkatesh, 2000). If a user enjoys using the BI&A system they will routinely use it. Explorative use assumes the user is actively engaged in exploring the IS features (Saeed & Abdinnour, 2013). Individuals who enjoy using the system are expected to indulgently use it without any expected outcomes or specific beneficial results, thereby becoming exploitative (Venkatesh, 2000). When the BI&A system gives a pleasant experience to the user in the form of curiosity, attention and control, it will likely result in greater use of the system. Thus in line with Li *et al*. (2013), the following hypothesis is proposed:

H4a: Perceived enjoyment has a positive effect on exploitative use of the BI&A system

Rich intrinsic motivation includes motivation towards accomplishment, motivation to know, and motivation to experience stimulation promotes routine and innovative information system use (Li *et al.,* 2013). Motivation to know can be associated with curiosity; if a user is curious about a BI&A system, they will spend more time practising or experimenting with the system and over time can start being explorative The various elements that can stimulate enjoyment and improve user experience in using BI&A include appealing visuals and attractive interface, colour, the level of detail, interesting system features and interactivity of the BI&A system (Peters *et al.,* 2016). Thus, enjoyment is associated with BI&A system characteristics. An intrinsically enjoyable experience increases the user's sense of engagement (Peters *et al.,* 2016). When users are engaged they become actively involved and motivated to use a product or system. If individuals are intrinsically motivated, they will be open to new ideas or exploration of possible solutions to tasks (Malek *et al.,* 2020). When a person commits to using a feature of an IT application, they actively explore and maybe expand how to use system features to complete their tasks (Jasperson *et al*., 2005). Thus the following hypothesis is proposed:

H4b: Perceived enjoyment has a positive effect on the explorative use of the BI&A system

3.7 PERCEIVED USEFULNESS AND EXPLOITATIVE AND EXPLORATIVE BI&A SYSTEM USE

In TAM and IS continuance literature, perceived IS usefulness is a good predictor of user intention to use IS, extended use and exploratory IS usage (Koo *et al.,* 2015). The intention is the possibility of an individual using IS, which is crucial in the actual use of new technology (Mohammadi, 2015). Individuals' desire to use a certain IS for operational activities is determined by their usefulness perception. In the information system continuance literature, perceived usefulness and user satisfaction are the critical antecedents of IS usage behaviours (Rezvani *et al.,* 2017; Wang *et al.*, 2013). PU is positively associated with innovation in IT (IwIT). IwIT focuses on users' continuance with the use of IT and applying IT in the most novel ways. If individuals believe that using IT would improve their performance, they will be willing to spend more time and effort experimenting, and eventually, they will find new ways to use it (Wang *et al*. 2013). Thus, the following hypotheses:

H5a: Perceived usefulness has a positive effect on the exploitative use of the BI&A system

H5b: Perceived usefulness has a positive effect on the explorative use of the BI&A system

3.8 EXPLOITATIVE AND EXPLORATIVE BI&A SYSTEMS USE

Exploitative usage measures include frequency or volume of IT usage and use of IS features (i.e. the number of times a user uses an IS) (Saeed & Abdinnour, 2013). This indicates that if a user is exploitative, they will spend more time using the system. Explorative use entails exploring new features to enhance work effectiveness (Saeed & Abdinnour, 2013). A higher level of experience and knowledge will improve users' abilities to creatively use the IS (Koo *et al.*, 2015). Therefore, the following hypothesis:

H6: Exploitative use of the BI&A system has a positive effect on explorative use

3.9 CHAPTER SUMMARY

Drawn upon theories of data visualisation literacy, motivational theories and usage behaviour theories, various hypotheses were discussed and a proposed conceptual model in Figure 10 is derived. For BI users to be data visualisation literate, they should be able to read the graphically represented data provided by the BI&A system, read between the data and finally read beyond the data, as per data literacy literature. Also, Users need to be motivated to use an IS, elements like curiosity, enjoyment, importance, and usefulness enhance motivation in people.

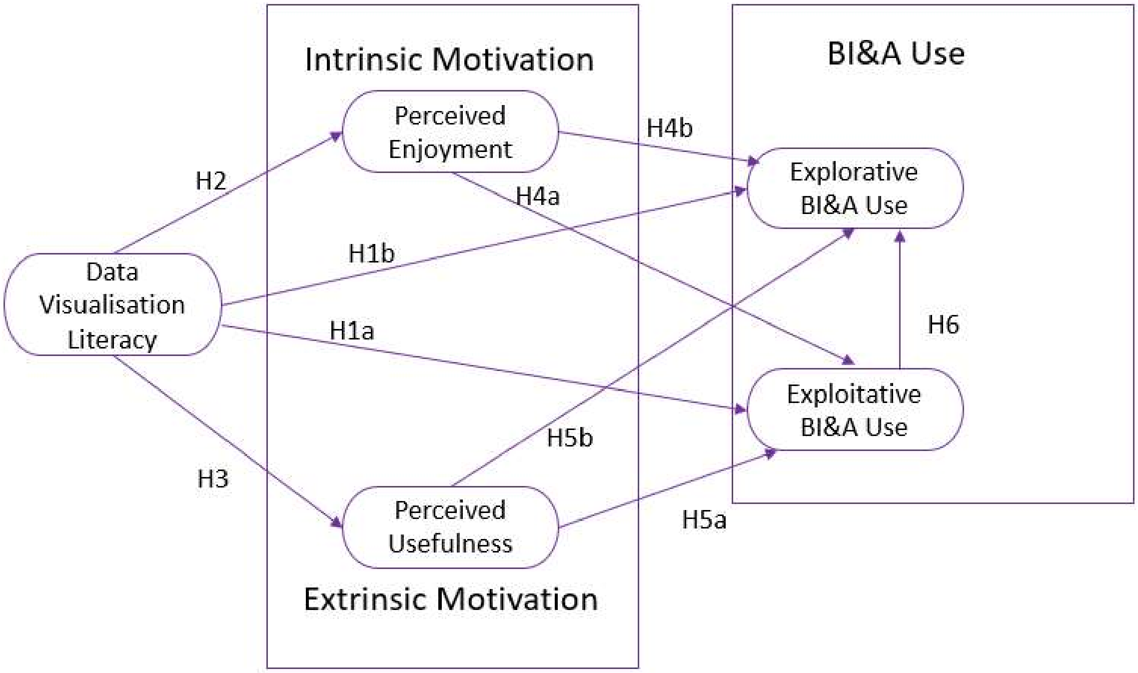


Figure 3: Conceptual Framework of the influence of motivation on BI&A use Based on (Gefen *et al*., 2003; Kim & Gupta, 2014; Lee *et al*., 2016; Venkatesh, 2000)

Chapter 4

METHODOLOGY

4.1 INTRODUCTION

This chapter outlines the research design plan which provides a framework for the study by describing theoretical assumptions in the chosen research philosophy that supports the research strategy and methodological choice of the study. The plan also presents how the research outcomes were obtained to accomplish the objective of the study. It describes the development of the research instrument, the sampling process, including the data collection process and analysis, and ethical considerations to take into account for this study.

4.2 RESEARCH DESIGN

4.2.1 Research Philosophy

There are four research paradigms popular in information systems research, namely, positivism, interpretivism, pragmatic, and critical paradigms (Kivunja & Kuyini, 2017). In positivist research, factual reality exists independent of human senses and valid knowledge is created and measured statistically (Scotland, 2012). In interpretivism research, the reality is a social construct that varies among individuals and knowledge is subjectively created and gathered through interaction between the researchers and participants. Pragmatic uses a mixed method (positivism and interpretivism) to allow a more practical and pluralistic approach to research; artefacts are developed based on theory. The critical paradigm interrogates values and assumptions and challenges conventional social structures. Knowledge is socially constructed and can be influenced by social beliefs, politics, culture and gender values (Kivunja & Kuyini, 2017; Scotland, 2012).

This study follows the positivist research philosophy, as there is factual evidence that can be gathered and statistically measured for data visualisation literacy, motivation, and business intelligence and analytics use. In positivist research, data is collected on observable reality. Existing theories on data visualisation literacy, motivation and usage behaviours (Koo *et al*., 2015; Li *et al*., 2013; McDowall *et al.*, 2020; Wolff *et al.*, 2016) were used to formulate testable hypotheses, in which the researcher searched for regularities and established causal relationships in the data to create a generalisation of a phenomenon (Saunders *et al.,* 2012).

4.2.2 Methodology of choice

The data collected is quantitative, as it is appropriate for statistically testing the outlined hypotheses, and there is an existing model to be tested, and hypotheses were formulated. Quantitative is generally associated with positivist research, as data needs to be collected numerically in a standardised manner normally using a questionnaire and analysed using statistical techniques (Kivunja & Kuyini, 2017; Saunders *et al.*, 2012).

4.2.3 Research Approach

The researcher aims to independently and objectively observe the effect of motivation in determining the relationship between data visualisation literacy and BI&A use in organisations. The study is based on testing a proposed model based on existing theories. Thus, the approach to theory is deductive. The deductive approach starts with a theory and tests theoretical hypotheses using empirical data. The deductive approach states that the researcher should be independent of what is being observed. The researcher and the researched matter are separate entities (Saunders *et al.,* 2012). In addition, concepts need to be brought up in a way that enables facts to be measured quantitatively (Kivunja & Kuyini, 2017). The study followed these outlined stages of deductive positivist research, namely: (i) A conceptual model was developed based on existing theories of data visualisation literacy, motivation, and user usage behaviours (ii) Relationships between variables (data visualisation literacy, perceived enjoyment, perceived usefulness, exploitative use, and explorative use) was established (iii) Hypotheses were formulated based on the existing literature on literacy, motivation and usage behaviours and the logic of the argument was examined in comparison with existing theories (iv) Data was collected and statistically analysed to test hypotheses (v) Based on the statistical results, the hypotheses were either accepted or rejected (Saunders *et al.,* 2012).

4.3 SAMPLING

4.3.1 Target population

The research population of the proposed study is executives, business managers, operational supervisors, analysts and decision-makers (information consumers) across a range of organisations that are already using BI&A systems. Criteria for selecting participants included finding individuals that are using BI&A systems in their organisations.

4.3.2 Sampling method

It is not feasible to collect data from the whole population, therefore to obtain the target sample, a snowball non-probability sampling technique was used to identify BI&A users. This is because there is no publicly available database for organisations that have implemented BI systems or an official list of BI users. In the reviewed literature, researchers conduct their BI studies for a specific context (e.g. Health, Banking) or country (Mudzana & Maharaj, 2017; Olszak, 2016). Snowball sampling is a non-probability sampling technique where subsequent respondents are recruited by the initial seed respondents.

The initial seeds are selected via convenience sampling of members of the rare population. In this study, the initial sample were users from organisations that have implemented BIS known by the researcher. The initial group was asked to forward the survey to members in their network, which was regarded as the second group. The second group serves as gatekeepers, a technique proven to reduce the possibility of sampling bias, which is a popular disadvantage of snowball samples (Torres & Sidorova, 2019). This sampling method was used in various studies in information systems (Torres *et al.*, 2018). Non-probability sampling can be a viable alternative to probability sampling if it is difficult for the researcher to obtain a sampling frame and where random sampling is not feasible (Saunders *et al.*, 2012). Snowball sampling is quick and cost-effective, as a cross-sectional research timeframe is used to conduct this study because the study must be completed within the course duration (Saunders *et al.*, 2012).

4.3.3 Sample size

Previous studies on BI users in organisations have a sample size of 150 on average (Peters *et al.*, 2016; Torres & Sidorova, 2019; Torres *et al.*, 2018). For this study, the target sample size is 200 BI users, which is in line with the sample size of similar studies, with a minimum sample size of 100 participants. The minimum sample is calculated in line with Ahmad et al. (2016), who calculated the minimum sample size based on 20 participants per construct for the quantitative research. In this study, there are five constructs (data visualisation literacy, perceived usefulness, perceived enjoyment, exploitative BI&A use and explorative BI&A use), which led to 100 being the minimum sample size.

4.4 DATA COLLECTION

4.4.1 Survey method

There are various techniques for collecting primary data these include the use of questionnaires, observations and interviews. Questionnaires can either be self-administered or interviewer-administered. Self-administered can use an electronic questionnaire or questionnaires can be delivered by hand to each respondent and collected later (Saunders *et al.*, 2012). The target population for this study is a range of decision-makers in organisations. It is important to reach the various decision-makers in the organisations and most decision-makers are very busy. Thus, the study makes use of a self-administered survey strategy, which was conducted through the use of close-ended online web-based questionnaires. Online surveys can be cheaper and more cost effective than other methods if used properly. Participants can answer the questions at their most convenient time and diverse geographically dispersed participants can be reached, but there is a high possibility of participants ignoring the survey. Surveys are usually associated with a deductive research approach and allow for the collection of quantitative data, which can be used to explain possible reasons for particular relationships between variables (Saunders *et al.*, 2012). The online survey link was distributed via email, social media, and the LinkedIn platform.

4.4.2 Measurement

Data visualisation and data analyses are integral parts of both data visualisation literacy and business intelligence and analytics. The Visualisation Literacy Assessment Test (VLAT) by Lee et al. (2016) was used to measure the level of individual data visualisation literacy. VLAT consists of fifty-three items and eight analytical tasks are associated with the twelve data visualisation types. Thirty-three items were four-options multiple-choice items, three were three-option multiple-choice items and seventeen were true or false items. Each question on the VLAT had an “omit” option which allowed users to skip the question if they do not know the answer. To avoid potential bias from context familiarity, the underlying datasets used to create these visuals are from news articles (i.e general context). Six datasets used catered for different contexts specifically: oil, internet, websites, coffee, smartphones, and metro transport system. Data attributes included nominal (e.g countries, smartphones, months of the year), ordinal (e.g stating specific range), and numerical (e.g price values) types. The test takes an average of 22 minutes to answer the 53 questions. Classical test theory was adapted in developing the VLAT where the question difficulty index and item discrimination index were evaluated. Item difficulty index evaluation classified each question into either easy, moderate, or hard while item discriminate classified each item as high, medium or low.

For this study, six data visualisation types were chosen so that the questionnaire does not become too long and to improve the response rate. The instrument had twenty-one questions relating to data visualisation literacy. The measure consisted of multiple-choice items (seventeen questions) and true or false (four questions) items covering the three most popular well-recognised primitive visuals data visualisation tasks (line chart (four questions), bar chart (four questions) and pie chart (three questions)) (Lee *et al.*, 2015; Saket *et al.,* 2018) and three unfamiliar data visualisation tasks (area chart (three questions), bubble chart (four questions) and treemap (three questions)). The questionnaire focused on the four analytical tasks retrieve, extremum, range, comparison and hierarchy was added for a treemap as the hierarchical structure was identified as a critical task in reading and interpreting visual data (Lee *et al.,* 2016). The omit option was replaced with the word "skip" as skip was the most appropriate word to use, see Appendix A for the research instrument (Tahir *et al*., 2020).

The individuals were assessed by reading the visualised data and reading between the data. Reading beyond the data was not included as the existing instrument does not evaluate tasks related to reading beyond the stated data (predicting). VLAT was developed to assess the level of users' data visualisation literacy, especially non-expert users in data visualisation. Grids were included in visualisations with a Cartesian coordinate system to assist potential test takers in reading values on axes. VLAT is the ideal way to evaluate user data visualisation literacy in the BI context, as one can evaluate whether users can correctly read and interpret the visualised data.

The perceived usefulness measures were adopted from Gefen et al. (2003), and the questions were modified in line with tasks related to business intelligence and analytics systems. Perceived enjoyment measures were adopted from Venkatesh (2000), these measures were used to evaluate the usage behaviour of information technologies. The two-dimension of BI&A system use (exploitative and explorative use) was adapted from Kim and Gupta (2014) and modified for use in the BI&A context. Motivation and BI&A use constructs were measured using a seven-point Likert scale (ranging from one strongly disagree to seven strongly agree).

4.4.3 Pre-testing and Pilot testing

Before distributing the questionnaire for data collection, the research instrument was pilot tested by three BI&A users, one BI&A developer and two academic BI&A experts known by the research. This was to ensure that the length is appropriate, the wording is understandable, there is no ambiguity in the measurement items, and to allow for suggestions to the structure and content validity. It is important to ensure that questions are properly articulated so that every participant understands questions in the same manner. There was an omission of grid lines on the visuals and participants indicated difficulty in reading the line graph.

Participants' feedback was used to refine the research instrument. Thus, grid lines were included in the line, bar chart, area chart and bubble chart. The preliminary analysis was done after reaching 30 participants to ensure that the collected data will enable the answering of the stated research questions. The frequency distribution table was run to analyse data visualisation literacy evaluation, user distribution and perform accuracy screening of the data. Item reliability of the other four constructs (perceived enjoyment, perceived usefulness, exploitative use, and explorative use) was also evaluated.

4.5 DATA ANALYSIS

The construct validity and reliability of the research instrument were assessed. Construct validity entails verifying that the instrument items selected for a given construct combined altogether actually measure what the researcher intends to assess. There are two main components of construct validity- namely, convergent validity and discriminant validity, which can be assessed using confirmatory factor analysis (CFA) (Straub *et al.*, 2004). Factor loading can indicate if there is an overlap across different dimensions, which is referred to as discriminant validity. In contrast, convergent validity is assessed by evaluating whether indicators of the same construct have a high correlation amongst themselves and load together. A high factor loading (greater than 0.5 and close to 1) indicates good convergent validity.

Reliability refers to the extent to which the respondent can answer the same questions, in the same manner, each time (i.e. consistency of the data collected and accuracy of the instrument) (Straub *et al*., 2004). A Cronbach alpha measurement was used to determine the reliability of a research instrument. A Cronbach alpha measurement of 0.7 or higher is considered reliable, although a Cronbach Alpha of 0.6 and above is considered acceptable for positivist research in the field of information systems (Straub et al., 2004).

Data was then imported into Excel so that it can be cleaned by the researcher. Using statistical software (SPSS version 28.0.1.0) for analysis, structural equation modelling (SEM) was used to test the formulated hypotheses. SEM has become popular in information systems research. SEM is a regression analysis that allows comparisons between multiple independent and dependent variables (Straub *et al.*, 2004). It is more appropriate for multivariate casual predictive analysis and exploratory research and testing theories that are less developed (Sparks & McCann, 2015). It is ideal when the sample size is too small, or when there are missing values in the data or multicollinearity (correlation coefficient above r = 0.80). The independent variable was data visualisation literacy while perceived enjoyment and perceived usefulness were the mediating variables, and exploitative use and explorative use were the dependent variables. Hypotheses are supported if the p-value is less than 0.05. The demographic data of respondents was used to perform descriptive analysis. Using SPSS software frequency, the mean scores standard deviation and correlation between constructs were calculated to describe the sample population.

4.6 ETHICS

Prior to the collection of data, the researcher received ethical clearance from the University of Pretoria Research Ethics Committee. The online survey was distributed once approval had been granted. The first page of the survey outlined the purpose and benefits of the research, and the participant's right to decline to participate or withdraw. The first page further included consideration for anonymity, confidentiality and privacy of participants' information. Non-identifying respondents' demographic data was collected and was used for the description of participants' profiles only. Consent from the participant was required, so a self-filled check box with the option “Agree” and “Disagree” was included as an indication of participant consent, see Appendix B for the cover letter. There were no ethical issues discovered during the study (no one was injured or felt uncomfortable). A secure online platform Qualtrics was used to collect the data, once the data was downloaded from the server, it was stored on a password-protected computer and later uploaded to the university repository.

4.7 CHAPTER SUMMARY

The research follows a deductive positivist quantitative approach to investigate the research questions. Theory on literacy, motivation and user usage behaviour were used to develop the instrument that was used to test the hypotheses. The hypotheses were analysed using SEM and descriptive statistics were performed to describe the sampled population.

Chapter 5

ANALYSIS OF FINDINGS

5.1 INTRODUCTION

This chapter provides information related to the data collection and cleaning process in preparation for the analysis of the data. Then a detailed analysis of the collected data is presented. The respondents' characteristics are discussed to describe the sample. The data collected is tested for internal consistency and accuracy. The proposed research model is tested for goodness of fit before the testing of the hypotheses. The hypotheses are then tested using statistical methods. Lastly, the findings are presented.

5.2 DATA COLLECTION

The survey was developed using Qualtrics software and an anonymous survey link was distributed via emails and social media platforms. The survey ran for a period of 21 weeks, until October. The initial sample consisted of professionals from the researcher's contact list. Through snowball sampling, a total of 181 participants started the survey, inclusive of 69 questionnaires that were partially complete. This leaves 112 complete records, giving a 62% completion rate. There were no reminders sent to the in-progress respondents because the survey was distributed through an anonymous link. During data cleaning the researcher identified one record where the respondent skipped every question on data visualisation literacy and straight-lining (answering questions identically) in answering Likert scale questions, that record was regarded as invalid, resulting in 111 valid usable records. The data was collected from the employees of organisations that have implemented BI&A solutions. Employees were encouraged to spend a maximum of 25 seconds answering each data visualisation literacy question, but compliance with this instruction could not be assessed as the instrument had additional other questions.

5.3 DEMOGRAPHIC PROFILE

The Spss version 28.0.1.0 (142) software package was used to analyse the data. Table 4 shows the sample characteristics. The age of respondents was recorded using a polychotomous variable with the youngest user being 18 and the oldest user being above 55. The majority of respondents belong to the age band 25 to 44 years (79%). A significant proportion of respondents (96%) had a tertiary qualification, and 93% of the respondents had a minimum of a bachelor's degree. The majority of the respondents belong to the operational level (64%), while 36% were from the management level inclusive of a small proportion (4%) from the executive level from a variety of business functions. The majority of respondents were from the information systems department (39%), followed by reporting and data analytics (16%), sales and marketing (11%), accounting and finance (8%), human resources (7%), project management (6%) and others (risk management and compliance, research, administration, production) (11%).

The participants were from various industries with most respondents from non-government (23%), followed by health (20%), telecommunications (11%), education (11%), and financial services (10%). These organisations were based in Lesotho (42%), South Africa (24%) and other countries (34%). 67 % of respondents had one to above four years of experience in the BI&A environment, thus they are expected to have sufficient knowledge of BI&A. The majority of the respondents were familiar with using one BI tool (73%), while (27%) were using two to three BI tools. Microsoft Power BI seems to be the most popular BI tool (57%) among the respondents followed by Tableau (24%) and Oracle BI (8%). This was expected because in Gartner guardant for analytics and business intelligence platforms, Microsoft is the first in line among the leaders followed by Tableau (Kopp & Orlovskyi, 2022). The combination of Microsoft PowerBI and Tableau seems to be popular among users who use more than one BI tool.

Table 4: Profile of the participants (*n=111*)

Participants	Frequency	%
Age Group		
18 – 24 years	13	12%
25 – 34 years	50	45%
35 – 44 years	38	34%
45 – 54 years	9	8%
55 years and above	1	1%
Highest level of education		
Doctoral Degree	2	2%
Master’s Degree	30	27%

Postgraduate Diploma/ Degree	33	30%
Undergraduate/ 1st Degree	38	34%
National Diploma	4	4%
Other	4	3%
Departments		
Information Systems	43	39%
Reporting and Data Analysis	18	16%
Sales and Marketing	12	11%
Finance and Accounting	9	8%
Human Resource	8	7%
Project Management	7	6%
Industries		
Non-government	25	23%
Health	22	20%
Telecommunications	12	11%
Education	12	11%
Financial services	11	10%
Other	29	25%
Experience in the BI environment		
Less than 1 year	37	33%
1 – 4 years	49	44%
Above 4 years	25	23%
BI Platform *n=127*		
Microsoft PowerBI	72	57%
Tableau	31	24%
Oracle BI	10	8%
Other BI tools	14	11%

5.4 DESCRIPTIVE STATISTICS ON DATA VISUALISATION LITERACY (DVL)

The DVL construct was created by adding correct responses to the 21 questions indicating an individual level of data visualisation literacy similar to the Tahir *et al.* (2020) financial literacy study. Those who replied with "skip" are treated as incorrect answers because it implied a wrong response as the respondent did not know the answer. Correct answers were recorded with two, wrong answers with a one and skipped with a zero. Each correct question carries one mark and there is only one correct or best answer for each test item, thus the maximum score one can get is 21.

An item analysis was performed to check item difficulty and discriminability based on classical test theory. Item difficulty index is the proportion of respondents who answered the item correctly over the total number of respondents. An item is classified as easy if the item difficulty index is above 0.85, moderate if it is between 0.5 and 0.85 and hard if below 0.5 (Lee et al., 2016). Table 5 shows the results of the item analysis. The item difficulty index ranged from 0.24 to 0.97 with an average of 0.73. Item discrimination index measures how well an item distinguishes between the highest score and lowest score. It is a proportion of the difference between the number of respondents who correctly answered the item in the upper group and the number of respondents who correctly answered the item in the lower group over the total respondents. The value ranges from -1.0 to 1.0. Item discriminability is classified as high if the value is above 0.3, medium if the value is between 0.1 and 0.3 and low if below 0.1 (Lee *et al.,* 2016). The discriminability index ranged from -0.03 to 0.80. There were thirteen highly discriminating items, six medium, and two low. If the questions are too easy for the respondents the discriminability index is lower.

The skewness and kurtosis DVL distribution scores using the Shapiro-Wilk test indicated a left-skewed distribution (skewness= -0.608 kurtosis = 0.104) indicating that the data deviates from a normal distribution, see Figure 10. In a left-skewed distribution, a bulk of observations are around the median or maximum (Ferreira & Steel, 2006). The distribution test helps in the interpretation of individual scores and in classifying DVL in this study. Individual competency level is then classified as per the percentiles see Table 6 for DVL descriptive statistics and percentiles. Individuals belonging to the 25th percentile are classified as having low DVL, those belonging to the 50th percentile as average and the 75th percentile as high. Table 7 shows the categorised distribution of data visualisation literacy scores among respondents. Forty-two per-cent of the respondents were highly literate with a score of above 80%. The proportion of high to average to low DVL levels is 4:4:2 which indicates that individuals performed well on data visualisation literacy assessment. The respondents' score for data visualisation literacy ranges from 23% to 95%, with a mean score of 69% indicating that generally, individuals were data visual literate. The average percentage performance score of each visual is as follows pie chart 91%, treemap 84%, bar chart 81%, line chart 73%, bubble chart 61%, area chart 44%, Table 8 illustrates the performance scores per visual. Some questions had 30% or more of the responses incorrect, necessitating further investigation into the response.

Table 9 displays the frequency Table for the response analysis where 30% or more of the respondents did not perform well on the question. In the line chart determining range question, respondents who answered the question incorrectly looked at the starting point of the line and end point of the line to come up with the range, hence they answered 37.04 - 48.36, while in the make comparison question respondents did not calculate the difference between the two points but instead took the data value from the last data point "to variable". Respondents failed to read the x-axis correctly in the area chart retrieve data and in find extremum questions, taking values for 2014 rather than 2013, while in determining the range, they were able to identify the minimum but not the maximum. They failed to read the y-axis value correctly and identify the correct interval on the scale. In the bubble chart retrieve value question, respondents looked at the end of the circle of the bubble instead of the centre of the bubble to retrieve the value, while in determining range, respondents took the value of the bubble that appears first along the x-axis, similar to how they interpreted range in a line chart. In the bubble chart make the comparison question they ignored the bubble size (ridership) but checked the values on the y-axis (total length). Generally, respondents struggled in reading and interpreting the axis. Respondents performed well on analytical tasks regarding a pie chart and the least performed on the area chart. No respondent got all DVL questions correct and out of the seven top scorers (scored 95%), four had challenges with the area chart while the other three were each challenged by a bar chart, bubble chart and treemap. The data visualisation literacy scores of respondents range from 0% to 100% for all visuals, except for the pie chart which ranges from 33% to 100%, indicating that among the three questions associated with a pie chart all the respondents managed to at least answer one question correctly.

Table 5: DVL difficulty and discrimination index

(difficulty index green= easy, orange = moderate, red = hard; discrimination index green = high, orange = medium, red =low)

	Difficulty	Discrimination
Line graph retrieve	0.784	0.500
Line graph extremum	0.964	0.100
Line graph range	0.541	0.567
Line chart comparison	0.649	0.800
Bar chart retrieve	0.811	0.300
Bar chart extremum	0.973	0.100
Bar chart range	0.748	0.567
Bar chart comparison	0.748	0.433
Area chart retrieve	0.649	0.400
Area chart extremum	0.243	0.400
Area chart range	0.450	0.533
Pie chart retrieve	0.829	0.433
Pie chart extremum	0.964	0.067
Pie chart comparison	0.955	0.133
Bubble chart retrieve	0.541	0.500
Bubble chart extremum	0.721	0.400
Bubble chart range	0.568	0.800
Bubble comparison	0.586	0.533
Treemap extremum	0.946	0.200
Treemap comparison	0.820	0.333
Treemap hierarchy	0.820	-0.033

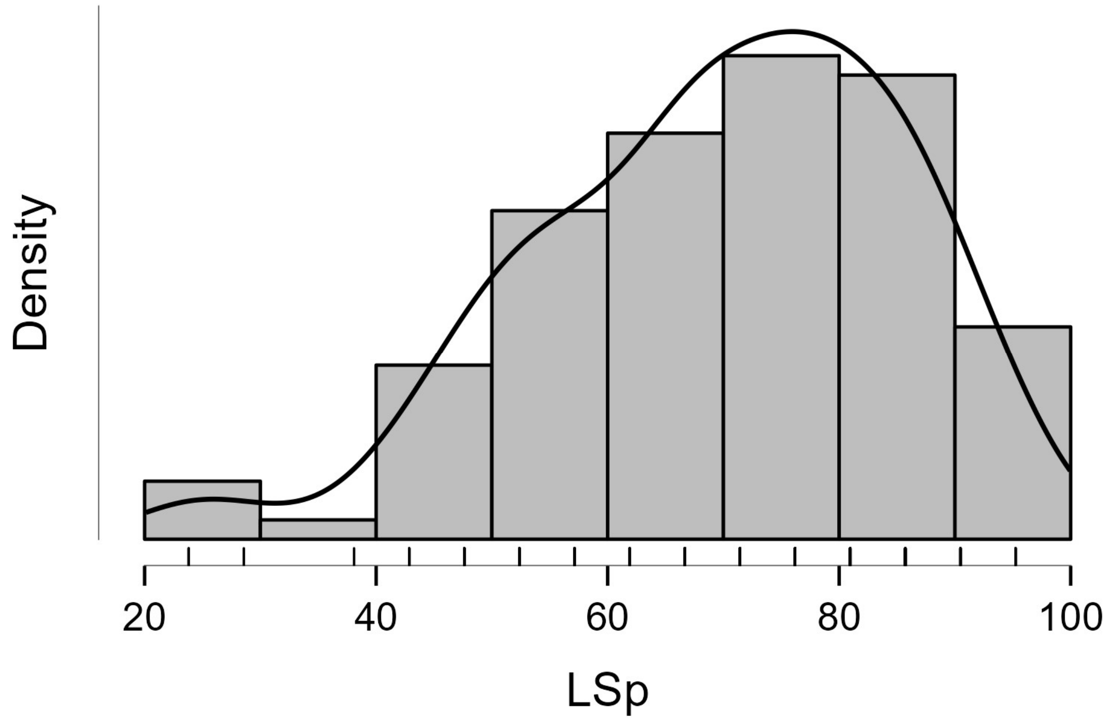


Figure 5: DVL scores distribution plot

Table 6: Descriptive Statistics For Data Visualisation Literacy Scores

	Literacy Scores Percentage(LSp)
Valid	111
Missing	0
Mean	69.455
Std. Deviation	15.760
Skewness	-0.608
Std. Error of Skewness	0.229
Kurtosis	0.104
Std. Error of Kurtosis	0.455
Shapiro-Wilk	0.959
P-value of Shapiro-Wilk	0.002
Minimum	23.810
Maximum	95.238
25th percentile	57.143
50th percentile	71.429
75th percentile	80.952

Table 7: Data visualisation literacy respondents distribution *n*=111

Percentiles	Literacy Level	Frequency	Percentage
25th Percentile	low	18	17%
50th Percentile	average	46	41%
75th percentile	high	47	42%

Table 8: Data visualisation literacy items based on the six data visuals (*n*=111)

Measuring item	Number of items	Analytical task	Correct responses	Wrong responses	Skipped	Correct percentage
Line graph	4	Retrieve	87	19	5	78%
		Extremum	107	4	0	96%
		Range	60	47	4	54%
		Comparison	72	31	8	64%
Bar Chart	4	Retrieve	90	18	3	81%
		Extremum	108	3	0	97%
		Range	83	19	9	73%
		Comparison	83	28	0	73%
Pie Chart	3	Retrieve	92	12	7	83%
		Extremum	107	3	1	96%
		Comparison	106	5	0	95%
Area Chart	3	Retrieve	72	36	3	64%
		Extremum	27	82	2	24%
		Range	50	44	17	45%
Bubble	4	Retrieve	60	44	7	54%
		Extremum	80	29	2	72%
		Range	63	41	7	57%
		Comparison	65	37	9	56%
Tree map	3	Extremum	105	2	4	95%
		Comparison	91	9	11	81%
		Hierarchy	83	11	17	75%

Table 9: Response frequency for items with 30% or above incorrect answers

(green = correct, red= incorrect)

Type of visual	Analytical Task	Responses	Frequency	Percentage
Line chart	Determine range	skip	4	3.6%
		37.04 - 48.36	47	42.3%
		37.04 - 60.95	60	54.1%
	Make comparison	skip	8	7.2%
		45	31	27.9%
		15	72	64.9%
Area Chart	Retrieve data	skip	3	2.7%
		5.2	36	32.4%
		5.1	72	64.9%
	Find Extremum	skip	2	1.8%
		June 2014	82	73.9%
		December 2014	27	24.3%
	Determine range	skip	17	15.3%
		4.6 – 6.1	44	39.4%
		4.6 – 6.0	50	45.0%
Bubble Chart	Retrieve data	skip	7	6.3%
		560km	44	39.6%
		530km	60	54.1%
	Determine range	skip	7	6.3%
		240 – 560km	41	36.9%
		180 – 560km	63	56.8%
	Make comparison	skip	9	8.1%
		True	37	33.3%
		False	65	58.6%

5.5 RELIABILITY AND CONSTRUCT VALIDITY

Reliability evaluation is a measure of attribute internal consistency. There are several methods to evaluate construct reliability: test-retest reliability, parallel test forms reliability, single administration reliability, Kuder Richardson coefficient and Cronbach's coefficient alpha (Streiner, 2003). The reliability measure is an indicator that the construct was measured precisely, and consistently (Straub et al., 2004). Kuder Richardson test was used to evaluate DVL reliability. Kuder Richardson (KR-20) is used to measure internal consistency where each question has only two answers (right and wrong) (Streiner, 2003). The equation for KR-20 is as follows in Equation 1. KR-20 coefficient of DVL is 0.738.

Cronbach alpha was used to assess the internal consistency of the other four constructs and the results are in Table 10. Cronbach alpha and KR-20 of 0.70 or higher is an indicator that the measurement was reliable (Straub *et al.*, 2004). All items had a reliability coefficient above 0.70, indicating that the instrument was reliable.

Construct validity was assessed using Confirmatory Factor Analysis (CFA) to evaluate instrument accuracy, see Table 11 for factor loading of items used to measure the constructs. The factor loadings are all greater than 0.5 indicating construct validity was established.

Equation 1: Kuder and Richardson Reliability Index

$$KR\text{-}20 = (k / (k-1)) * (1 - \Sigma p_j q_j / \sigma^2)$$

Where k: Total number of questions
pj: Proportion of individuals who answered question j correctly
qj: Proportion of individuals who answered question j incorrectly
σ2: Variance of scores for all individuals who took the test

Table 10: Items reliability

Construct	Number of Items	Cronbach Alpha
Perceived usefulness	4	0.933
Perceived enjoyment	3	0.906
Exploitative use	3	0.907
Explorative use	3	0.863

Table 11: Factor loading results

							95% Confidence Interval		
Factor	**Indicator**	**Symbol**	**Estimate**	**Std. Error**	**z-value**	**p-value**	**Lower**	**Upper**	**Std. Est**
Perceived usefulness	PerUseI1	λ11	1.168	0.064	18.135	< .001	1.041	1.294	0.847
	PerUseI2	λ12	0.976	0.053	18.442	< .001	0.873	1.080	0.826
	PerUseI3	λ13	1.165	0.064	18.116	< .001	1.039	1.291	0.891
	PerUseI4	λ14	1.263	0.064	19.772	< .001	1.138	1.389	0.966
Perceived Enjoyment	PerEnjoy1	λ21	1.220	0.071	17.243	< .001	1.081	1.358	0.826
	PerEnjoy2	λ22	1.259	0.073	17.273	< .001	1.116	1.402	0.848
	PerEnjoy3	λ23	0.913	0.045	20.483	< .001	0.826	1.001	0.913
Exploitative BI&A use	ExploitUse1	λ31	0.908	0.025	36.466	< .001	0.859	0.957	0.908
	ExploitUse2	λ32	0.891	0.023	38.115	< .001	0.845	0.936	0.891
	ExploitUse3	λ33	0.902	0.024	37.108	< .001	0.854	0.949	0.902
Explorative BI&A use	ExploreUse1	λ41	0.811	0.030	27.318	< .001	0.752	0.869	0.811
	ExploreUse2	λ42	0.919	0.031	29.634	< .001	0.858	0.979	0.919
	ExploreUse3	λ43	0.840	0.032	26.259	< .001	0.777	0.902	0.840

5.6 MEANS, STANDARD DEVIATION AND CORRELATION ANALYSIS OF CONSTRUCTS

The mean score for DVL is fourteen on a scale of zero to twenty-one, while for other variables (PU, PE, exploitative and explorative) the mean scores are above four on a scale of one to seven, with the highest being perceived usefulness (6.14) see Table 12, indicating that respondents were quite competent and perceived BI&A as useful. Spearman correlation was calculated to measure how strong is the relationship between variables. Spearman was used instead of Pearson because most of the data deviated from a normal distribution (skewness of PU, PE and exploitative were way higher than 0). Spearman correlation measures the relationship between two variables even if there is no linear relationship between the variables (Bonett & Wright, 2000). Table 13 shows the results of the correlation test. There were significant positive correlations at *p*<0.01 level among some variables, see highlighted in green in Table 13. There is no significant correlation between data visualisation literacy and any of the four constructs. There is a strong positive relationship with r > 0.5 between PU and PE (*r =0.627*), PU and exploitative (*r =0.551*), PE and explorative (*r= 0.597*), and exploitative and explorative (*r*= 0.567), while the correlation between PU and explorative (*r*= 0.370) and PE and exploitative (*r*= 0.501) is moderate.

Table 12: Mean, standard deviation, skewness and kurtosis of constructs

	DVL	PU	PE	Exploitative	Explorative
Valid	111	111	111	111	111
Missing	0	0	0	0	0
Mean	14.586	6.142	5.628	5.441	4.913
Std. Deviation	3.310	1.187	1.368	1.448	1.422
Skewness	-0.608	-2.496	-1.428	-1.323	-0.835
Std. Error of Skewness	0.229	0.229	0.229	0.229	0.229
Kurtosis	0.104	7.826	2.011	1.590	0.875
Std. Error of Kurtosis	0.455	0.455	0.455	0.455	0.455

Table 13: Spearman's Correlations

Variable		DVL	PU	PE	Exploitative	Explorative
1. DVL	Spearman's rho	—				
	p-value	—				
2. PU	Spearman's rho	0.126	—			
	p-value	0.188	—			
3. PE	Spearman's rho	0.161	0.627	—		
	p-value	0.091	< .001	—		
4. Exploitative	Spearman's rho	0.016	0.551	0.501	—	
	p-value	0.871	< .001	< .001	—	
5. Explorative	Spearman's rho	0.090	0.370	0.597	0.567	—
	p-value	0.350	< .001	< .001	< .001	—

5.7 MODEL FIT

The Chi-square test was used to evaluate the goodness of the model fit. Chi-square indicates the difference between the sample covariance matrix and the estimated covariance matrix. *p-value*> 0.05 indicates the model is a good fit (Kline, 2015). Table 14 shows the fit indices for the model. The results are as follows for the hypothesised model: $X^2 = 29.806, df = 59, p = 0.999$. Additionally, a good fit model is also indicated by Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) >= 0.90, Root Mean Square Error of Approximation (RMSEA) <0.08, Standardised Root Mean Square Residual (SRMR)<0.08 and Cmin/dfvalue <5. RMSEA for the model is 0, which indicates there were no discrepancies between the hypothesised model and chosen parameter estimates; thus an acceptable model fit. Similarly, CFI and TLI are both one, indicating an acceptable model fit.

Table 14: Fit indices for CFA and SEM

	Chi-square	df	p	Cmin/df	CFI	TLI	RMSEA	SRMR
Model	29.806	59	0.999	.505	1.0	1.0	0.0	0.0

5.8 HYPOTHESES TESTING

The model was a good fit, hence it could be evaluated using Structural Equation Modelling (SEM). SEM has been proven useful in analysing small sample sizes in medium and highly complex research models (Božič & Dimovski, 2019b). SEM allows analysis of the causal relationship between variables with either Covariance-Based Structural Equation Modelling (CB-SEM) or variance-based using Partial Least Squares Structural Equation modelling (PLS-SEM) (Sparks & McCann, 2015). CB-SEM is used in confirmatory theory research. CB-SEM was considered for this study in analysing individuals' paths because it allows testing of individual paths while also testing the goodness of fit and allows for comparison of competing models (Mitchell, 1992). CB-SEM provides quite a number of fit indices compared to the PLS-SEM.

Figure 11 illustrates path coefficients for the research model and Table 15 shows the summary of the hypotheses findings. The results show that six of the nine hypothesised associations are supported and six are in the expected positive direction while among the three rejected there is one in the negative direction. DVL is positively associated with PE (ß= 0.070, p< 0.05) and PU (ß= 0.073, p<0.05), these findings support H2 and H3.

There is a very significant positive association of PE with exploitative use (ß= 0.406, p<0.001) and explorative use (ß=0.528, p<0.001), hence H4a and H4b are accepted.

There is a direct positive strong association of PU with exploitative use (ß=0.468, *p*<0.001) and a moderate negative association with explorative (ß=-0.325, *p* <0.01), indicating that when PU increases, exploration is predicted to decrease, thus H5a is supported and H5b is rejected based on the negative beta value.

Exploitative use is positively related to explorative use (ß =0.597, p<0.001), hence H6 is strongly supported. H1a and H1b are not supported hence there is no direct association between data visualisation literacy with exploitative and explorative BI&A use, but an indirect relationship through perceived usefulness and perceived enjoyment.

Table 15: Summary of the hypotheses findings

Hypothesis	Path description	beta	z-value	*p*	Decision
H1a	Data visualisation literacy → Exploitative use	-0.045	-1.398	0.162	Reject hypothesis
H1b	Data visualisation literacy → Explorative use	0.033	1.033	0.302	Reject hypothesis
H2	Data visualisation literacy → Perceived enjoyment	0.070	1.982	0.047	Accept hypothesis at p<.05
H3	Data visualisation literacy → Perceived usefulness	0.073	2.061	0.039	Accept hypothesis at p<.05
H4a	Perceived enjoyment → Exploitative use	0.406	4.175	< .001	Accept hypothesis at p<.001
H4b	Perceived enjoyment → Explorative use	0.528	4.629	< .001	Accept hypothesis at p<.001
H5a	Perceived usefulness → Exploitative use	0.468	4.922	< .001	Accept hypothesis at p<.001
H5b	Perceived usefulness → Explorative use	-0.325	-2.997	0.003	p-value significant at p<.01, but reject hypothesis based on the negative beta value
H6	Exploitative use → Explorative use	0.597	4.693	< .001	Accept hypothesis at p<.001

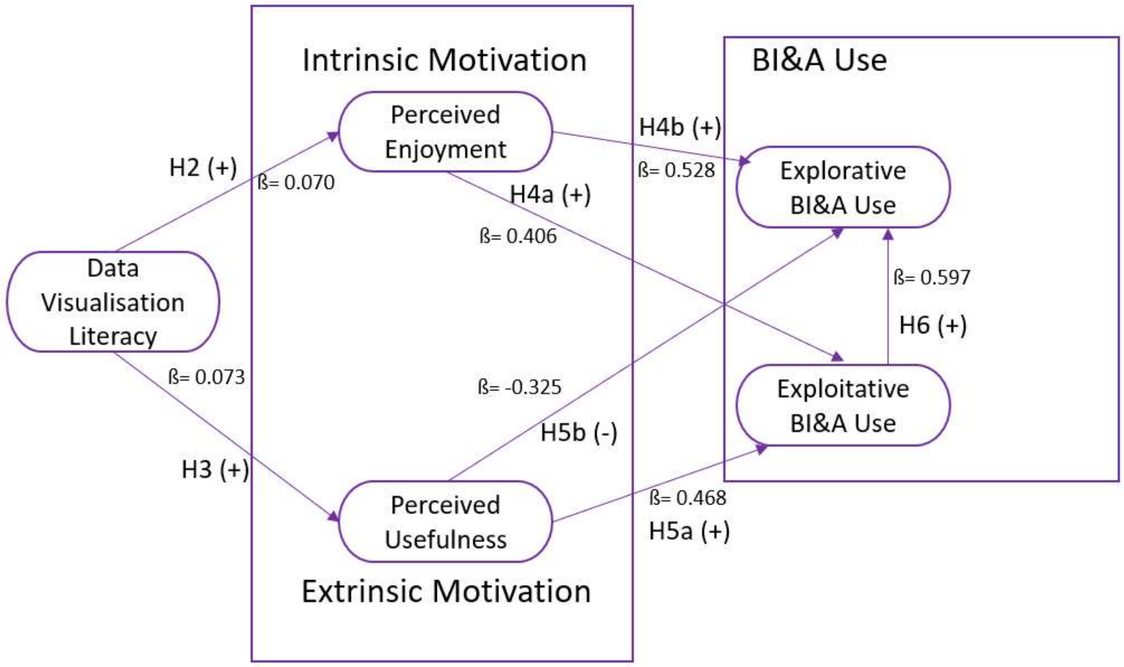


Figure 6: The revised model of the influence of motivation on BI&A use

5.9 CHAPTER SUMMARY

Generally, respondents to the survey were highly data literate in terms of reading and interpreting data visuals, which resulted in the use of percentiles to categorise DVL competency levels. A significant proportion had one year or above of being exposed to the BI&A environment, which could be the reason for a high level of literacy. All constructs had an acceptable reliability coefficient and goodness of fit tests indicated a good model fit. CB-SEM was used to test the hypotheses and of the nine hypothesised associations six are supported. Six are in the expected positive direction while among the three rejected, one is in the negative direction. The significance of the p-value was evaluated at p<0.001 (very strong), p<0.01(strong), and p<0.05 (moderate).

Chapter 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

This chapter provides key summary findings of the study by answering the research questions and highlighting the implications of the key findings for practitioners, and researchers in terms of theory development and advancement of the body of knowledge. Key findings related to data visualisation literacy will be discussed followed by the discussion of the hypothesised model. Next, the study limitations will be highlighted and recommendations for future research emphasised.

6.2 SUMMARY OF FINDINGS

Although respondents had a higher level of data visualisation literacy and a significant proportion (96%) had a tertiary qualification, they struggled with finding the range in both line charts and bubble charts, yet they were able to determine extremum. They did not understand that in determining range one considers the minimum and maximum values in a dataset, not the start and end values on the x-axis (Lee *et al.,* 2016; Lee *et al*., 2019). They performed fairly well (78%) in retrieving values on the line chart, although Saket *et al*. (2018) indicated that line charts should be avoided in retrieving absolute numbers but recommended the use of tables. In this case, the use of grid lines could have helped in improving the correct retrieval of values. Respondents also had challenges interpreting the axis and the axis is among the primary components of a data visual (Tegarden, 1999), thus data visual literate users have to be able to interpret and determine the axis scale to correctly use the visual. Users performed well on the tasks associated with these visuals: pie, bar, line and treemap. Pie, bar, and line were classified as popular visuals (Boy *et al.,* 2014), hence good performance was expected. The treemap was among the unpopular visuals although, treemap and pie charts can be used interchangeably as they are both composition visuals (Galesic & Garcia-Retamero, 2011), hence it could be the reason respondents performed well on tasks associated with treemap even though it was unpopular. Users performed badly on the area and bubble charts and these charts were classified as unpopular (Lee *et al*., 2016), hence users should be exposed to a variety of visuals to increase their data visualisation vocabulary (Bendoly, 2016).

The research examined the role of motivation in regulating the extent to which data visualisation literacy influences business intelligence and analytics use in organisations. The motivation was evaluated in terms of perceived enjoyment as an intrinsic motivator and perceived usefulness as an extrinsic motivator, the following hypotheses were examined and their outcome are listed below in Table 16:

Table 16: Summary of the hypotheses and outcomes

Hypothesis		Outcome
H1a	Data visualisation literacy has a positive effect on the exploitative use of the BI&A system	Reject
H1b	Data visualisation literacy has a positive effect on the explorative use of the BI&A system	Reject
H2	Data visualisation literacy has a positive effect on BI&A system perceived enjoyment among users	Accept
H3	Data Visualisation literacy has a positive effect on the BI&A system's perceived usefulness among users	Accept
H4a	Perceived enjoyment has a positive effect on the exploitative use of the BI&A system	Accept
H4b	Perceived enjoyment has a positive effect on the explorative use of the BI&A system	Accept
H5a	Perceived usefulness has a positive effect on the exploitative use of the BI&A system	Accept
H5b	Perceived usefulness has a positive effect on the explorative use of the BI&A system	Reject
H6	The exploitative use of the BI&A system has a positive effect on the explorative use	Accept

The empirical findings indicate that there is no significant direct relationship between data visualisation literacy and BI&A use but an indirect relationship through motivation. This was contrary to TRA theory where the availability of resources such as skills drives system use (Kulviwat *et al.,* 2014). Also, in Koo et al. (2015) user competency is the main determinant for the exploitative and explorative use of an IS. Respondents in this study were highly competent, which may have led to them taking their data visualisation literacy competency for granted, hence rejecting H1.

H2 and H3 were supported by confirming Davis and Wiedenbeck (2001) where competency evokes intrinsic motivation and good job performance is a result of the user being competent (Mohammadi, 2015; Rezvani *et al.*, 2017). In SDT, intrinsic motivation is based on an individual inherent need for competency and in extrinsic motivation goal achievement is a result of one being skilful (Gagné & Deci, 2005). H4 was also fully supported; perceived enjoyment as an intrinsic motivator significantly influences user exploitative and explorative use, this is in line with Li *et al*. (2013) where perceived enjoyment stimulates IS usage and intrinsic motivation leads to creativity.

H5 was partially supported where perceived usefulness positively influences exploitative use but negatively influences explorative use. H5a is supported in line with TAM user usage behaviour theory where perceived usefulness leads to extend technology use (Venkatesh *et al.*, 2003). H5b is rejected contrary to Wang et al. (2013) where perceived usefulness is positively associated with applying IT innovatively. PU is based on user expectations being met in the confirmatory theory (Limayem *et al.*, 2003), hence it could be when users' expectations are met users are no longer willing to explore the BI&A system further, they are just happy with what BI&A system is offering. Also, extrinsic rewards sometimes lead to negative effects (Altin Gumussoy, 2016; Vilnai-Yavetz & Levina, 2018).

H6 was supported in line with Koo *et al*. (2015) where frequent use leads to innovativeness.

The answer to the research question based on the results of the hypotheses: there is no direct influence of data visualisation literacy on business intelligence and analytics use in organisations but an indirect influence through intrinsic and extrinsic motivation. The mediation analysis demonstrated a fully positive mediation role intrinsic motivation plays in regulating the extent to which data visualisation literacy influences business intelligence and analytics use in organisations, while extrinsic motivation positively regulates the extent to which data visualisation literacy influences BI&A exploitative use but negatively regulates the extent to which data visualisation literacy influences BI&A explorative use. This is in line with SDT where motivation regulates performance (Manninen et al., 2020). Thus, this also indicates that intrinsic motivation has the most positive impact on regulating the relationship between data visualisation literacy and BI&A use in organisations compared to extrinsic motivation.

6.3 CONCLUDING REMARKS

Although the charts chosen for the data visualisation literacy test measured similar tasks across the board, in practice developers must have a clear purpose in mind, whether they want to describe, compare, explore, or tabulate, before selecting a specific visual (Moore, 2017; Szabo *et al.*, 2019). The effectiveness of the visual varies across the task associated, hence the visual should be compatible with the question being answered (Camba *et al.,* 2022; Saket *et al*., 2018). Data visualisation literacy initiatives should highlight more on the interpretation of different axis (x, y, z) and determining the range as users had challenges in reading the axis and calculating the range. Motivation plays a significant role in mediating the relationship between data visualisation literacy and business intelligence and analytics use in organisations. Intrinsic motivation has the most positive impact in regulating the relationship between data visualisation literacy and BI&A use.

Thus, data visualisation developers should consider including elements that evoke fun and enjoyment in the development of data visuals. The elements include appealing visuals and attractive interface, colour, the level of detail, interesting system features, interactivity of the BI&A system and using game-based methods during training of the BI&A system (Peters *et al.*, 2016). In addition, a system is enjoyable to users if users find it meaningful, flexible, satisfying, and fulfilling (Li *et al*., 2013), thus great thought should be given to selecting indicators included in BI&A reports. Flexibility and efficiency foster intrinsic motivation (Torres & Sidorova, 2015). The reports should also spark the user's curiosity to be enjoyable, which will lead to increased exploitative and exploratory use. Perceived usefulness as an extrinsic motivator should be monitored closely because the more useful the system is the less explorative users become. Developers should also consider factors that can demotivate individuals like the difficulty in using and interpreting visualised data and the amount of time taken to complete a task (Fernández-Avilés et al., 2020).

6.4 SUMMARY OF CONTRIBUTIONS

The study introduced motivation in the business intelligence and analytics setting and highlighted the inclusion of motivation in BI&A. The results supported the importance of motivation in user usage behaviour in Business Intelligence and Analytics. This will assist BI developers in developing fun BI&A tools. The study further distinguishes between the two types of use. Popularly, usage in IS has been evaluated in terms of frequency but organisations are now interested in innovativeness and thus, interested in the factors that can promote innovative use, thus contributing to the body of knowledge. This study can act as a support document for organisations embarking on their BI&A journey that want to promote different types of usage. Additionally, BI managers and training managers for organisations that have implemented BIS and are in need to promote data-driven decision-making can benefit from this study, as the study can act as a supporting tool to determine data visualisation literacy initiatives or training that can enable richer BI&A usage, whilst also incorporating motivation elements. The study can also act as a supporting document for the development of subject content for data visualisation initiatives. The DVL assessment can also act as a tool for assessing users' level of data visualisation literacy. In promotion of innovative use, the study gives an organisation insight into how motivation can be used to spark system use exploration.

6.5 LIMITATIONS AND FUTURE RESEARCH

The sampling method used in this study is not ideal for the generalisation of the results, it would be ideal to conduct a similar study as a case study for an organisation and use a familiar dataset relevant to the environment, hence there is also a need to revise the VLAT. This study used the VLAT that was developed in 2016 for general purposes, hence there is a need to update the VLAT to include various data visuals available and popular in the BI&A environment. Also, analytical tasks evaluated in the VLAT excluded reading beyond the data hence the need to include analytical tasks associated with advanced analytics. In the development of a revised VLAT visuals should be compatible with the analytical task most suitable for that type of analysis. This study doesn't consider the BI maturity level of the organisations to which the users belong, hence, future research can explore the implication of BI maturity level on how the users use BI. There are various initiatives that organisations use to promote data literacy (e.g game-based training, self-directed learning), so future research can compare these various methods in order to come up with the most effective method that will promote data visualisation literacy in organisations.

7 REFERENCES

Aggarwal, R., Kryscynski, D., Midha, V., & Singh, H. (2015). Early to adopt and early to discontinue: The impact of self-perceived and actual IT knowledge on technology use behaviors of end users. *Information systems research, 26*(1), 127-144.

Ahmad, A., Ahmad, R., & Hashim, K. F. (2016). Innovation traits for business intelligence successful deployment. *Journal of Theoretical and Applied Information Technology, 89*(1), 96-107.

Ain, N., Vaia, G., DeLone, W. H., & Waheed, M. (2019). Two decades of research on business intelligence system adoption, utilization and success–A systematic literature review. *Decision Support Systems, 125*(1), 1-13.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211.

Akhtar, P., Frynas, J. G., Mellahi, K., & Ullah, S. (2019). Big data-savvy teams' skills, big data-driven actions and business performance. *British Journal of Management, 30*(2), 252-271.

Alpar, P., & Schulz, M. (2016). Self-service business intelligence. *Business & Information Systems Engineering, 58*(2), 151-155.

Altin Gumussoy, C. (2016). Acceptance of the virtual item auctioning system in online games: The role of intrinsic motivation, extrinsic motivation, and trust. *Human Factors and Ergonomics in Manufacturing & Service Industries, 26*(5), 627-637.

Avgerinou, M., & Ericson, J. (1997). A review of the concept of visual literacy. *British journal of educational technology, 28*(4), 280-291.

Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technological Forecasting and Social Change, 168*, 1-12.

Baabdullah, A. M., Alalwan, A. A., Rana, N. P., Kizgin, H., & Patil, P. (2019). Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model. *International Journal of Information Management, 44*, 38-52.

Baker, J. (2012). The technology–organization–environment framework. *Information systems theory*, 231-245.

Barr, H. M., Smitherman, R. C., Mesmer, B., Weger, K., Van Bossuyt, D., Semmens, R., & Tenhundfeld, N. L. (2022). *Use, Acceptance, and Adoption of Automated Systems with Intrinsic and Extrinsic Motivation Based Incentive Mechanisms*. Paper presented at the Systems and Information Engineering Design Symposium, Charlottesville, City of Virginia.

Bendoly, E. (2016). Fit, bias, and enacted sensemaking in data visualization: frameworks for continuous development in operations and supply chain management analytics. *Journal of Business Logistics, 37*(1), 6-17.

Bonett, D. G., & Wright, T. A. (2000). Sample size requirements for estimating Pearson, Kendall and Spearman correlations. *Psychometrika, 65*(1), 23-28.

Börner, K., Bueckle, A., & Ginda, M. (2019). Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. *Proceedings of the National Academy of Sciences, 116*(6), 1857-1864.

Boy, J., Rensink, R. A., Bertini, E., & Fekete, J.-D. (2014). A principled way of assessing visualization literacy. *IEEE transactions on visualization and computer graphics, 20*(12), 1963-1972.

Boyton, J., Ayscough, P., Kaveri, D., & Chiong, R. (2015). Suboptimal business intelligence implementations: understanding and addressing the problems. *Journal of Systems and Information Technology, 17*(3), 307-320.

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Božič, K., & Dimovski, V. (2019a). Business intelligence and analytics for value creation: The role of absorptive capacity. *International Journal of Information Management, 46*, 93-103.

Božič, K., & Dimovski, V. (2019b). Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective. *The Journal of Strategic Information Systems, 28*(4), 1-20.

Brooks, P., El-Gayar, O., & Sarnikar, S. (2015). A framework for developing a domain specific business intelligence maturity model: Application to healthcare. *International Journal of Information Management, 35*(3), 337-345.

Burton-Jones, A., & Grange, C. (2013). From use to effective use: A representation theory perspective. *Information systems research, 24*(3), 632-658.

Camargo-Perez, J., Puentes-Velasquez, A., & Sanchez-Perilla, A. (2019). *Integration of big data in small and medium organizations: Business intelligence and cloud computing.* Paper presented at the Journal of Physics: Conference Series, San José de Cúcuta, Colombia.

Camba, J. D., Company, P., & Byrd, V. L. (2022). Identifying Deception as a Critical Component of Visualization Literacy. *IEEE Computer Graphics and Applications, 42*(1), 116-122.

Cech, T. G., Spaulding, T. J., & Cazier, J. A. (2018). Data competence maturity: developing data-driven decision making. *Journal of Research in Innovative Teaching & Learning, 11*(2), 139-158.

Chan, S. H. (2009). The roles of user motivation to perform a task and decision support system (DSS) effectiveness and efficiency in DSS use. *Computers in human behavior, 25*(1), 217-228.

Chang, V. (2014). The business intelligence as a service in the cloud. *Future Generation Computer Systems, 37*, 512-534.

Chang, Y.-W., Hsu, P.-Y., & Wu, Z.-Y. (2015). Exploring managers' intention to use business intelligence: the role of motivations. *Behaviour & Information Technology, 34*(3), 273-285.

Chen, X., & Siau, K. (2020). Business analytics/business intelligence and IT infrastructure: impact on organizational agility. *Journal of Organizational and End User Computing (JOEUC), 32*(4), 138-161.

Cheng, C., Zhong, H., & Cao, L. (2020). Facilitating speed of internationalization: The roles of business intelligence and organizational agility. *Journal of Business Research, 110*, 95-103.

D'Ignazio, C. (2017). Creative data literacy: Bridging the gap between the data-haves and data-have nots. *Information Design Journal, 23*(1), 6-18.

Davis, S., & Wiedenbeck, S. (2001). The mediating effects of intrinsic motivation, ease of use and usefulness perceptions on performance in first-time and subsequent computer users. *Interacting with computers, 13*(5), 549-580.

de Jager, T., & Brown, I. (2016). *A descriptive categorized typology of requisite skills for business intelligence professionals.* Paper presented at the Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists, South Africa.

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior, 4*, 19-43.

Dimara, E., Bezerianos, A., & Dragicevic, P. (2016). The attraction effect in information visualization. *IEEE transactions on visualization and computer graphics, 23*(1), 471-480.

Djerdjouri, M. (2020). Data and Business Intelligence Systems for Competitive Advantage: prospects, challenges, and real-world applications. *Mercados y Negocios: Revista de Investigación yy Análisis, 1*(41), 5-18.

Donohoe, D., & Costello, E. (2020). Data Visualisation Literacy in Higher Education: An Exploratory Study of Understanding of a Learning Dashboard Tool. *International Journal of Emerging Technologies in Learning (iJET), 15*(17), 115-126.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers, 21*(3), 719-734.

Fernández-Avilés, D., De Antonio, A., & Villalba-Mora, E. (2020). A systematic mapping study on the use of motivational theories in the design of motivational software. *IEEE Access, 8*, 176840-176863.

Ferreira, J. T. S., & Steel, M. F. J. (2006). A constructive representation of univariate skewed distributions. *Journal of the American Statistical Association, 101*(474), 823-829.

Fink, L., Yogev, N., & Even, A. (2017). Business intelligence and organizational learning: An empirical investigation of value creation processes. *Information & management, 54*(1), 38-56.

Fischer, C., Malycha, C. P., & Schafmann, E. (2019). The Influence of Intrinsic Motivation and Synergistic Extrinsic Motivators on Creativity and Innovation. *Frontiers in Psychology, 10*(137), 1-15. doi:10.3389/fpsyg.2019.00137

Fishbach, A., & Woolley, K. (2022). The structure of intrinsic motivation. *Annual Review of Organizational Psychology and Organizational Behavior, 9*(1), 339-363.

Frank, M., Walker, J., Attard, J., & Tygel, A. (2016). Data Literacy-What is it and how can we make it happen? *The Journal of Community Informatics, 12*(3), 4-8.

Gagné, M., & Deci, E. L. (2005). Self-determination theory and work motivation. *Journal of Organizational behavior, 26*(4), 331-362.

Galesic, M., & Garcia-Retamero, R. (2011). Graph literacy: A cross-cultural comparison. *Medical Decision Making, 31*(3), 444-457.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51-90.

George, A., Schmitz, K., & Storey, V. C. (2020). A Framework for Building Mature Business Intelligence and Analytics in Organizations. *Journal of Database Management (JDM), 31*(3), 14-39.

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems, 27*(1), 101-113.

Ghazanfari, M., Jafari, M., & Rouhani, S. (2011). A tool to evaluate the business intelligence of enterprise systems. *Scientia Iranica, 18*(6), 1579-1590.

Giner, J. L. C. (2011). Business Information Visualization. *The European Journal for the Informatics Professionals, XII*(3), 3-13.

Gray, J., Gerlitz, C., & Bounegru, L. (2018). Data infrastructure literacy. *Big Data & Society, 5*(2), 1-13.

Grublješič, T., & Jaklič, J. (2015). Conceptualization of the business intelligence extended use model. *Journal of Computer Information Systems, 55*(3), 72-82.

Gudfinnsson, K., Strand, M., & Berndtsson, M. (2015). Analyzing business intelligence maturity. *Journal of Decision Systems, 24*(1), 37-54.

Günther, W. A., Mehrizi, M. H. R., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems, 26*(3), 191-209.

Hannam, K., & Narayan, A. (2015). Intrinsic motivation, organizational justice, and creativity. *Creativity Research Journal, 27*(2), 214-224.

Higgins, E. T., Cesario, J., Hagiwara, N., Spiegel, S., & Pittman, T. (2010). Increasing or decreasing interest in activities: The role of regulatory fit. *Journal of personality and social psychology, 98*(4), 559-572.

Hunter-Thomson, K. (2018). Data literacy 101 How do we set up graphs in science? *Science Scope, 42*(2), 78-82.

Hwang, Y. (2005). Investigating enterprise systems adoption: uncertainty avoidance, intrinsic motivation, and the technology acceptance model. *European Journal of Information Systems, 14*(2), 150-161.

Hwang, Y. (2014). User experience and personal innovativeness: An empirical study on the Enterprise Resource Planning systems. *Computers in human behavior, 34*, 227-234.

Irtaimeh, H. J., Obeidat, A. M., Abualloush, S., & Khaddam, A. (2016). Impact of business intelligence on technical creativity: A case study on AlHekma Pharmaceutical Company. *European Scientific Journal, 12*(28), 502-519.

Işık, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & management, 50*(1), 13-23.

Jasperson, J., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly, 29*(3), 525-557.

Jivet, I., Scheffel, M., Schmitz, M., Robbers, S., Specht, M., & Drachsler, H. (2020). From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education. *The Internet and Higher Education, 47*, 1-14.

Johansson, V., & Stenlund, J. (2021). Making time/breaking time: critical literacy and politics of time in data visualisation. *Journal of Documentation*.

Kiani Mavi, R., & Standing, C. (2018). Cause and effect analysis of business intelligence (BI) benefits with fuzzy DEMATEL. *Knowledge Management Research & Practice, 16*(2), 245-257.

Kim, H.-W., & Gupta, S. (2014). A user empowerment approach to information systems infusion. *IEEE Transactions on Engineering Management, 61*(4), 656-668.

Kivunja, C., & Kuyini, A. B. (2017). Understanding and applying research paradigms in educational contexts. *International Journal of higher education, 6*(5), 26-41.

Klee, S., Janson, A., & Leimeister, J. M. (2021). How Data Analytics Competencies Can Foster Business Value–A Systematic Review and Way Forward. *Information Systems Management, 1*, 1-18.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*: Guilford publications.

Koltay, T. (2015). Data literacy: in search of a name and identity. *Journal of Documentation, 71*(2), 401-415.

Koo, C., Chung, N., & Kim, H.-W. (2015). Examining explorative and exploitative uses of smartphones: a user competence perspective. *Information Technology & People, 1*, 133-162.

Kopp, A., & Orlovskyi, D. (2022). Comparative Quantitative Analysis of Leading Business Intelligence Software Platforms. *Texas Journal of Multidisciplinary Studies, 7*, 23-29.

Kulviwat, S., Bruner II, G. C., & Neelankavil, J. P. (2014). Self-efficacy as an antecedent of cognition and affect in technology acceptance. *Journal of Consumer Marketing, 31*(3), 190-199.

Larson, D., & Chang, V. (2016). A review and future direction of agile, business intelligence, analytics and data science. *International Journal of Information Management, 36*(5), 700-710.

Lauer, C., & O'Brien, S. (2020). How people are influenced by deceptive tactics in everyday charts and graphs. *IEEE Transactions on Professional Communication, 63*(4), 327-340.

Lautenbach, P., Johnston, K., & Adeniran-Ogundipe, T. (2017). Factors influencing business intelligence and analytics usage extent in South African organisations. *South African Journal of Business Management, 48*(3), 23-33.

Lee, M. T., & Widener, S. K. (2016). The performance effects of using business intelligence systems for exploitation and exploration learning. *Journal of Information Systems, 30*(3), 1-31.

Lee, S., Kim, S.-H., Hung, Y.-H., Lam, H., Kang, Y.-a., & Yi, J. S. (2015). How do people make sense of unfamiliar visualizations?: A grounded model of novice's information visualization sensemaking. *IEEE transactions on visualization and computer graphics, 22*(1), 499-508.

Lee, S., Kim, S.-H., & Kwon, B. C. (2016). Vlat: Development of a visualization literacy assessment test. *IEEE transactions on visualization and computer graphics, 23*(1), 551-560.

Lee, S., Kwon, B. C., Yang, J., Lee, B. C., & Kim, S.-H. (2019). The correlation between users' cognitive characteristics and visualization literacy. *Applied Sciences, 9*(3), 488-508.

Lefebvre, H., & Legner, C. (2022). *How communities of practice enable data democratisation inside the enterprise*. Paper presented at the Thirtieth European Conference on Information Systems (ECIS 2022), Timisoara, Romania.

Lefebvre, H., Legner, C., & Fadler, M. (2021). *Data democratization: toward a deeper understanding.* Paper presented at the Proceedings of the International Conference on Information Systems (ICIS).

Lennerholt, C., Van Laere, J., & Söderström, E. (2020). User-Related Challenges of Self-Service Business Intelligence. *Information Systems Management, 38*(4), 309-323.

Li, X., Hsieh, J. P.-A., & Rai, A. (2013). Motivational differences across post-acceptance information system usage behaviors: An investigation in the business intelligence systems context. *Information systems research, 24*(3), 659-682.

Limayem, M., Cheung, C., & Chan, G. (2003). Explaining information systems adoption and post-adoption: toward an integrative model. *ICIS 2003 Proceedings, 59*, 720-731.

Lin, H., & Hwang, Y. (2014). Do feelings matter? The effects of intrinsic benefits on individuals' commitment toward knowledge systems. *Computers in human behavior, 30*, 191-198.

Lin, H. F. (2007). Effects of extrinsic and intrinsic motivation on employee knowledge sharing intentions. *Journal of information science, 33*(2), 135-149.

Locoro, A., Fisher, W. P., & Mari, L. (2021). Visual Information Literacy: Definition, Construct Modeling and Assessment. *IEEE Access, 9*, 71053-71071.

Loos, L., Verbeeck, K., & De Laet, L. (2019). Data visualisation as a tool for informed structural design. *Computer-Aided Design, 115*, 267-276.

Malek, S. L., Sarin, S., & Haon, C. (2020). Extrinsic rewards, intrinsic motivation, and new product development performance. *Journal of Product Innovation Management, 37*(6), 528-551.

Malhotra, Y., Galletta, D. F., & Kirsch, L. J. (2008). How endogenous motivations influence user intentions: Beyond the dichotomy of extrinsic and intrinsic user motivations. *Journal of Management Information Systems, 25*(1), 267-300.

Manninen, M., Deng, Y., Hwang, Y., Waller, S., & Yli-Piipari, S. (2020). Psychological need-supportive instruction improves novel skill performance, intrinsic motivation, and enjoyment: a cluster-randomised study. *International Journal of Sport and Exercise Psychology*, 1-25.

McDowall, A., Mills, C., Cawte, K., & Miller, J. (2020). Data use as the heart of data literacy: An exploration of pre-service teachers' data literacy practices in a teaching performance assessment. *Asia-Pacific Journal of Teacher Education*, 1-16.

Mitchell, R. J. (1992). Testing evolutionary and ecological hypotheses using path analysis and structural equation modelling. *Functional Ecology*, 123-129.

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in human behavior, 45*, 359-374.

Moore, J. (2017). *Visualisation of data to optimise strategic decision making.* (Masters). University of Cape Town, South Africa.

Mudzana, T., & Maharaj, M. (2015). Measuring the success of business-intelligence systems in South Africa: An empirical investigation applying the DeLone and McLean Model. *South African Journal of Information Management, 17*(1), 1-7.

Mudzana, T., & Maharaj, M. (2017). Toward an understanding of business intelligence systems success: A South African study. *Electronic Journal of Information Systems Evaluation, 20*(1), 24.

Mun, Y. Y., Jackson, J. D., Park, J. S., & Probst, J. C. (2006). Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & management, 43*(3), 350-363.

Namvar, M., Intezari, A., & Im, G. (2021). Sensegiving in organizations via the use of business analytics. *Information Technology & People*, 1-24.

Ngee, K. Y. (2020). The moderating role of trust and the theory of reasoned action. *Journal of Knowledge Management, 24*(6), 1221-1240.

Olszak, C. M. (2016). Toward better understanding and use of business intelligence in organizations. *Information Systems Management, 33*(2), 105-123.

Pangrazio, L., & Sefton-Green, J. (2020). The social utility of 'data literacy'. *Learning, Media and Technology, 45*(2), 208-220.

Perdana, A., Lee, H. H., Koh, S., & Arisandi, D. (2022). Data analytics in small and mid-size enterprises: Enablers and inhibitors for business value and firm performance. *International Journal of Accounting Information Systems, 44*, 1-20.

Peters, T., Işık, Ö., Tona, O., & Popovič, A. (2016). How system quality influences mobile BI use: The mediating role of engagement. *International Journal of Information Management, 36*(5), 773-783.

Pirolli, P., & Card, S. (2005). *The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis.* Paper presented at the Proceedings of international conference on intelligence analysis, McLean, Virginia.

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems, 54*(1), 729-739.

Porter, L. W., & Lawler, E. E. (1968). Managerial Attitudes and Performance. *Administrative Science Quarterly, 13*(1), 177-180.

Rezvani, A., Khosravi, P., & Dong, L. (2017). Motivating users toward continued usage of information systems: Self-determination theory perspective. *Computers in human behavior, 76*, 263-275.

Ruhode, E., & Mansell, I. J. (2019). Inhibitors of business intelligence use by managers in public institutions in a developing country: The case of a South African municipality. *South African Journal of Information Management, 21*(1), 1-8.

Russell, S., Haddad, M., Bruni, M., & Granger, M. (2010). *Organic Evolution and the Capability Maturity of Business Intelligence.* Paper presented at the Proceedings of the Americas Conference on Information Systems, Lima, Peru.

Ryan, R. M., Connell, J. P., & Deci, E. L. (1985). A motivational analysis of self-determination and self-regulation in education. *Research on motivation in education: The classroom milieu, 2*, 13-51.

Saeed, K. A., & Abdinnour, S. (2013). Understanding post-adoption IS usage stages: an empirical assessment of self-service information systems. *Information Systems Journal, 23*(3), 219-244.

Saket, B., Endert, A., & Demiralp, Ç. (2018). Task-based effectiveness of basic visualizations. *IEEE transactions on visualization and computer graphics, 25*(7), 2505-2512.

Sanchez, D. R., Nelson, T., Kraiger, K., Weiner, E., Lu, Y., & Schnall, J. (2022). Defining motivation in video game-based training: Exploring the differences between measures of motivation. *International Journal of Training and Development, 26*(1), 1-28.

Sangari, M. S., & Razmi, J. (2015). Business intelligence competence, agile capabilities, and agile performance in supply chain: An empirical study. *The International Journal of Logistics Management, 26*, 356–380.

Saunders, M., Lewis, P., & Thornhill, A. (2012). Research Methods for Business Students. In (6th ed.): Pearson education.

Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. *Contemporary educational psychology, 60*, 1-10.

Scotland, J. (2012). Exploring the philosophical underpinnings of research: Relating ontology and epistemology to the methodology and methods of the scientific, interpretive, and critical research paradigms. *English language teaching, 5*(9), 9-16.

Seddon, P. B., Constantinidis, D., Tamm, T., & Dod, H. (2017). How does business analytics contribute to business value? *Information Systems Journal, 27*(3), 237-269.

Shaaban, E., Helmy, Y., Khedr, A., & Nasr, M. (2012). *Business intelligence maturity models: Toward new integrated model.* Paper presented at the The international Arab conference on information technology Riyadh, Saudi Arabia.

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems, 23*(4), 433-441. doi:10.1057/ejis.2014.17

Shollo, A., & Galliers, R. D. (2016). Towards an understanding of the role of business intelligence systems in organisational knowing. *Information Systems Journal, 26*(4), 339-367.

Soleas, E. (2021). Environmental factors impacting the motivation to innovate: a systematic review. *Journal of Innovation and Entrepreneurship, 10*(1), 1-18.

Sparks, B. H., & McCann, J. T. (2015). Factors influencing business intelligence system use in decision making and organisational performance. *International Journal of Sustainable Strategic Management, 5*(1), 31-54.

Straub, D., Boudreau, M.-C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information systems, 13*(1), 380-427.

Streiner, D. L. (2003). Starting at the beginning: an introduction to coefficient alpha and internal consistency. *Journal of personality assessment, 80*(1), 99-103.

Sun, H. (2012). Understanding user revisions when using information system features: Adaptive system use and triggers. *MIS Quarterly, 36*(2), 453-478.

Sutherland, S., & Ridgway, J. (2017). Interactive visualisations and statistical literacy. *Statistics education research journal., 16*(1), 26-30.
Szabo, S. M., Johnston, K. M., & Lloyd, A. J. (2019). Advanced data visualisation in health economics and outcomes research: opportunities and challenges. *Applied health economics and health policy, 17*(4), 433-441.
Tahir, M. S., Richards, D. W., & Ahmed, A. D. (2020). Financial literacy, attitudes, and financial satisfaction: an assessment of credit card debt-taking behavior of Australians. *Financial Services Review, 28*(4), 273-301.
Tegarden, D. P. (1999). Business information visualization. *Communications of the Association for Information systems, 1*(1), 1-38.
Thatcher, J. B., Wright, R. T., Sun, H., Zagenczyk, T. J., & Klein, R. (2018). Mindfulness in information technology use: Definitions, distinctions, and a new measure. *MIS Quarterly, 42*(3), 831-848.
Torres, R., & Sidorova, A. (2015). The effect of business process configurations on user motivation. *Business Process Management Journal, 1*, 541-563.
Torres, R., & Sidorova, A. (2019). Reconceptualizing information quality as effective use in the context of business intelligence and analytics. *International Journal of Information Management, 49*, 316-329.
Torres, R., Sidorova, A., & Jones, M. C. (2018). Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective. *Information & management, 55*(7), 822-839.
Tucker, M., Jubb, C., & Yap, C. J. (2019). The theory of planned behaviour and student banking in Australia. *International Journal of Bank Marketing*, 113-135.
Vallerand, R. J., Deshaies, P., Cuerrier, J.-P., Pelletier, L. G., & Mongeau, C. (1992). Ajzen and Fishbein's theory of reasoned action as applied to moral behavior: A confirmatory analysis. *Journal of personality and social psychology, 62*(1), 98.
van Geel, M., Keuning, T., Visscher, A., & Fox, J.-P. (2017). Changes in educators' data literacy during a data-based decision making intervention. *Teaching and teacher education, 64*, 187-198.
Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information systems research, 11*(4), 342-365.
Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences, 39*(2), 273-315.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.
Villalobos-Zúñiga, G., & Cherubini, M. (2020). Apps that motivate: A Taxonomy of App features based on self-determination theory. *International Journal of Human-Computer Studies, 140*, 1-24.
Vilnai-Yavetz, I., & Levina, O. (2018). Motivating social sharing of e-business content: intrinsic motivation, extrinsic motivation, or crowding-out effect? *Computers in human behavior, 79*, 181-191.
Vroom, V. H. (1964). *Work and motivation*. New York: Wiley.
Wainer, H. (1980). A test of graphicacy in children. *Applied Psychological Measurement, 4*(3), 331-340.
Wang, W., Li, X., & Hsieh, J. P.-A. (2013). The contingent effect of personal IT innovativeness and IT self-efficacy on innovative use of complex IT. *Behaviour & Information Technology, 32*(11), 1105-1124.
Weng, S.-S., Yang, M.-H., Koo, T.-L., & Hsiao, P.-I. (2016). Modeling the prediction of business intelligence system effectiveness. *SpringerPlus, 5*(1), 1-17.

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary educational psychology, 25*(1), 68-81.

Wolff, A., Gooch, D., Montaner, J. J. C., Rashid, U., & Kortuem, G. (2016). Creating an understanding of data literacy for a data-driven society. *The Journal of Community Informatics, 12*(3), 10-26.

Yeoh, W., & Popovič, A. (2016). Extending the understanding of critical success factors for implementing business intelligence systems. *Journal of the Association for Information Science and Technology, 67*(1), 134-147.

Yildiz Durak, H. (2019). Examining the acceptance and use of online social networks by preservice teachers within the context of unified theory of acceptance and use of technology model. *Journal of Computing in Higher Education, 31*(1), 173-209.

Zou, L., Wei, S., Ke, W., & Wei, K. K. (2020). Creativity of Participants in Crowdsourcing Communities: The Effects of Promotion Focus and Extrinsic Motivation. *Journal of Database Management (JDM), 31*(3), 40-66.

APPENDIX A: RESEARCH INSTRUMENT

PART ONE

GENERAL INFORMATION

This part consists of the demographic profile of the respondent. **Please tick (x)** into the appropriate box.

Abbreviation: Business Intelligence Systems – BIS
Business Intelligence and Analytics – BI&A

1. Organizational BI platform/vendor

☐ Microsoft Power BI

☐ Tableau

☐ SAP Lumira

☐ IBM Cognos

☐ Oracle BI

☐ Qlikview/QlikSense

Other (Specify)………………

2. The number of years of experience in a BI environment?

Less than 1 year ☐ 1 – 4 years ☐ Above 4 years ☐

3. What is your functional area (department) in your organisation?

☐ Sales and Marketing

☐ Accounting and Finance

☐ IT / IS

☐ Production

☐ Purchasing

☐ Human Resource

Other (specify)………………………

4. Level in the organization

☐ Executive

☐ Management

☐ Operational

5. In which industry does your organisation belong?

☐ Education

☐ Financial Services

☐ Health Care

☐ Manufacturing

☐ Mining

☐ Non- Government Financial Services

☐ Retail

☐ Telecommunications

Other (specify)……………………..

6. Organisation Operating Country: ……………………..

☐ Lesotho

☐ South Africa

Other (specify)……………………..

7. What is your Educational Level

☐ Doctoral Degree

☐ Masters Degree

☐ Postgraduate Diploma/ Degree

☐ Undergraduate/ 1st Degree

☐ National Diploma

☐ Higher Certificate

☐ National Certificate and Occupational Awards

☐ High School Matriculated

8. What is your age category

☐ 18 – 24 years

☐ 25 – 34 years

☐ 35 – 44 years

☐ 45 – 54 years

☐ 55 years and above

PART TWO

Part two of the questionnaire contains 21 multiple-choice questions about 6 graphs/charts. The purpose is to measure the users' ability to read and interpret visually represented data. Select the **BEST** answer to the questions. You are advised to take a **maximum of 25 seconds** to answer each question. **DO NOT GUESS**. Please select **SKIP** if you are not sure about your answer.

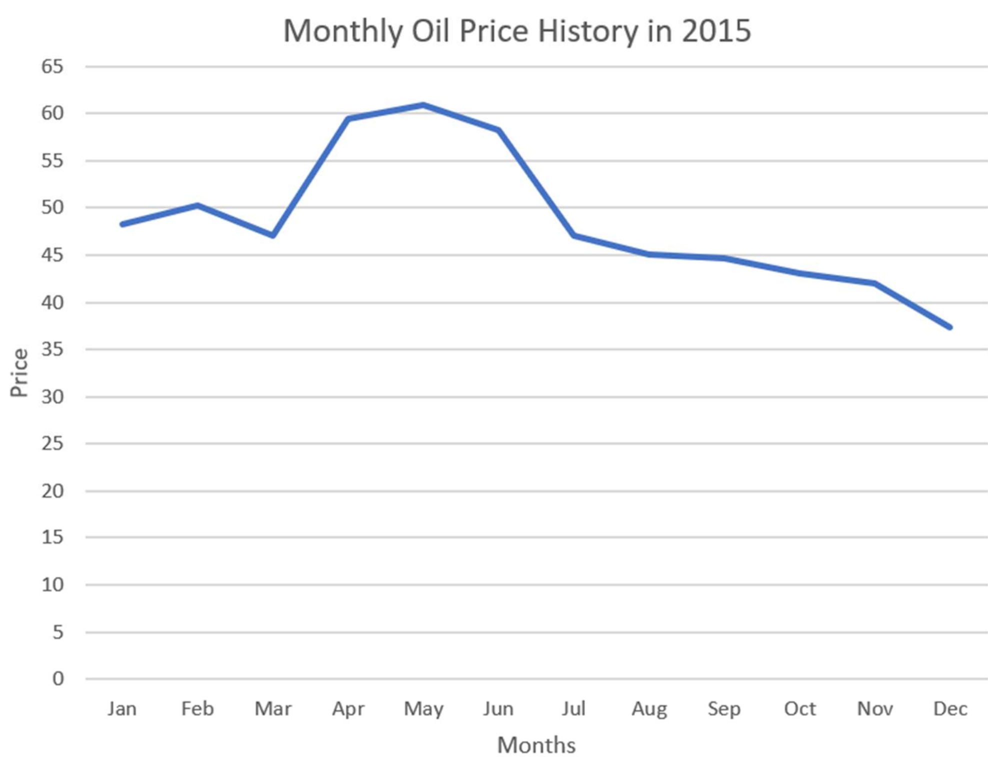


Figure 1: Monthly Oil Price History in 2015

1. What was the price of a barrel of oil in February 2015 from Figure 1?

57.37 ☐ 47.82 ☐ 50.24 ☒ 39.72 ☐ Skip ☐

2. In which month was the price of a barrel of oil the lowest in 2015 from Figure 1?

March ☐ May ☐ July ☐ December ☒ Skip ☐

3. What was the price range of a barrel of oil in 2015 from Figure 1?

35 – 65 ☐ 48.36 – 60.95 ☐ 37.04 – 48.36 ☐ 37.04 – 60.95 ☒

Skip☐

4. About How much did the price of a barrel of oil fall from April to September 2015?

4 ☐ 15 ☒ 20 ☐ 45 ☐ Skip ☐

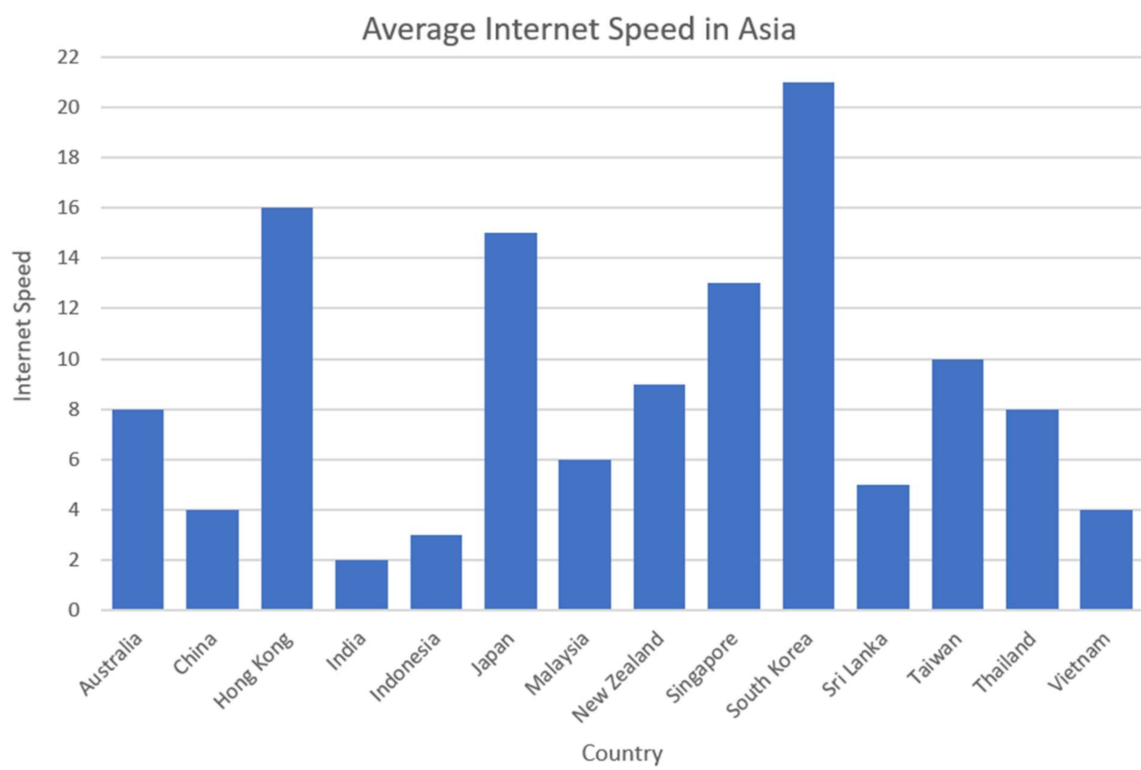


Figure 2: Average Internet Speed in Asia

5. What is the average internet speed in Japan from Figure 2?

10 Mbps ☐ 14 Mbps ☐ 15 Mbps ☒ 16 Mbps ☐ Skip ☐

6. In which country is the average internet speed the fastest in Asia from Figure 2?

China ☐ Hong Kong ☐ South Korea ☒ Vietnam ☐

Skip ☐

7. What is the range of the average internet speed in Asia, from Figure 2?

0 – 22 Mbps ☐ 2 – 21 Mbps ☒ 3- 20 Mbps ☐ 3.4 – 20 Mbps Skip ☐

8. How many countries in Asia is the average internet speed slower than in Thailand Figure 2?

5 Countries ☐ 6 Countries ☒ 7 Countries ☐ 8 Countries ☐ Skip ☐

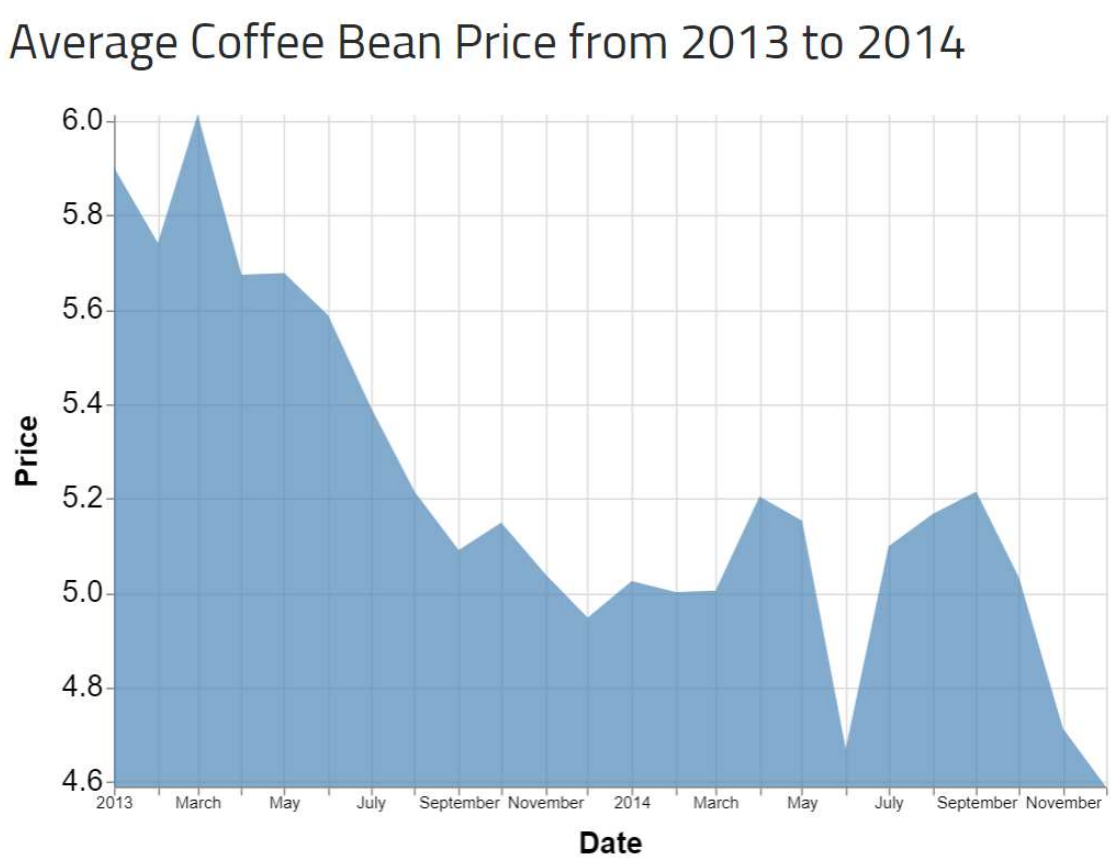


Figure 3: Average Coffee Bean Price From 2013 to 2014

9. What was the average price of a pound of coffee beans in September 2013, from Figure 3?

4.9 ☐ 5.0☐ 5.1☒ 5.2 ☐ Skip ☐

10. When was the average price of a pound of coffee beans at a minimum, from Figure 3?

April 2013 ☐ September 2013 ☐ June 2014 ☐ December 2014 ☒ Skip ☐

11. What was the range of the average price of a pound of coffee beans between January 2013 and December 2014, from Figure 3?

4.4 – 6.2 ☐ 4.6 – 5.9 ☐ 4.6 – 6.0 ☒ 4.6 – 6.1 ☐ Skip ☐

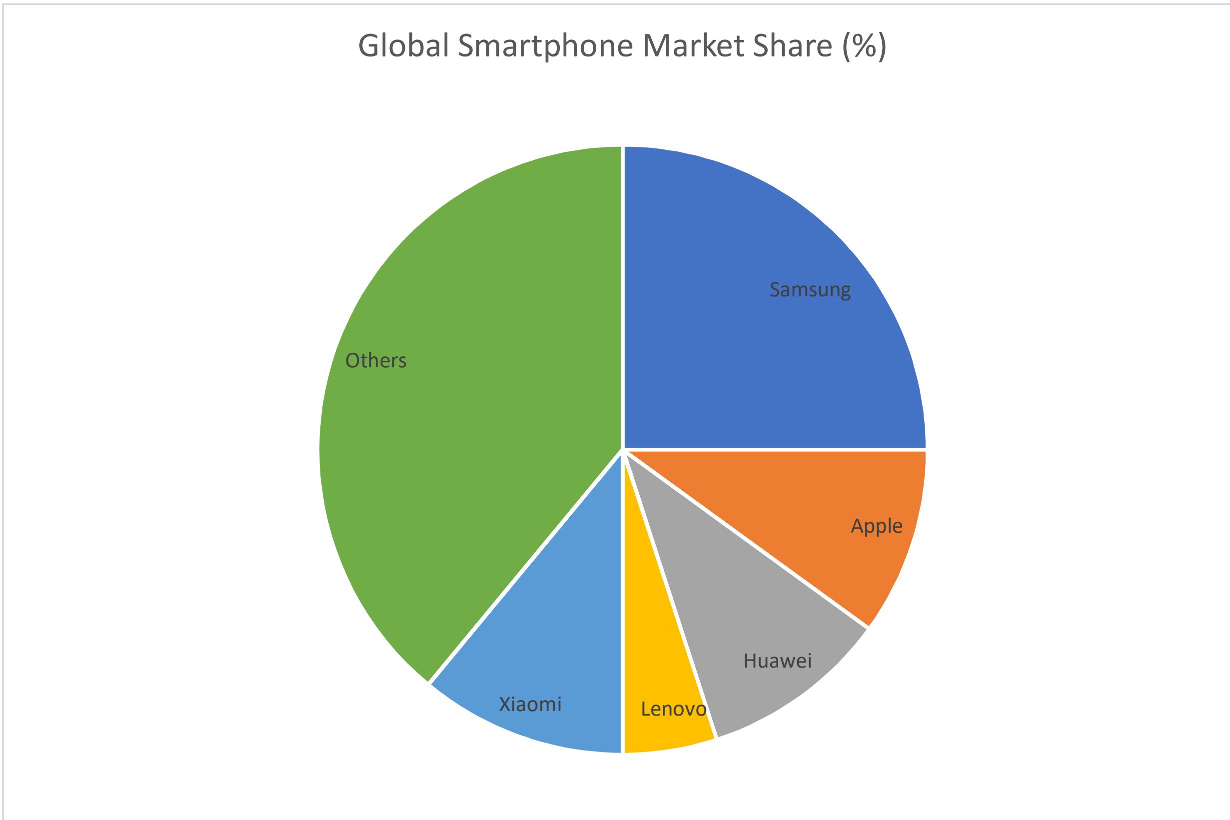


Figure 4: Global Smartphone Market Share (%)

12. What is the global smartphone market share of Samsung, From Figure 4?

75% ☐ 25% ☒ 100% ☐ 50% ☐ Skip ☐

13. In which company is the global smartphone market share the smallest, from figure 4?

Apple ☐ Xiaomi ☐ Lenovo ☒ Huawei ☐ Skip ☐

14. The global smartphone market share of Apple is larger than that of Huawei, from figure 4.

True ☒ False ☐ Skip ☐

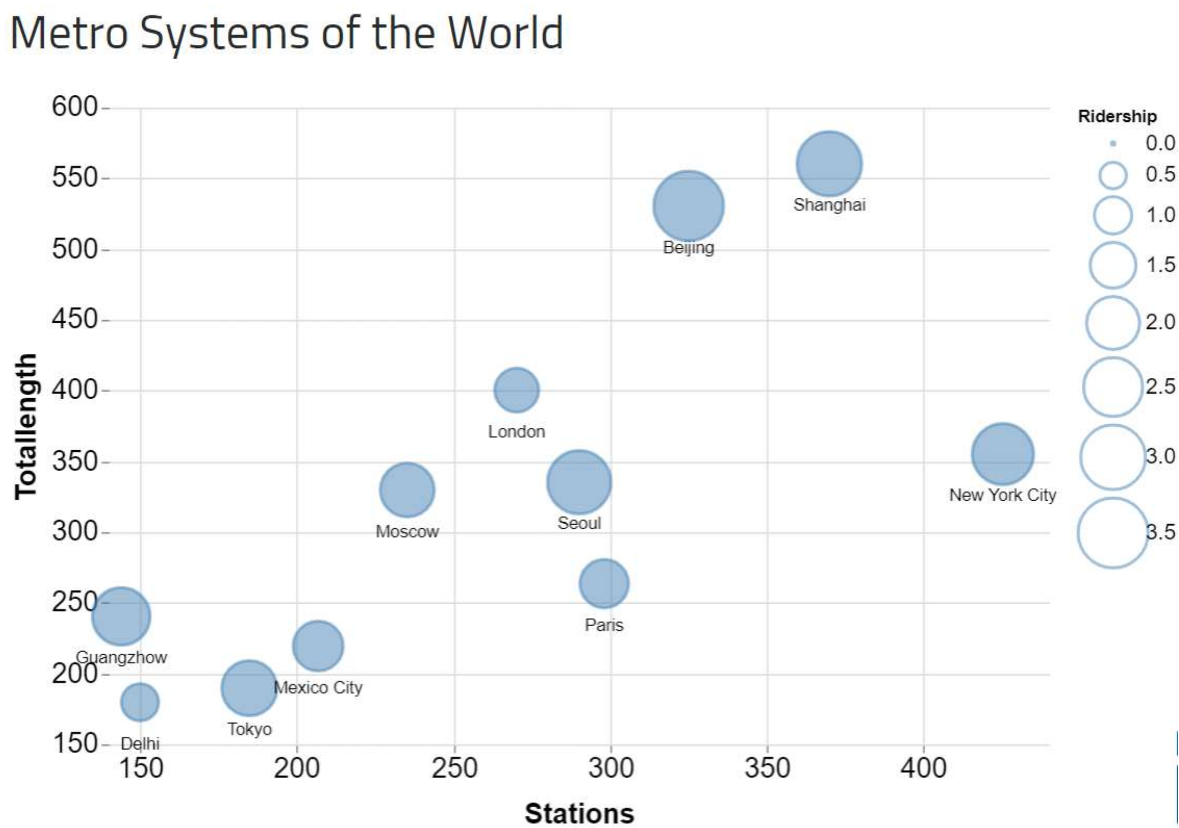


Figure 5: Metro System of the world

15. What is the total length of the metro system in Beijing, from figure 5?

330km ☐ 400km ☐ 530km ☒ 560km ☐ Skip ☐

16. Which city's metro system has the largest number of stations, from figure 5?

Seoul ☐ Beijing ☐ New York City ☒ Shanghai ☐ Skip ☐

17. What is the range of the total length of the metro systems, from figure 5?

150 – 600 km ☐ 240 – 380 km ☐ 240 – 560 km ☐ 180 – 560 km ☒ Skip ☐

18. The metro systems in Shanghai has more ridership than the Metro system in Beijing? figure 5.

True ☐ False☒ Skip ☐

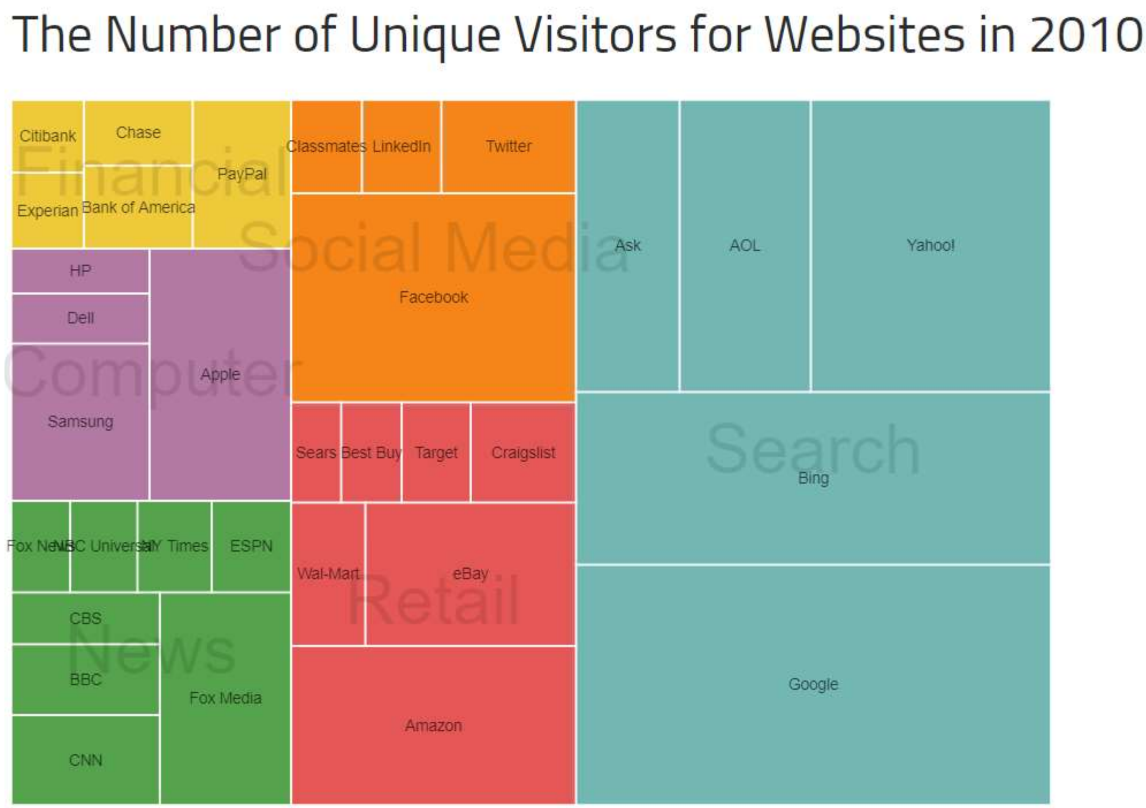


Figure 6: The number of Unique Visitors for Websites in 2010

19. For which website was the number of unique visitors the largest in 2010, from figure 6?

Facebook ☐ Amazon ☐ Bing ☐ Google ☒ Skip ☐

20. The number of unique visitors for Amazon was more than that of Yahoo in 2010, from figure 6.

True ☐ False☒ Skip ☐

21. Samsung is nested in the Financial category from figure 6.

True ☐ False☒ Skip ☐

PART THREE

Part three of the questionnaire deals with motivation and BI&A use. The following questions are given to measure perceived usefulness and perceived enjoyment as the dimension of motivation, and BI&A use with a seven-point Likert scale ranging from strongly disagree to strongly agree, indicating to what extent you agree or disagree with the statement.

Please circle the scale closest to your views.

Strongly Disagree 1	Disagree 2	Slightly Disagree 3	Neutral 4	Slightly Agree 5	Agree 6	Strongly Agree 7

	Motivation							
	Perceived usefulness	1	2	3	4	5	6	7
1	Business Intelligence and Analytics improve my performance in improving decision making and reporting.	1	2	3	4	5	6	7
2	Business Intelligence system enables me to make decisions/ identifying problems or risks faster	1	2	3	4	5	6	7
3	Business Intelligence and Analytics enhance my effectiveness in decision making	1	2	3	4	5	6	7
4	Business Intelligence system increases my productivity in monitoring or reporting/ predicting organisational performance	1	2	3	4	5	6	7
	Perceived Enjoyment							
1	I find using BI&A system to be enjoyable	1	2	3	4	5	6	7
2	The actual process of BI&A is pleasant	1	2	3	4	5	6	7
3	I have fun using the BI system and analysing data	1	2	3	4	5	6	7

Business Intelligence and Analytics Use								
	Exploitative BI&A use							
1	I use most of the Business Intelligence and Analytics system features (dashboards, standard reports, dynamic reporting) to support my work	1	2	3	4	5	6	7

2	I use all available system features (dashboards, standard reports, dynamic reporting) to help me in performing my tasks	1	2	3	4	5	6	7
3	I make use of the available system features (dashboards, standard reports, dynamic reporting) thoroughly to complete my tasks	1	2	3	4	5	6	7
Explorative BI&A use								
1	I discovered new features of BI&A system	1	2	3	4	5	6	7
2	I found new uses of BI&A system	1	2	3	4	5	6	7
3	I often use the BI&A system in novel ways to perform my tasks	1	2	3	4	5	6	7

APPENDIX B: SURVEY COVER PAGE

Welcome to: The Role of Motivation in Regulating the Extent to which Data visualisation Literacy Influences Business Intelligence and Analytics Use in Organisations.
I am a Master's student in the Graduate School of Technology Management, University of Pretoria.

My research titled The Role of Motivation in Regulating the extent to which Data Visualisation Literacy Influences Business Intelligence and Analytics Use in Organisations aims to understand the role motivation plays in regulating the extent to which data visualisation literacy influences Business Intelligence and Analytics (BI&A) use in organisations. For this study, you will be presented with information relevant to motivation, data visualisation literacy and BI&A use. To participate in this study, you must be above 18 years and a user of BI applications such as data reporting and visualisation platforms.

Your participation is voluntary and you can withdraw at any time without penalty. Throughout the survey, your privacy will be protected and your participation will remain confidential. I do not wish to analyse data individually and all the data will be transferred to a computer programme to analyse the entire group. This means that you are assured of anonymity.

If you agree to participate, please complete the survey that follows this cover letter. It should take about 12 minutes of your time at the most. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact me with the detail provided below. Thank you for your cooperation.

Researcher name: Boithatelo Malibeng

Email: u19149982@tuks.co.za

Question 1:

By selecting the "Agree" option I hereby voluntarily grant my permission to participate in this anonymous survey. The nature and the objective of this research have been explained to me and I understand them.

I understand my right to choose whether to participate in the research project and that the information provided will be handled confidentially. I am aware that the results of the survey may be used for academic publication.

□ Agree

□ Disagree