Antecedents of Business Intelligence System Use

A Study Investigating Kuwait's Telecom and Banking Industries

Thesis submitted for the degree of Doctor of Philosophy

by

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Declaration

I hereby declare that this thesis is my original work and has never been previously submitted for a degree in this or any other university.

I also declare that the information provided in this thesis has been collected in accordance with academic rules and ethical conduct.

Dedication

To those who preserve privacy and follow principles of right conduct when accessing data. To the ones that put morals before data monetisation, this thesis is dedicated to you.

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Abstract

Organisational reliance on information has become vital for organisational competitiveness. With increasing data volumes, Business Intelligence (BI) becomes a cornerstone of the decision-support system. However, employee resistance to use Business Intelligence Systems (BIS) is evident. This creates a problem to organisations in realising the benefits of BIS. It is thus important to study the enablers of sustained use of BIS amongst employees.

This thesis identifies existing theories that can be used to study BI system use. It integrates and extends technology use theories through a framework focusing on Business Intelligence System Use (BISU). Empirical research is then conducted in Kuwait's telecom and banking industries through a close-ended, self-administered questionnaire using a five-point Likert scale. Responses were received from 211 BI users. The data was analysed using SmartPLS to study the convergent and discriminant validity and reliability. Partial least squares structural equation modelling (PLS-SEM) was used to study the direct and indirect relationships between constructs and answer the hypotheses. In addition to SmartPLS, SPSS was used for descriptive analysis.

The results indicated that UTAUT factors consisting of performance expectancy, effort expectancy and social influence positively impact BI system use. Voluntariness of use was found to positively moderate the relationship between social influence and BI system use. Furthermore, BI system quality positively impacts both performance expectancy and effort expectancy. The BI user's self-efficacy also positively impacts effort expectancy. In addition, social influence was found to be positively influenced by organisational factors, namely top management support and information culture.

The findings of this research contribute to literature by determining and quantifying the factors that influence BISU through the lens of employee perspectives. This thesis also explains how employees' object-based beliefs about BI affect their behavioural beliefs, which in turn impact

BISU. Limitations of this research include the omission of UTAUT's facilitating conditions and the limited variance of respondent demographics.

Keywords: Business Intelligence, Business Intelligence System Use, Unified Theory of Acceptance and Use of Technology (UTAUT), Business Intelligence Extended Use Model (BIEUM), Business Intelligence System Use Model (BISUM)

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List of abbreviations

AUS	Adoption, utilisation, and success
AVE	Average variance extracted
BA	Business analytics
BDA	Big data analytics
BI	Business intelligence
BIEUM	Business intelligence extended use model
BISU	Business intelligence system use
BISUM	Business intelligence system use model
CAIT	Central agency for information technology
CDR	Call detail record
CMB	Common method bias
CSF	Critical success factor
DBMS	Database management system
DOI	Diffusion of innovation
DSS	Decision support systems
DWH	Data warehouse
EE	Effort expectancy
HCI	Human-computer interaction
HTMT	Heterotrait-monotrait ratio
IBV	Information behaviour values
IC	Information culture
IMF	International monetary fund
IQ	Information quality
IS	Information system
ISCM	Information system continuance model
IT	Information technology

KPI	Key performance indicator
MIS	Management information systems
OLAP	Online analytical processing
PE	Performance expectancy
PIIT	Personal innovativeness in information technology
PLS	Partial least squares
RBV	Resource-based view
ROI	Return on investment
RTC	Readiness to change
SD	Standard deviation
SE	Self-efficacy
SEM	Structured equation modelling
SI	Social influence
SLR	Systematic literature Review
SMS	Short message service
SPSS	Statistical product and service solutions
SQ	System quality
TAM & TAM2	Technology acceptance model
TMS	Top management support
TOE	Technology organisation environment
TPB	Theory of perceived behaviour
TRA	Theory of reasoned action
TTF	Task-technology fit
UTAUT	Unified theory of acceptance and use of technology
VU	Voluntariness of use

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Chapter 1: Introduction

1.1 Overview

There has been a substantial growth in business technology demands in recent times, with an increase in the quantity of data and information stored in different business systems. Business intelligence has become widely used and implemented in many organisations, particularly in the ones that value digital transformation. Business intelligence systems have advanced in their underlying technologies, thereby using recent software and hardware solutions. Through applying BI processes, organisations can become more scalable, intelligent and flexible at the data management level. Business intelligence systems are resource intensive applications that enable decision makers to derive proper insights, thus developing strategies to enhance their business (El Ghalbzouri and El Bouhdidi, 2022).

The term business intelligence dates back to 1958, which was an abstract term that came in with the publication of Hans Peter Lohan, an IBM computer expert. The article by Lohan was titled “Business Intelligence System” and described an “automated system” structured to spread information to different parts of any industrial, scientific, or governmental organisation. Business intelligence refers to a set of technologies and processes that enable individuals of every organisational level to get access and be able to analyse data, and hence, take the correct decisions.

This chapter will focus on key definitions, needs and benefits of BI, the problem statement, purpose, objectives, questions, methodology and data analyses used. This will be followed with an outline of the remaining thesis structure.

1.2 Key Definitions

1.2.1 Business intelligence (BI) definitions

Literature has provided many definitions to BI. Tunowski (2020) argues that it has taken many years to have a proper definition of a BI system. The term BI was defined for the first time in 1958 by H.P. Luhn, who worked for the IBM Corporation, as "the ability to understand the relationship between the facts presented in such a way as to take action towards the set goal" (Tunowski, 2020; p. 1). In addition to this, Oncioiu et al. (2019) state that in the present-day context, it denotes the broad concept of business analytics. BI class systems have a user-oriented process of collecting, exploring, interpreting, and analysing data, which results in restructuring and rationalising the decision-making process. These systems aid management in making the right decisions given the data in hand (Oncioiu et al., 2019).

This section provides different definitions related to BI. We begin with the definition from a broader perspective which is described by Ahmad et al. (2016) who categorise BI into three types: strategic, tactical, and operational:

- Strategic: "Developed to support long-term corporate goals and objectives and applications include aggregations, statistical analysis, multidimensional analysis, data mining, and exploration" (p. 97).
- Tactical: "Developed for business analysts and experts whose daily jobs involve accessing and analysing data and were targeted at making short-term business decisions" (p. 97).
- Operational: "Used to manage and optimize daily business operations and evolved to meet the need to respond to specific events that happen in the operational world" (p. 97).

Aside from the categorical definition provided by Ahmad et al. (2016), some authors focus on definitions relating to the technology itself. Papadopoulos and Kanellis (2010) point to BI as a set of enterprise architecture decision support applications. This describes BI as technologies that support decision making. Airinei and Berta (2012) also agree to the technology narrative. They state that BI is "a set of economic applications used for analysing data from companies in order to transform them into information that will substantiate the decisions taken by managers." (p. 72). Both definitions describe BI in the means of being an application or a set of applications

Other authors have focused on the information lens of BI. Kaur and Singh (2020) describe BI as "information needs in an organisation; information gathering; information processing; analysis; dissemination; and utilisation of the information for decision-making and giving feedback" (p. 2488). This definition stresses on the term information and how it is acquired, processed, disseminated, and analysed to support decisions. However, the acquisition, process, and dissemination of information given the substantial amount of data, requires systems.

In a broader view, Skyrius et al. (2018) define BI as "the organisational practice that includes a coherent set of people, informing processes and conventions using a comprehensive technology platform to satisfy business information needs that range from medium to high complexity" (p. 1). This definition brings together different aspects related to BI such as: the organisation, the people, the technology, and the information. However, these authors point to the combination of all these entities to satisfy business information needs without stating how.

The rapid spread of the internet in the mid-1990s, alongside the fast development of technology, resulted in the evolution of Business Intelligence Systems (BIS) (Ain et al. 2019). BIS typically refers to a complete set of tools, methodologies, and techniques that help organisations understand the bigger data sets to be able to recognise weaknesses, strengths, and opportunities (Harrison et al., 2015; Niño et al., 2020). A BIS is an information system (IS) which helps in decision making through (i) management, aggregation, and integration of unstructured and structured data; (ii) managing large datasets like big data; (iii) offering ad-hoc enquiries, commenting, forecasting, and analysis solutions; (iv) end-users support with advanced processing abilities to study new knowledge (Ain et al., 2019).

BIS can enhance the process of internationalisation of organisations by means of sorting, summarising, filtering, and integrating data from multiple channels like host markets, competitors, and local governments (Cheng et al., 2020; Veeramisti et al., 2020). In modern business, strong competition and advances in technology have led to the need to analyse and study big data (Zhao et al., 2014; Ahmad et al., 2020b). BI technology represents one of the best technological priorities of several decision-making authorities, including Business Owners, Chief Executive Officers (CEOs), and Chief Information Officers (CIOs) (Yeoh and Popovič, 2015; Arnott et al., 2017; Ain et al., 2019).

1.2.2 Business analytics (BA) definitions

Similar to BI, Business Analytics (BA) has been discussed in the decision support narrative. Housbane et al. (2020) define BA as “a broad category of applications, technologies, and processes for gathering, storing, accessing, and analysing data to help business users make better decisions” (p. 147). Whereas, Power et al. (2018) define BA as “a systematic thinking process that applies qualitative, quantitative, and statistical computational tools and methods to analyse data, gain insights, inform, and support decision-making” (p. 51). Furthermore, and in line with BI, BA has been discussed in the information lens. According to Shen and Tzeng (2016) BA refers to acquiring useful information for improving the efficiency of the organisation and adding business value.

However, Sharda et al. (2014) perceive BA in a statistical model lens. They define BA as “the application of models directly to business data. Business analytics involve using decision support system tools, especially models, in assisting decision makers" (p. 393). This definition describes BA as the application of statistical models to predict outcomes that support in making decisions.

In a wider perspective, Yin and Fernandez (2020) describe BA as "a broad umbrella entailing many problems and solutions, such as demand forecasting and conditioning, resource capacity planning, workforce planning, salesforce modelling and optimization, revenue forecasting, customer/product analytics, and enterprise recommender systems" (p. 287). Apart from the statistical model focus, we find that BA has commonalities with BI. In fact, the terms are commonly used interchangeably. This interchangeability and attempt to find distinctions is further discussed in the literature review.

1.2.3 Big data definitions

Big data is considered as a new strategic management trend and organisations greatly derive value from big data to improve their green engagement (Calza et al., 2020). The continuous study on big data greatly focuses on the provision of infrastructure for data capturing, storing, networking, and system distribution across parallel computing (Ali et al., 2021). In the past decades, big data was introduced into various research fields, bringing in motivating innovations to the corresponding technologies and theories (Elgendy and Elragal, 2014; Hashem et al., 2015).

Big data has different approaches as per Zraqat (2020) pointing to "data because of its size, the speed at which it reaches it, and the variety of shapes it takes" (Zraqat, 2020; p. 73); it "consists of massive data sets (large volumes) that are updated quickly and repeatedly (high speed) which displays a large collection of different shapes and contents (wide variety)" (Zraqat, 2020; p. 73) and "differs from 'normal' four-dimensional data, or '4 Vs' – its Volume, Velocity, Variety, and Veracity" (Zraqat, 2020; p. 73). Thus, the focus here is on the infrastructure and dynamics of the data. Therefore, in terms of topology, big data technologies are underlying layers of BI systems.

Hasan et al. (2020) point out that it is essential for the financial industry to have big data technologies as it is important for future innovations. We extend this argument to the telecom industry where large data related to customers are frequently utilised. This argument also agrees with Wei and Xie (2021) in which the researchers studied customer churn in the telecommunication industry. The authors further added that when the customer data is complex, large, and wide, it becomes necessary for organisations to analyse it from different angles, to find out valuable customer data, which is time-consuming (Wei and Xie, 2021).

1.2.4 Definition adopted in this research

Finally, this research adopts the BI definition by Paradza and Daramola (2021) that points to the "processes and systems (such as data warehouses, data marts, analytical tools such as reporting tools, ad hoc analytics and OLAP, in-memory analytics, planning, alerts, forecasts, scorecards and data mining) that transform raw data into meaningful and useful information and enable an effective, systematic and purposeful analysis of an organisation and its competitive environment" (p. 2).

The definition brings together the relationship between Big Data, BA, and BI as an interrelated concept of information systems, which can also be interchangeably adopted.

1.2.5 Understanding business intelligence and big data

Business intelligence (BI) is now the forerunner of information systems and on-line analytical processing technology (OLAP) in the early decade of the 21st century. Business intelligence comprises of several technologies like that of real-time processing which procures relevant information from the data warehouse and helps organisations in making decisions based on timely information.

BI provides a structured approach to the build-up of knowledge by supporting policymakers in strengthening their corporate statement processes and developing organisational efficiency and productivity (Lederer and Schmid, 2021). BI systems help in the advanced and complex study of business data through source systems in organisations. The application of BI has made the process of managerial decision making more focused. It is evident that BI has evolved to be a key solution to handle information and manage huge sections of data within different private and public sectors. BI is crucial in the exploitation of business data across organisational source systems. It can derive, handle, and alter data to become more concrete and visual. This supports in enhancing the decision-making process (Jorgensen et al., 2021).

BI aims to offer the right users with accurate information at a timely manner to enhance the decisions in favour of their organisations (Singh et al., 2019). BI is used in different areas to overcome risks and suggest appropriate compensations, with customers approaching various areas of knowledge depending on requirements. The implementation of the customer needs of the information system has an important role in its performance since most of the BI consumers are not aware of what to demand from a successful introduction. Both societal and operational considerations must be evaluated while studying the market criteria for raising the usage of a new BI framework (Sun et al., 2018).

BI systems are becoming more important with organisations striving to use new methods to analyse complex data sets (Zhu et al., 2015). With the presence of computers and technology has come the concept of data explosion (Zadeh et al., 2015). There has also been a great increase in data collection and analysis, where data mining and analysis ranks as the second most important technology following mobile technology (Rouhani et al. 2016). This is due to the great value of data analytics, as organisations already implement the insights obtained from newly available data sources to explain their strategies. In recent times, the term ‘big data’ has come into use to explain the large data sets which demand advanced data management techniques (Varma, 2018). The volume, velocity, variety and reliability of features differentiate big data from 'traditional' data (Chen et al., 2012; Zraqat, 2020).

The notion of big data came about with these wide and dynamic data (Zong et al., 2021; Hsu et al., 2021). Big data helps BI in providing insights which permit companies to analyse their customers in a better manner, boost marketing technology, make personalisation possible, and recognise real-time problems and opportunities. In the recent times, big data has attained great amount of interest due to its ability to create market value. In 2019, 39% of respondent entities used advanced analyses and 84% applied advanced examinations in four years (Garmaroodi et al., 2020; Kumar et al., 2020). It is wise for organisations to review larger quantities of data in order to understand the current state of the market and systems, including customer conduct, which undergo constant changes. A major number of organisational problems can be addressed by big data analytics (Gao et al., 2020).

On one hand, big data allows firms to derive a strategic benefit over their competitors in many ways, while on the other hand, big data analysis introduces problems. The key challenge of big data analysis is absence of smart big data sources, lack of accessible real-time analysis capacities, and access to adequate network capacity for running applications (Araz et al., 2020). The necessity to raise the data protection, network spans and legislation on data protection, interoperability, disparate data fragmentation, and inadequate availability have been emphasised with the introduction of big data (Niu et al., 2021).

Big data may represent a significant competitive advantage to an organisation by reducing cost and enabling further revenue generation. Business intelligence (BI) tools have become important for understanding and utilising big data and, consequently, the organisation's overall competitiveness (Ahmad et al., 2016). Several organisations in various industries have become BI-based, making significant investments for BI implementation. Comparative to overall IT budgets, BI spending has increased (Puklavec et al., 2014). BI has become a necessity for competing in the marketplace. BI applications comprise of forecasting the product demand, establishing the selling price for products, customer segmentation analysis, market basket analysis, product recommendations, campaign planning and management, customer and product profitability analysis, web analytics, supply chain integration, and fact-based decision making (Basole et al., 2013).

1.3 Needs and benefits of BI

1.3.1 Needs for BI

Anything that is tracked in business may be the source of BI. The data of an organisation may be used to assess multiple factors, including the ROI, revenues, profits, turnovers, expenses, and many other areas. Through BI, managers can view the patterns, trends and outliers from where the forward step may be planned (Tutunea and Rus, 2012). Kaur and Singh (2020) propose the following for understanding the need of BI:

Take action For the improvement of business performance, managers should take the necessary action. With the help of BI insights, it is possible for managers to create marketing campaigns that would lead to the best ROI. Customers can also be targeted more accurately. Logistics and operations may be enhanced with sales forecasting and targets adjusted accordingly.

Begin transformation The process of transformation starts as managers begin to take appropriate action on the basis of BI insights. There will also be changes in the overall thinking process in the cases of reassessment, and necessary actions can be taken depending on the business intelligence operations.

Get ahead The opportunity to perform better than competitors can only be attained on the basis of trustworthy data and appropriate analytics. It is also essential to understand weaknesses. With the help of BI, it is possible to discover and focus on strengths. It is essential to be able to foresee the future as BI visualisation helps in this.

1.3.2 Benefits of BI

BI comprises the numerous procedures, devices and technologies that are required to transform data into information and information into knowledge; BI applications help to speed up the procedure of making business decisions about data quality. In addition, business intelligence is a structure for increasing the organisational efficiency and integration of decision-making processes at different levels of the organisation. An increase in the quality of data in the business environment through business intelligence systems results in better corporate performance and finally boosts the financial reporting quality (Ahmadi et al., 2021).

It is possible to deploy BI applications in a strategic manner across functional departments or tactically inside functional departments (Oliveira and Martins, 2011). By offering a holistic picture of the organisation to senior managers, strategic BI has the potential for big rewards. With BI, organisations can recognise trends and chances for development as well as for setting key performance indicators (KPI). Organisations can use tactical BI in 'bottleneck' areas. Such BI usage provides organisations with the insights and knowledge to obtain quick and high quality results (Ahmad et al., 2016).

In several industries, BI-related strategies and technologies have been used. The international application of BI was in 1967 when it was used to monitor foreign currency instabilities (Oyeniyi and Abiodun, 2010). Typically, organisations apply BI in order to understand the business environment through competitor analysis, marketing research, business process reengineering (Huang and Kechad, 2013; Shollo and Galliers, 2015).

Several strategic advantages are provided by BI to those organisations who utilise it (Alaskar and Efthimios, 2015). BI helps to eradicate pointless guesswork inside the organisation and to enable proper communication amongst departments (Sharma and Gandhi, 2019). Daily tasks and activities can be coordinated, which also helps organisations to respond quickly. BI enhances the overall performance of an organisation. Naturally, information is a main resource for a given organisation. It is on the basis of this available information that an organisation takes relevant decisions. Accurate and timely data, and its effective analysis, enable companies in boosting financial performance. Hence, BI has an important role to play since it uses data and provides information to aid the decision-making process (Kaur and Singh, 2020).

BI may improve customer experiences, creating the atmosphere for an appropriate and timely response to the priorities and issues of the customer. In the modern customer-centric business culture, managers come across a lot of information and try to seek understanding and intelligence from their organisation's data. Thus, the adoption and use of BI becomes appealing for managers (Kaur and Singh, 2020).

1.3.3 Importance of BI in telecommunications

The telecom industry has provided customers with the freedom to choose their service providers for voice and wireless internet connectivity (Rashidirad et al., 2017). Currently, with the existence of numerous service providers, it becomes easy for the customers to change their service premiums and networks, while also influencing the total framework of the organisation. Changes in technology have made it possible for telecom organisations to recognise crucial needs and demands of the customers for facilitating customised products.

These kinds of changes do not just support the service providers but even raise the risk of losing the existing customers and keeping them from moving towards the attractive offers put in by the competitors. Due to deregulation and private parties, there has been a big shift in the number of customers from outdated product operations to consumer operations (Pucciarelli and Kaplan, 2016). The focus on customers based on these circumstances leads to developing new services with lower costs and higher efficiency (Brockhoff, 2017).

One of the biggest producers and consumers of large volumes of data is the telecommunications industry (Ashraf and Khan, 2015). Since this huge amount of data is available to service providers, the task of being able to monetise this data from a sales perspective, as well as making proper decisions from an operations perspective, is very promising for service providers. Big data in telecoms comprises of the information derived from several internal as well as external sources like social media, transactions, enterprise content, sensors and mobile devices. Telecommunication businesses have access to several of these sources (Ashraf and Khan, 2015).

The telecommunication industry also particularly recognises the potential gain which may be attained from the use of BI (Hameed et al., 2012). Telecoms attempt to recognise the market trends, detect fraud and also predict customer retention through BI analytics in order to hasten and also enhance the process of decision making for retaining their position in the unpredictable business environment (Oliveira and Martins, 2011). There is a substantial volume of Call Detail Records (CDRs) that are generated in telecommunications daily. The BI applications of fraud detection and churn analysis require the collection and mining of these records on a regular basis. Customer profiling is a vital element of most of these applications, as it aims to discern patterns of behaviour through the collection of transactional records, and also the comparison of such patterns. For example, in telecommunication applications, the calling behaviour of the customer is portrayed by the structure and periodic appearance of the called party, the time-windows (when the calls are made), and the duration (how long the calls last). With the implementation of e-commerce applications, the shopping behaviour of a customer may be represented by advertisements viewed, the products selected, products that are bought, time windows, price, and so on. There is a high degree of similarity between the techniques for customer profiling and comparison (Haigang, 2005).

The business pattern of most of the telecom providers may require alterations to meet the needs of customers. With this, there should be more focus given to altering bigger databases pertaining information of customers into solid evidence for future predictions and decisions making. With BI systems, several service providers could solve various challenges of the value chain to attain the objectives of a telecom operator (Ramana et al., 2019). The current BI deployments are, however, known to be expensive, complicated, and time-consuming since these software applications are rather complex in nature and are seen as high-risk and high-return projects. Advanced BI systems that help in tactical and strategic decision-making require (1) requirement modelling of big historical data, (2) application of highly analytical applications to carry out analytics functions and (3) visualisation of data in the form of dashboard to be displayed at various levels of decision making (Ahmad et al., 2016). Dedicated people with special skills are required to carry out the tasks. The incorporation of advanced analytics in a BI program like predictive analytics, data mining, and text mining would work only if statisticians, data scientists, and predictive modellers are put to work (Ahmad et al., 2016).

There is an increase in the volume and complexity of data in the telecom industry, and by studying this data, telecom operators will be able to manage as well as retain customers. Organisations should also be able to foresee the income which they may derive from their active customers. This implies that in the presence of such complex situations, inappropriate BI applications would result in failure, and also make organisations data rich and information poor. In the absence of careful considerations, the BI initiatives for constructing innovation would not be successful.

1.3.4 Importance of BI in banking

Banks are organisations that function in the financial business domain, associated with activities including loaning, deposits management, and investments in capital markets. Since the banking industry is very important for an economy, it has become a topic of immense interest for researchers across several areas like marketing, management science, finance, and information technologies (Moro et al., 2015). Banking is an industry notable for innovation related to information systems and technologies (Shu and Strassmann, 2005). The new technologies, for instance, have initiated new communication channels which were instantly taken up by banks. Advanced data analysis techniques are now implemented to understand the risk in credit approvals (Huang et al., 2004) and fraud detection (Ngai et al., 2011).

Areas of banking including branch performance, credit evaluation, customer segmentation and retention, and e-banking are the best areas for the use of BI techniques and concepts, including data mining, data warehouses, and decision support systems (DSS). To ensure the survival and success of the firms in the current active business environment, bank managers must possess a continual focus on exploiting opportunities and solving challenging problems. For this, it is essential to have computerised support of managerial decision making which implies the need of decision support and business intelligence systems (Moro et al., 2015).

When it comes to new information systems and technologies, the banking sector is a rich industry for BI and DSS (Shu and Strassmann, 2005). As a core element of machine learning and big data, business Intelligence comprises of tools, architectures, databases, and methods of data analysis to aid the decision making for business executives (Agarwal and Dhar, 2014). Areas such as e-banking, branch efficiency, customer segmentation and retention, amongst many others, offer an opportunity for the implementation of business intelligence techniques and methods like that of data mining, data warehouses, and decision support systems (Pulakkazhy and Balan, 2013; Moro et al., 2015). Data mining methods of business intelligence are used to enhance banking operations like fraud detection (Bhattacharyya et al., 2011; Ngai et al., 2011; Wei et al., 2012), credit assessment (Huang et al., 2004; Yap et al., 2011; Gulati et al., 2018), and customer churn prediction (Ali and Arýtürk, 2014). Banks are already alert of the value of the data associated with the customer. They have had to adapt their recording of transaction data for complex examination including customer relationships, risk management, market valuation, profit and production channels, and operational efficiency (Curko et al., 2007). In cases of failure in these areas, there would be certain unfavourable results like property damage, loss of customers, heavy fines, and also loss of credit (Pulakkazhy and Balan, 2013). It may also be said that required data attributes are not combined and organised in order to carry out data analysis. In these areas, for the creation of knowledge, it is necessary to have the significant data derived by the information system. Hence, the lack of appropriate data becomes a major problem in the application of data mining techniques for banks.

Banks can enhance their products, customer information, risk measurement, and market expectations. Despite the fact that many banking institutions have accepted analytics, there is still a problem with transforming the analytical insights into business outcomes. To succeed, business adoption and change management become necessary. It may be noted that in 2018, only 7% of banks in the EMEA (Europe, Middle East & Africa) area had achieved complete incorporation of important analytics use cases. 15% of banks in the EMEA region consider that the management depends on analytics for decision making. 20% of staff in EMEA banks assume that it is possible to convince their management by big data analytical insights that go against their original beliefs. In the surveyed banks of the EMEA region, almost half of the management responded in a positive manner to the value that analytics offers their institution with only 25% of effectively communicating how operational capacity can be improved (Pillay et al., 2021).

Banks currently encounter several problems that need to be adhered, for instance, process mechanisation, market division, mergers, and acquisitions, raised client desires, forceful challenge, and new improvement. Therefore, banks need to manage risks and combine their business activities with the emerging national and universal laws. Top management would need to make quick decisions that must be data driven. Great amount of data is recorded by banks each day, with information of all clients comprising of: property and cash choices, charge, exchanges per account, credit liabilities, and so on. These types of data are created inside a bank's core framework and secured in value-based databases (Nithya and Kiruthika, 2021).

1.3.5 Country and industry relevance

The benefits of BI systems are particularly observed in the telecommunications and banking industries, where large volumes of data are processed daily. The telecommunication data contains valuable information regarding consumer behaviour, internet usage, content-based data, and call detail records (Oliveira and Martins, 2011; Hameed et al., 2012; Ashraf and Khan, 2015; Ahmad et al., 2016), while banking data leads to valuable information focusing on credit risk and fraud detection (Huang et al., 2004; Ngai et al., 2011). Therefore, these settings are suitable to study due to the large volume and value of data in telecommunications and banking when compared to other industries. Consequently, this research will focus, in part, on the telecommunications industry in Kuwait, where mobile penetration rates and consequent data volumes are high (CAIT, 2016; GSMA Intelligence, 2017). The other area of focus will be Kuwait's banking industry due to the importance of BI for bank managers' decision making (Moro et al., 2015).

In 2019, the GPD for Kuwait stood at US$143.2 billion, with a population of 4.2 million, a per capita GDP of US$33,700 (World Bank, 2020), and a mobile penetration rate of around 80% as of 2019 (GSMA, 2019). In contrast, Kuwait's Central Agency for Information Technology (CAIT) reports estimated mobile penetration at 240%, with 8,719,000 mobile cellular subscriptions and 100% mobile coverage existing across the country (CAIT, 2016). Kuwait's telecommunications industry is oligopolistic having three competing operators: Zain, Ooredoo and STC (formerly VIVA) (CAIT, 2016). Telecom operators are the dominant provider of internet services with mobile broadband connections accounting for 87% of the total internet service providing market (GSMA Intelligence, 2017). Kuwait's CAIT reports that 51% of Kuwaiti businesses indicated that their data volumes have increased by 24%

(CAIT 2016). Thus, implementations of BI systems have been a focal point to businesses with an objective of extracting meaningful insights from data (CAIT, 2016).

The telecommunications industry in particular can potentially obtain unique benefits from BI. Telecom networks typically generate large volumes of Call Detail Records (CDRs), around 100 million to 500 million CDRs a day and they are able to use these records to drive sales and marketing initiatives (Kumar, 2012). Apart from actual voice calls, CDRs can contain SMS and internet (data) records (Ishaya and Folarin, 2012). The advantage of having such data enables telecom operators to reduce churn, ensure billing accuracy, deploy revenue assurance programs in accordance to call behaviour, and optimise network operations (Kumar, 2012). Furthermore, telecom operators are able to identify the customer's location, thereby offering well-tailored services not only to the right customer at the right time, but also at the right location (van den Dam, 2013).

The IMF points to the strong reliance of Kuwait on oil revenue as the source of economic growth and stability. However, with oil prices dropping over the past few years, the strong reliance on a single source of revenue has impacted the Kuwait economy. Kuwait is facing a challenge in reducing its oil dependence and identifying other sources of revenue, with an emphasis on strengthening the private sector. The IMF report adds that Kuwait has large financial buffers and low debt, therefore the country has the flexibility in diversification and venturing various growth opportunities. This is important for the future stability of the country as 'without a course correction, fiscal and financing challenges will intensity' (IMF, 2020; p. 3). This can be achieved through 'ambitious, growth-friendly, and socially equitable fiscal adjustment', with reforms in the financial sector that is aimed at 'bolstering resilience and deepening inclusion' (IMF, 2020: p. 3). The recommendation to the financial sector to 'enhance the corrective action framework, establish a special resolution regime for banks, and unwind the blanket deposit guarantee' (IMF, 2020: p. 3).

As per the *47th Economic Report for the Year 2018* published by the Central Bank of Kuwait, there are twenty-three banks in Kuwait, five of which are conventional, five are Islamic, one specialised bank, and twelve foreign branches that include one Islamic bank. The aggregated balance sheet at the end of 2018 stood at 66.545 billion KDs. The aggregated figure for 2017 stood at 63.411 billion KDs, which indicates a growth of 4.9% between 2017 and 2018 (CBK, 2020). Banks in Kuwait have adequate short-term liquidity with a capital adequacy ratio of 17.6% as of September 2019 (IMF, 2020).

This research studies the use of BI in the telecom and banking industries in Kuwait. Telecom and Banking are customer-centric facing competition in customer acquisition and retention. Both industries have similarities in data size and customer-centricity. Kuwait has three telecom operators (table 1.1) and four important banks that are studied in this thesis (table 1.2).

Table 1.1: Kuwait mobile telecom operators

Telecom	Overview	Revenue
Zain	Kuwait owned and operated	KD 333 million (Q4 2019)
Ooredoo	A subsidiary of Qatar mobile telecom with the same name	KD 294 million (Q1 2020)
STC	Previously named as VIVA and majority-owned by Saudi Telecom Company	KD 293.7 million (Q4 2019)

Table 1.2: Total assets in Kuwait in 2019 (in billion US dollars)

Bank	Assets
National Bank of Kuwait (NBK)	96.07
Burgan	23.24
Gulf Bank Kuwait (GBK)	20.5
Boubyan	17.4

As shown in table 1.1, there are three mobile telecom service providers in Kuwait. Zain is a Kuwaiti company whereas Ooredoo is a Qatari telecom and STC is the Saudi Telecom Company, all operating in Kuwait. The Central Bank of Kuwait (CBK) is the supervising authority over all financial firms in Kuwait. The banks are categorised mainly into conventional banks and Islamic banks. As per the CBK, there are five conventional banks – the National Bank of Kuwait, Commercial Bank of Kuwait, Gulf Bank, Al Ahli Bank of Kuwait, and Burgan Bank (cbk.com, 2021a) – and five Islamic banks, Ahli United Bank, Kuwait International Bank, Kuwait Finance House, Boubyan Bank, and Warba Bank (cbk.com, 2021b). In addition to these banks, there is only one specialised bank which is the Industrial Bank of Kuwait (cbk.com, 2021).

1.4 Problem statement

In order to compete in traditional markets and even online businesses, BIS has obtained much attention of the industry practitioners to help in offering optimum products and services with better processes and managerial practices (Trieu, 2017). This is demonstrated in the drastic rise in the value of the worldwide BIS market which went up to about 7.3% in 2017, with revenues up to $18.3 billion; this is estimated at $22.8 billion by the end of 2020 (Ahmad et al., 2020b; Ain et al., 2019; Gartner.com 2017).

The implementation of BI requires the organisation and its leaders to be prepared with several changes in order to adopt BI. After implementation, many employees remain resistant to BI system use (Popovič 2017), therefore wasting organisational resources. Shirish and Batuekueno (2021) point out that adoption and resistance are twin concepts that go hand in hand with any digital transformation or change management initiatives. User resistance is defined as an “implicit or explicit defence’s expression toward a change” (Shirish and Batuekueno 2021; p. 4). Thus, resistance to change is viewed as a behaviour that organisations should strive to eliminate.

In addition to this, the limited body of work that is available focuses on the initial adoption of BI systems and fails to investigate post-implementation BI system use (Côrte-Real et al., 2014). Canhoto and Arp (2017) state that inconsistent data can lead to users abandoning the system. The focus on adoption gives an incomplete picture because the factors that impact adoption may be different from those that enable continued use. Moreover, studies that address the adoption of technology are largely based on the initial perception of the individual where it can be argued that this may not lead to actual use; fewer studies focus on the actual use of technology after its initial adoption. Further studies that are based on actual use are based on experiences of using the system. Similar arguments are also raised by other researchers (for example, Coorevits and Coenen, 2016; Epstein et al., 2016; Kari et al., 2016; Maher et al., 2017; Buchwald et al., 2018; Nascimento et al., 2018).

Overcoming the hurdle of resistance is crucial in achieving the required productivity and benefits from BI systems. Technology plays a significant role in business operations and this emphasis is stressed by the sustained use of technology by its users. Therefore, the overlooked perspectives and opinions of employees towards the system are important (Awa and Ukoha, 2020; Yusof et al., 2020).

Determinants of employees' acceptance and use of BI systems have consequently become a focal point for researchers and practitioners alike. The topic of user acceptance of technology has long been addressed in information systems literature. However, this body of work offers only limited insight regarding the adoption and use of BI systems (Côrte-Real et al., 2014), leaving a gap for academic researchers and business practitioners. Leaving this gap unexplored can lead to limited use of BI systems, and not realising the potential of employees. In addition to this, organisations have invested heavily in implementing BI systems with the aim of improving organisational performance. Therefore, lack of understanding of the use of BI can limit organisational goals and performance.

It is also important to emphasise the differences in demands and skills among BI users, as this could influence employee use and consequently the productivity of BI systems. Power users – individuals who are able to perform complex analytical tasks easier and faster (Michalczyk et al., 2020) – may use the BI system extensively and increase their productivity as a result (Alpar and Schulz, 2016). The self-service features of BI systems provide users with the ability not only to use information, but also to create information and harness new information sources. If capitalised upon effectively, this would diminish the information requests of business users to BI specialists (Alpar and Schulz, 2016).

In recent years, the adoption and use of BI systems has changed fundamentally with the growth of technology, information systems, and big data that requires extensive analytical tools (Ain et al., 2019). Despite this, academic research has failed to reflect that evolution, and has dedicated limited attention to this topic (Bach et al., 2016; Puklavec et al., 2017). A review of the literature on BI system use revealed a lack of academic publications from a global perspective and in Kuwait where this research is carried out.

1.5 Research purpose, objectives, and questions

1.5.1 Research purpose

The purpose of this research is to identify key factors that contribute to effective use of BI systems in the telecom and banking industries in Kuwait. The findings will contribute to developing a framework that is suitable in the context where a BI system is implemented and used on regular basis. This will be achieved by collecting primary data through survey from BI users in the mobile telecom and banking companies in Kuwait.

1.5.2 Research objectives

The research objectives are as follows:

- To measure the effect of BI systems and information quality characteristics, BI individual characteristics (self-efficacy, personal innovativeness in IT, and readiness to change), and BI organisational factors (top management support and information culture) in affecting different behavioural beliefs.
- To quantify and analyse the degree to which different behavioural beliefs affect BI system use.
- To analyse the effect of demographic moderating factors and voluntariness of BI use.

1.5.3 Research questions

The following research questions have been developed in order to achieve the research objectives:

- To what degree do different system and information quality characteristics, individual characteristics, and organisational factors influence different behavioural beliefs of employees regarding BI system use?
- To what degree does performance expectancy, effort expectancy, and social influence affect BI system use?
- Does gender, age, experience, and voluntariness of use have a moderating effect between different behavioural beliefs and BI system use?

1.6 Research methodology and data analysis

1.6.1 Research methodology

This positivist research relies on previous theories and identifying factors that impact BI usage by adopting a deductive approach based on previously existing theories. The chosen method is quantitative administered by paper-based surveys to ensure that participants are actual BI users. The quantitative method is required for quantifying the relationships between the studied factors considered.

This research collects primary data from BI users in Kuwait's telecom and banking industries through a survey. A self-administered questionnaire was designed using literature sources and was distributed in hard copy to the sample population (BI users). The questionnaire was close-ended with demographic questions using multiple options. The studied variables were described using five-point Likert scales. The questionnaire was distributed to 400 BI users and a total of 211 responses were received and used for data analysis.

The independent variables are from BIEUM that contains the BI system and information quality, BI individual characteristics (that contains self-efficacy, personal innovativeness in IT, and readiness to change), and BI organisational factors (top management support and information culture). The framework studies the role of independent variables on the UTAUT model (performance expectancy, effort expectancy, and social influence). The dependent variable is BI system use (BISU). Since this study is based on a post-implementation context, behavioural intention was removed from the framework. Furthermore, facilitating conditions was later omitted in this study due to vagueness of the construct (combining many constructs into one). The UTUAT model also studies the moderating role of gender, age, experience, and voluntariness of use between performance expectancy, effort expectancy, social influence, and BI system use.

1.6.2 Data analysis

The quantitative data is analysed using SmartPLS 3. The data is first studied for validity using convergent validity where the outer loading of the framework is studied. This leads to studying the validity using the average variance extracted (AVE). The internal consistency is studied using Cronbach's Alpha and Composite Reliability. The discriminant validity is studied using cross-loadings, Fornell-Larcker criterion, and Heterotrait-Monotrait Ratio

(HTMT). The direct and indirect effects of the variables are studied using the partial least squares structural equation modelling (PLS-SEM). The PLS-SEM answers the hypotheses.

In addition to the SmartPLS, the research also uses the statistical package for social sciences (SPSS) for descriptive analysis that studies the demographics and the summary of the responses using a five-point Likert scale.

1.7 Thesis structure

Chapter 1 provides the overview of the research along with the key definitions, needs and benefits of BI, problem statement, research purpose, research objectives, research questions, overview of research methodology, and overview of data analysis.

Chapter 2 conducts a review of the literature on BI and related theories of system use. It starts with discussing the approach by which the review is conducted. This is followed by a discussion on BI current state of knowledge, BI components and evolution, BI and decision making, BI implementation, BI user skills and use behaviour, determinants of system use, and ends with the literature gap.

Chapter 3 discusses the conceptual framework development. It explains the constructs including the dependent variable, the mediators, the independent variables, and the moderators. This is followed by presenting the developed conceptual framework and the hypotheses.

Chapter 4 is the methodology chapter. It begins with presenting research philosophies, discussing the positivist stance taken. The discussion then moves on to the research approach, research method, research strategy, research type, time horizon, data collection, and data analysis methods.

Chapter 5 is the data analysis and findings chapter where the primary is analysed using SmartPLS and SPSS. The chapter also presents acceptance or rejection of each hypothesis.

Chapter 6 is the discussion chapter where the primary data findings are discussed in relation to the reviewed literature.

Chapter 7 is the conclusion and recommendations chapter where the research questions are answered, the theoretical contributions are stated, and managerial recommendations are provided. This chapter also presents the limitations and directions for future research.

Chapter 2: Literature review

2.1 Introduction

This chapter conducts a review of the literature on BI and related theories of system use. It starts with discussing the approach by which this review is conducted. This is followed by a discussion on BI current state of knowledge, BI components and evolution, BI and decision making, BI implementation, BI user skills and use behaviour, determinants of system use, and ends with the literature gap.

2.2 Approach

The literature review focuses on understanding different aspects of BI. It begins with a review of the literature discussing the current state of knowledge, components and evolution, decision making, and implementation of BI. This is followed by a critical review involving the theories discussing the determinants of system use and the evolvement of theories regarding the subject. Critical reviews discuss the relevant topic with an aim of emphasising weaknesses, discrepancies, controversies and contradictions (Paré et al., 2015). This research aims at investigating BI system use, hence critically reviewing existing theories that explain system use in general, and for BI in specific, is vital.

We start with a generic understanding of searching for the keyword 'Business Intelligence' across five different academic sources as depicted in table 2.1. The search was conducted on Web of Science and Scopus which are global citation databases that search several academic databases. In addition to this, ProQuest, ScienceDirect, and Emerald were consulted, which host notable databases of research in business and social sciences with highly regarded journals.

Table 2.1: BI search results

Keywords (Title)	Web of Science	Scopus	ProQuest	Science Direct	Emerald
(Title) Business Intelligence	1,991	3,036	2,259	249	122

Note: Topic = Title

The topic of business intelligence adoption, utilisation, and success (AUS) has been studied by many authors. It has gained wide attention by researchers since the early 2000's with a significant increase in publications from 2011 onwards (Ain et al., 2019). The existing body of knowledge mainly focuses on the lens of the organisation with gaps in user-perspectives (Ain et al., 2019).

2.3 BI current state of knowledge

Technology is growing rapidly in today's world, and the BI domain is also gaining significance by offering forces to industries to satisfy the needs of the customer (Nithya and Kiruthika, 2021). Business intelligence (BI) describes a set of applications, technologies, and processes that assist in decision making through gathering, storing, accessing, and analysing data (Davenport 2006; Wixom and Watson 2010).

2.3.1 Interchangeability and distinctions of the terms

BI has been popular since the 1980s. It was not until the late 2000s that the term Business Analytics (BA) came into use as the analytical element of BI; the more recent term Big Data Analytics (BDA) is used to refer to large data sets upon which analytics are applied (Davenport, 2006; Chen et al., 2012; Grublješič et al., 2017; Jayakrishnan et al., 2018). The terms are commonly used interchangeably, and therefore, the terms BI and BA are at times less clearly defined or well-expressed, while Big Data (BD) is an evolving term referring generally to voluminous quantities of data. However, the distinction between BI and BA is well clarified by Chang et al. (2015), who suggest that BI is divided into reporting and analytics. In terms of reporting, users of BI platforms can use drag and drop features to create their own reports and share those reports with other users. With BA, users can apply advanced statistical analysis and predictive modelling as well as gain more insight into their organisation's data (Chang et al., 2015). Due to the interchangeable use of BI and BA, this thesis will use the term BI, because it "involves several distinct areas and technologies that converge in the common goal of having access to data in order to help businesses by facilitating knowledge and supporting better management decisions" (Moro et al., 2015, p. 5). In specific cases, where literature discusses BI and BA separately, the terms shall be delineated with respect to the usage of the authors.

2.3.2 Aspects of the existing body of literature on BI

BI is displayed in literature as a means that can help business progression via better decision-making processes and hence, firm performance and business value (Trieu, 2017; Bach et al., 2018). The current business environment is greatly dynamic and heavily competitive; hence, it becomes mandatory for business organisations to make correct decisions to guarantee long-term profitability and sustainability in the long term (Aydiner et al., 2019; El-Haddadeh et al., 2021). BI helps in the crunching and study of massive amounts of organisational data to produce strategic information. This is done by identifying variable correlations and finding structures which can help offer rational organisational decisions which would help boost organisational strategic decision making (Aydiner et al., 2019; Božič and Dimovski, 2019).

The methods used in earlier BI-related publications were mostly quantitative (56%). This is respectively followed by fewer qualitative, conceptual, and mixed methods (Ain et al., 2019). The focus on quantitative methods may be due to the fact that this topic has been researched over the past two decades and most publications focus of objective measurement tools to understand cause and effect relationships. Around 28 theories were used in BI research where

DeLone and McLean's IS success model, the technology acceptance model, and the diffusion of innovation theory were the theories mostly used in the context of adoption, utilisation, and success (Ain et al., 2019; UL-Ain et al., 2019). Other theories have been discussed in the context of realising the business value (BV) of BI. Those theories are, respectively, the Resource-Based View (RBV), Dynamic Capability Theory (DCT), Technology Organisation Environment (TOE), and Contingency Theory (Paradza and Daramola 2021).

The literature indicates that the majority of publications from 2000 to 2019 have focused on BI success while the other publications focused on BI utilisation and adoption respectively. However, success is dependent upon continued use of BI systems by users. Ain et al. (2019) use the terms together 'use and success' when discussing issues facing BI. Those issues are infrastructural (Oslzak, 2016), communicational between business and IT (Richards et al, 2017) and issues related to the inexistence of a strong information culture (Popovič 2017). Ain et al. (2019) agree to the narrative and believe that management must encounter these issues for employees to continually use BI systems. Nonetheless, attaining business value from BI systems, a distinct subject area in itself, may go beyond adoption and use. For instance, small-medium sized enterprises face issues with data volumes and resource acquisition which linearly related to BI business value (English and Hoffmann 2018; Salisu et al., 2021). In addition, information quality is a vital factor in realising business value (Jaklič et al., 2019). Moreover, further determinants of BI business value include analytical leadership, enterprise-wide analytics orientation, well-chosen targets, extent to which decision making is rooted in the "DNA" of the organisation, and on-going business analytics improvement projects (Seddon et al., 2016). Business value is also gained through BI assimilation. Wang et al. (2019) found that BI assimilation, the extent to which BI is diffused and routinised within the organisation, is a direct determinant of gaining competitive advantage. BI capabilities, on the other hand, only determine business value through BI assimilation. Although these business value factors are crucial, it is important to note that in terms of process, BI system use is a prerequisite for realising BI business value (Seddon et al., 2016).

Literature has specified that the elements required for BI use and success come through three perspective elements. Those perspective elements are of the: organisational perspective (e.g., organisational goals, strategies, and plans); information systems (IS) perspective (e.g., IT infrastructure and dashboard presentation); and users' perspective (which include human resource factors) (Ain et al., 2019; UL-Ain et al., 2019). Certain authors have included a fourth perspective element, namely macro-environmental perspectives such as external market influences and regulatory compliance (Grublješič and Jaklič 2015; Lautenbach et al., 2017). However, it can be argued that factors of the macro-environment are indefinite, hence we cannot capture them into one theme. Salisu et al. (2021) agree to the three perspective categorisation and they illustrate each perspective more thoroughly. To them, the organisational perspective includes management support, organisational size, presence of champion, absorptive capacity, and organisation resource availability. It must be noted that Salisu et al. (2021) research's context looks at small-medium sized enterprises, thus the focus on organisational size and organisation resource availability. Furthermore, the IS perspective includes perceived compatibility, relative advantage, complexity, trialability, and observability while the users' perspective includes innovativeness, IT knowledge, and attitude toward IT (Salisu et al., 2021).

From these three perspectives, the existing body of literature has mostly focused on the organisational and the IS perspective (Ain et al., 2019). The user perspective, however, is less investigated and has more prospect for future research (Ain et al., 2019). In addition, there is limited research where organisational, IS and user perspectives are comprehensively studied.

2.4 BI components and evolution

2.4.1 Phases of BI evolution

Throughout the past two decades BI has evolved from systems with a pure focus on data warehousing and online analytical processing (OLAP) analysing structured content to systems that are capable of analysing unstructured, mobile and sensor-based content (Ain et al., 2019; Chen et al., 2012). This evolution has been characterised by Chen et al. (2012) in three phases each with different key characteristics and capabilities. The first phase is characterised by database management system (DBMS)-based structured content. The second phase is different in the type of content and the structure of the data where the content is web-based and the data is unstructured. The third phase handles mobile and sensor-based content. This evolution is a result of information demands that will continue to grow as information becomes more democratised within organisations (Ranjan, 2005).

Capabilities of BI were reported by Sallam et al. (2011) from Gartner's 2011 BI Magic Quadrant report. These capabilities were later categorised by Chen et al. (2012) into the three phases. Phase 1 includes: reporting, dashboards ad-hoc queries, search-based BI, OLAP, interactive visualisation, scorecards, predictive modelling, and data mining. The first stage of the World Wide Web (Web 1.0), which introduced the search-engine and e-commerce era and Web 2.0, characterised by consumer-generated content such as social media, requires capabilities different to phase 1 (Chen et al., 2012). Hence, phase 2 provides the ability to process and analyse the web-based unstructured data that emerged from Web 1.0 and Web 2.0 (Chen et al., 2012). Unlike phase 1, phase 2 possesses different capabilities to deal with the unstructured content, namely information extraction, topic identification, opinion mining, question answering, web mining, social network analysis, and spatial and temporal analysis (Chen et al., 2012).

With the growing number of mobile users, phase 3 has been introduced to deal with mobile and sensor-based content including location-aware analysis, person-centred analysis, context-relevant analysis and mobile visualisation, and human-computer interaction (HCI) (Chen et al., 2012).

2.4.2 Recent BI Trends

Moreover, a new trend in BI has emerged, namely 'BI service on demand' or 'Cloud BI'. Cloud BI, as opposed to traditional on-premises BI, comprises of software and hardware that are available on demand and require negligible management efforts (Olszak, 2016; Tamer et al., 2013). Being able to deliver BI as a service, this recent trend has gained special interest from enterprises wanting to improve agility and exploit the benefits of cloud computing while also aiming at reducing IT costs (Olszak, 2016).

Another trend that is being highlighted is prescriptive analytics. While data has previously been analysed in a descriptive and diagnostic manner, more recently the focus has moved to predictive and prescriptive analytics (Wang et al. 2018). Instead of historical reporting, predictive analytics provides insight on what will happen while prescriptive analytics suggests what to do with these predictions (Watson, 2014). Moving to predictive analytics will take time as organisations typically mature from descriptive and diagnostic analytics to predictive and later prescriptive analytics (Watson, 2014). Both cloud BI and prescriptive analytics are gaining focus, however, they remain relatively under-researched.

2.5 BI and decision making

As a cornerstone to enterprise decision making, BI has developed to become a topic that attracts many researchers in decision support systems (Côrte-Real et al., 2014; Audzeyeva and Hudson, 2015; Ain et al., 2019). Researchers justify the importance of BI-related research through the significant amounts of investments from organisations in BI tools

(Côrte-Real et al., 2014). The most important objective of BI investment is its capacity to provide timely and good quality information leading to improved courses of action (Ranjan, 2005). Ranjan (2005) describes BI as an organisational asset that discloses an organisation's competitive position, consumer behaviour and spending pattern changes, firm capabilities, market conditions, activity of firms in the marketplace, and macro-environmental conditions be it social, regulatory or political.

The timely and accurate information insights that BI systems provide can result in benefits in decision making. These benefits come in the form of strategic planning, business processes, increased performance, and gaining competitive advantage (Davenport et al., 2010; Popovič et al., 2014; Puklavec et al., 2017). Olszak (2016) explains that the most commonly used BI analyses are: cross-selling and up-selling support analysis, customer profiling and segmentation, parameter importance analysis, survival time analysis, customer loyalty, scoring credits, detection of fraud, optimisation of logistics, forecasting developments of strategic business processes, and web mining. Moreover, Olszak (2016) highlights findings from earlier case studies that discuss the ways in which BI is used to benefit organisations and categorises them as follows:

- Enhancing the effectiveness of planning, whether it is strategic, tactical or operational. This is done through variant modelling in the development of the organisation; providing information about the degree of realisation of the organisation's strategy, missions, goals and, tasks; ability to analyse information on trends and consequences of new changes; identifying problems and finding respective solutions; analysing the top performing and least performing products, employees, and regions; and providing information on the organisation's environment.
- Customer relationship creation and improvement. This may come in the form of providing sales agents with accurate information about customers to assist them in meeting customer needs; evaluating and tracking customers' satisfaction levels along with business practice efficiency; and market trends identification.

- Analysing and enhancing operational efficiencies and business processes by the means of delivering knowledge and experience when developing products and launching them to the market; providing knowledge related to specific business processes; knowledge exchange between research teams, and organisational departments.

Amongst the specific benefits is increasing response rates from different contact channels (i.e. email, telephone, internet), identify profitable customers, improving e-commerce strategies through analysing click-stream data, discovering money laundering and fraud detection, knowing which customers are interested in what product or service line, and when they are likely to make a purchase (Ranjan, 2005). In addition, BI has been found to contribute to corporate performance management (Richards et al., 2017). Richards et al. (2017) suggest that BI system effectiveness and measurement, planning, and processes effectiveness are strongly related.

While listing the benefits provides an understanding of why BI is important to organisations, measuring the bottom-line impact of BI is a challenge for researchers and practitioners, as is the case for many technologies (Dehning and Richardson, 2002; Elbashir et al., 2008; Kohli and Devaraj, 2003). Accounting measures such as profitability or Return on Investment (ROI) are not reflective of Decision Support Systems (DSS) since they neither reflect the organisation's strategic intention regarding the technology nor do they show immediate impact of such systems (Elbashir et al., 2008). To address the absence of a measure to know the actual business value of BI, Elbashir et al. (2008) developed a measure that reflects characteristics of BI systems and examines its impact on organisational performance. Their study reveals that business process performance significantly reflects customer intelligence, supplier relations, and internal efficiency have a positive and significant impact on organisational performance (Elbashir et al., 2008).

2.6 BI implementation

BI has become an inevitable part in organisations as it helps in watching the market trends and moves of the customers and competitors by giving the appropriate information to companies (Wanda and Stian, 2015). It intends to systematise and combine several business steps and functions, because of which the application and arrangement of BI systems are now a matter of great importance for senior information managers of organisations. BI plays a vital role on how a company functions since it is a key element of many organisations (Huang et al., 2022). BI systems are systems and procedures which turn raw data into appropriate information for managers and assist them in making suitable decisions (Al-Eisawi et al., 2021). Though BI systems belong to the category of information systems (IS), they are different from other information systems owing to their complete focus on data, data sources, and available analytical tools, intending mainly to aid the decision-making process (Loon, 2019). The BI system in an organisation is hierarchically defined, and top executives need to get summarised information, which means that the information must be formatted, summarised, and subsequently reported several times (Ahmadi et al., 2021).

In order to have an effective BI system, there are mainly steps to be considered: (a) Understanding the intelligent information that the organisation requires (Chen and Lin, 2021); (b) Obtaining and collecting data from the existing information sources (Yiu, et al., 2021); (c) Concentrating and organising data in a data warehouse (Strohmeier, 2021); (d) Arranging proper analytical tools and displaying results (Nuseir et al., 2021), and (e) Performing operations (Huang et al., 2022).

Implementation success can be viewed in three ways, namely, organisational implementation success, project implementation success, and technical implementation success. Each type of success is dependent on certain factors, some of which influence more than one type of implementation success (Wixom and Watson 2001). Organisational implementation success is influenced by management support, existence of a champion, resources, and user participation. The existence of a champion, resources, and user participation also influence project implementation success. Moreover, team skills impact project implementation success. Team skills also impact the technical implementation success. Factors that influence technical implementation success also include development technology and source systems (Wixom and Watson 2001).

2.7 BI user skills and use behaviour

Understanding BI user skills and use behaviour is critical in the post-implementation stage. While BI user skills are pre-requisite to operate the BI systems, use behaviour outlines the instruments that measure use, providing an understanding of how efficiently BI users use the system.

2.7.1 BI user skills

Utilising and achieving best results from BI systems require a certain set of user skills. Poonnawat et al. (2019) discuss the BI skills related in relation to job analysis. They argue that having mere technological and analytical skills is not sufficient for effective BI use. It is important for BI users to also have good business knowledge and communication skills. BI systems are commonly used by decision makers ,therefore, BI users should also have the ability to understand and interpret the business, and thereby carry out the required analytics and explain the results to others in the organisation. They suggest that knowledge, skills, and abilities to use technology to its best are foundational skills for BI use (Poonnawat et al., 2019).

Verma and Bhattacharyya (2017) stress on the importance of human assets related to technical skills, the need to understand the business, and problem-solving skills in order to handle analytical demands. They emphasise on knowledge, abilities, and competence of individuals to adopt and operate the system. Finally, Verma and Bhattacharyya (2017) refer to individuals requiring skills to handle data which means cleaning and organising data.

Romanow et al. (2020) point to individual skills such as the ability to manage increasing volume of data, ability to analyse different types of data, ability to handle the flow of data, and the knowledge and skills of managers to apply "descriptive, predictive, and prescriptive analytics to decision making" (Romanow et al., 2020; p. 218).

De Jager and Brown (2016) carried out a detailed literature review to summarise the typology of requisite BI skills. These are summarised as:

(1) Analytical skills that include telling a story using data, identify business improvements based on data, identify, discover and explore patterns, solving problems, and apply statistical techniques to data.

(2) Business skills that comprise of managing change with respect to BI operational and project work, controlling budgeting and forecasting for BI projects, elicit user requirements, manage expectations concerning BI delivery, understanding business processes, linking BI to corporate strategy, negotiate and influence change, prioritize business requests, and employ soft skills.

(3) IT skills that include managing data quality, design principles, establishing BI standards and best practice, extracting data, design IT Infrastructure, manage projects, employ technical skills, provide training and transfer knowledge, and learning new skills.

The information provided by De Jager and Brown (2016) therefore provides a cumulative understanding of skills required by BI users.

2.7.2 BI use behaviour

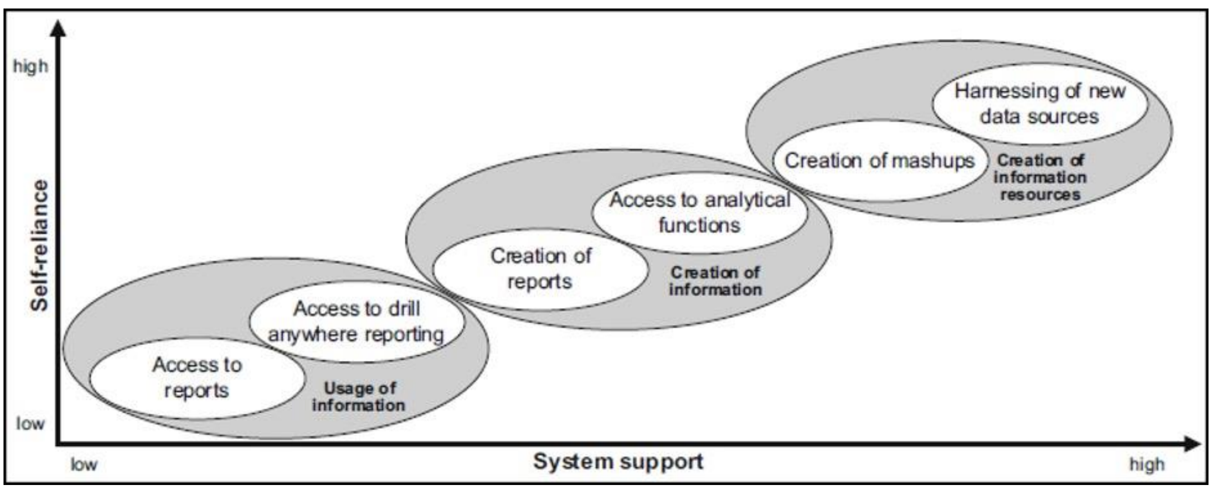
System use behaviour is often measured by the individual's frequency and duration of use (Grublješič and Jaklič, 2015; Ahmad et al., 2020a). These are generic measures that can be applied to any system. Although frequency and duration partially measure use behaviour, they cannot fully explain it, especially in the case of BI. This is because BI systems offer different tools, from basic reporting needs to advance predictive models (Sahay and Ranjan, 2008; Chen et al., 2012). Use behaviour becomes critical here because certain users utilise system tools and features more than others. Underutilisation of such tools and features may be preventive from gaining the full benefits of the system (Deng and Chi, 2012). In addition, several irrelevant features can create confusion, and thereby act as a barrier to use behaviour.

Grublješič and Jaklič (2015) studied BI system use from different perspectives. First is the intensity of use, understood as the level of cognitive absorption while using the system (Grublješič and Jaklič, 2015). Grublješič and Jaklič (2015) have used the terms intensity and frequency of use interchangeably. The second is the extent of use which looks at the degree to which an individual employs the system to carry out a task (Burton-Jones and Straub Jr., 2006; Grublješič and Jaklič, 2015). Here, emphasis is on how system use translates into decision making, which is not captured by the frequency instrument (Grublješič and Jaklič, 2015). The third is system embeddedness, which measures the degree to which the system is integral to the activities of the organisation (Furneaux and Wade, 2011; Grublješič and Jaklič, 2015). This is especially important in the post-implementation stage of BI diffusion, where BI system use becomes more routine (Grublješič and Jaklič, 2015). Bhattacherjee (2001) has highlighted the importance of embeddedness when discussing continuance of use, at this stage system use 'transcends conscious behaviour and becomes part of normal routine activity' (Bhattacherjee 2001, p. 352). Embeddedness of use, as argued by Grublješič and Jaklič (2015), focuses on how the system is used rather than how much it is used.

Furthermore, the ways in which BI is used vary among different groups of users. Alpar and Schulz (2016) discuss that grouping users based on their business functions is not required since users of one business function have different needs and variable skills. Therefore, a rough grouping scheme of power (expert) users and causal (non-expert) users may be more sensible (Alpar and Schulz, 2016). While casual users are known to be information consumers, power users become more engaged in the production of information (Alpar and Schulz, 2016). This becomes more relevant with recent BI technologies that are based on the concept of self-service where users can create their own reports and analysis (Abelló et al., 2013; Alpar and Schulz, 2016). Three types of self-service BI usage are reported by Alpar and Schulz (2016): the usage of information; the creation of information; and the creation of information resources. At the simplest level, the usage of information comes in the form of accessing pre-existing reports or only setting certain parameters before processing the prebuilt report (Alpar and Schulz, 2016).

In the second level, which is concerned with information creation, more experienced power users are able to access data at a deeper granularity and generate information from this data which can be shared to other users (Alpar and Schulz, 2016). The third level involves the creation of information sources, which allows power users to integrate new data sources that were not pre-processed within the system with the existing corporate data. This integration can be further presented in a single dashboard in what is known as a 'data-mashup' (Alpar and Schulz, 2016). While providing leverage to power users, self-service BI also enables casual users to make right decisions by making information accessible in surf and save modes where they can save, reuse, and share information (Abelló et al. 2013). Figure 2.1 depicts the levels of BI self-service.

Figure 2.1: Levels of BI self-service



Source: Alpar and Schulz (2016)

Once this understanding of use behaviour is conceived, we cannot simplify the construct to frequency-based instruments, neither can we conclude that users use BI in a unified manner. We should rather include measurements that register the three-dimensionality of BI system use (intensity, extent, and embeddedness), and that differentiate between users that use BI to consume information and the ones who are more engaged with creating information.

2.8 Determinants of system use

For a technology to be valuable, it must first be accepted and used (Venkatesh et al. 2003; Bananuka et al. 2020). This is the central reason why technology acceptance and use behaviour theories have developed and continue to be a topic of research. In the specific case of BI, system use becomes vital to organisational decision making as the major intention behind BI implementation is to reduce uncertainty through data-driven decisions (Chen et al., 2012; Grublješič and Jaklič, 2015). System use, in general, has been studied by many researchers (for example Yoon, 2008; Kohnke et al., 2011; Richards et al., 2017; Hou and Gao, 2018; Bananuka et al., 2020; Baishya and Samalia, 2020). These authors argue that positive perspective towards system use will enhance the actual use behaviour, which is in line with theories such as TPB, TAM, and UTAUT (Davis et al., 1989; Venkatesh and Davis, 2000; Venkatesh et al., 2003 and Venkatesh et al., 2012) and their extensions. The other stream of research has examined system use from the perspective of quality, be it information quality, system quality or service quality. The emphasis of system quality has been on adoption (for example, Nelson et al., 2005; Zhao et al., 2012; Grublješič et al., 2014; Bouchana and Idrissi, 2015) and use (Kositanurit et al., 2011; Grublješič and Jaklič, 2015). The two commonly used models here are the original Information Systems Success Model by DeLone and McLean (1992) and their updated version of the Information Systems Success Model (2003).

Although both technology acceptance theories and information system success theories study system use, the major difference is that technology acceptance theories are based on behavioural beliefs and attitudes, while information system success theories are based on object-based beliefs (Wixom and Todd, 2005). Object-based beliefs are the beliefs of the individual towards the system (in this case, the BI system) whereas behavioural-beliefs and attitudes are towards using the system (Grublješič and Jaklič, 2015).

Wixom and Todd (2005) have bridged the gap between the disparate theories, concluding that object-based beliefs about system and information quality influence user satisfaction, which in turn impacts the perceptions of the individual towards the usefulness and ease of use of the system. Consequently, those behavioural beliefs affect system use (Wixom and Todd, 2005). This paper applies Wixom and Todd's (2005) view of the BI context accepting the potential that certain BI object-based beliefs would provoke behavioural beliefs. The next section of the literature review will present various arguments and findings related to behavioural beliefs and object-based beliefs.

Different theories and past literature have focused on behavioural intention and use behaviour. However, the study by Grublješič and Jaklič (2015) has indicated the need to categorise the various determinants into two dimensions, namely object-based beliefs and attitudes and behavioural beliefs and attitudes. These authors have stated that BI system need should be studied on the basis of these dimensions in order for researchers to gather a wider picture about BI system use. The object-based beliefs and attitudes contain four constructs: (1) individual characteristics, (2) BIS quality characteristics, (3) organisational factors, and (4) macro environmental characteristics. The behavioural beliefs and attitudes contain five constructs: (1) performance perception, (2) result demonstrability, (3) effort perceptions, (4) social influence, and (5) facilitating conditions. These lead to BI system use which comprises of three constructs: (1) intensity to use, (2) extent of use, and (3) embeddedness of use. The categorisation of these determinants is based on various theories and studies which will be discussed in the following section, leading to the development of the conceptual framework of this research.

2.8.1 Behavioural beliefs

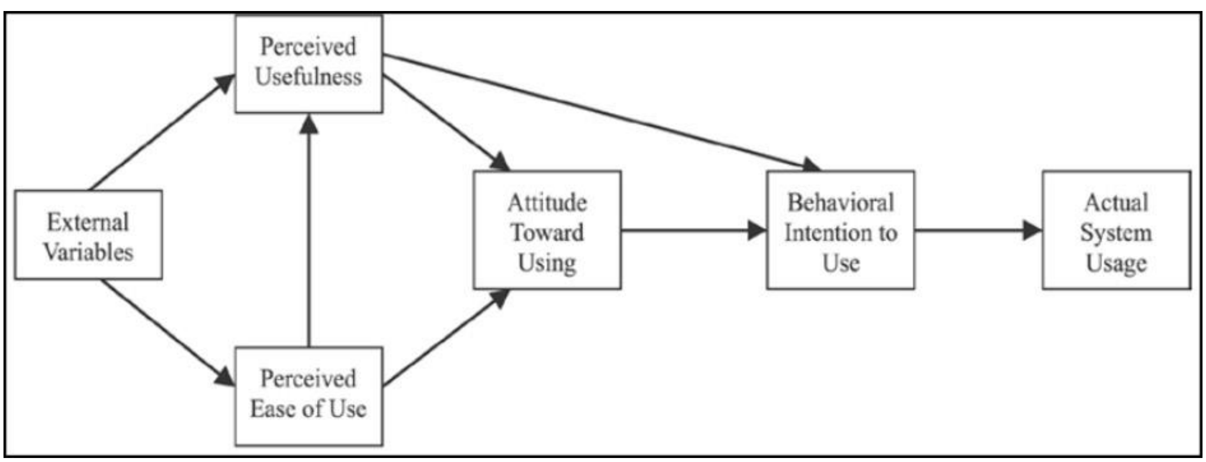
The discussion in this section pertains to the TAM, TAM2, and UTUAT models. The final section under behavioural beliefs will provide literature critique on UTAUT.

2.8.1.1 Technology Acceptance Model

The Technology Acceptance Model (TAM) constructed by Davis (1989) is one of the first models to study technology acceptance.

TAM studies the effect of the individual's perception of usefulness and ease of use to their attitude towards using a certain technology. This in turn affects the individual's behavioural intention of using the technology, which ultimately impacts its actual usage (Davis, 1989). A direct effect of a technology's perceived usefulness towards the behavioural intention to use the technology without attitude as a mediator has also been established in TAM. Figure 2.2 is a depiction of TAM.

Figure 2.2: TAM



Source: Davis (1989)

TAM is one of the most frequent and extensively used theories that study technology adoption. It was one of the initial theories and was developed from psychology theories such as the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB). Being one of the initial theories, it is criticised for lacking several factors. This led to the development of the TAM2, which is discussed in the next section.

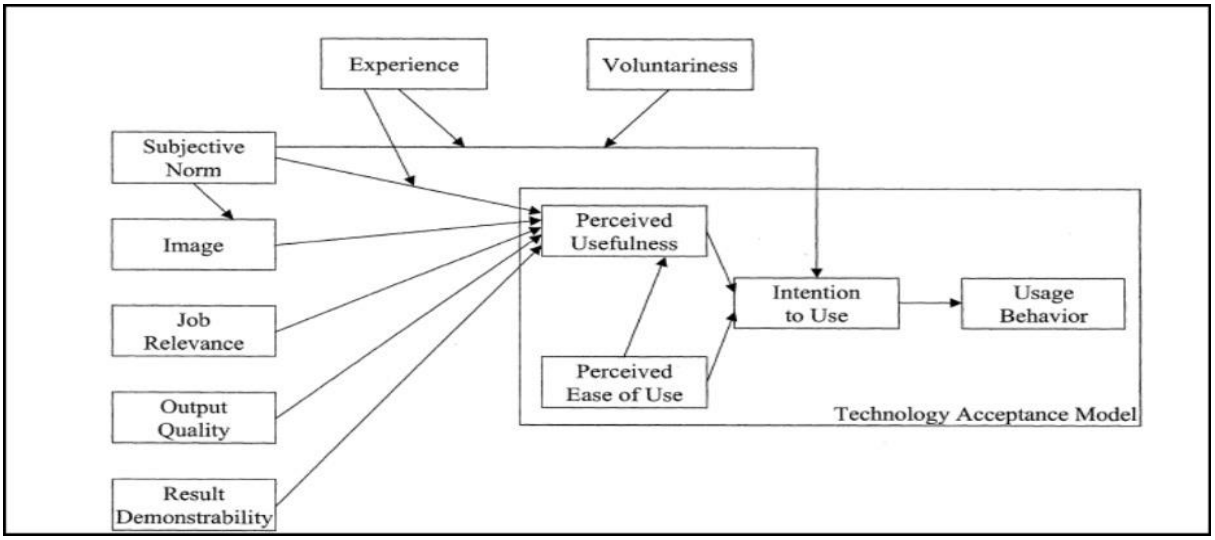
2.8.1.2 Technology Acceptance Model 2

TAM has later been criticised by many researchers. Bagozzi et al. (1992) have argued that attitudes towards using a technology and behavioural intentions may not be solid antecedents of actual usage.

The authors suggest that attitudes and intentions are fluid in construction and may form only after initial usage of a technology (Bagozzi et al., 1992). The Technology Acceptance Model Version 2 (TAM2) was developed as an extension of the original TAM (Venkatesh and Davis, 2000). The refined model has removed the mediating effect of attitudes on behavioural intention and has added social influence constructs such as voluntariness, subjective norms, and image as well as other moderating and mediating constructs which are experience, job relevance, output quality, and result demonstrability. Figure 2.3 illustrates TAM2.

TAM2 has maintained the original TAM and developed it by adding other factors such as the subjective norm, image, job relevance, output quality, and result demonstrability, with experience and voluntariness as moderators. The use of TAM2 is limited as this was also seen as inadequate in studying the intention and actual use. There are several other theories that have been developed in studying technology adoption and use.

Figure 2.3: TAM2



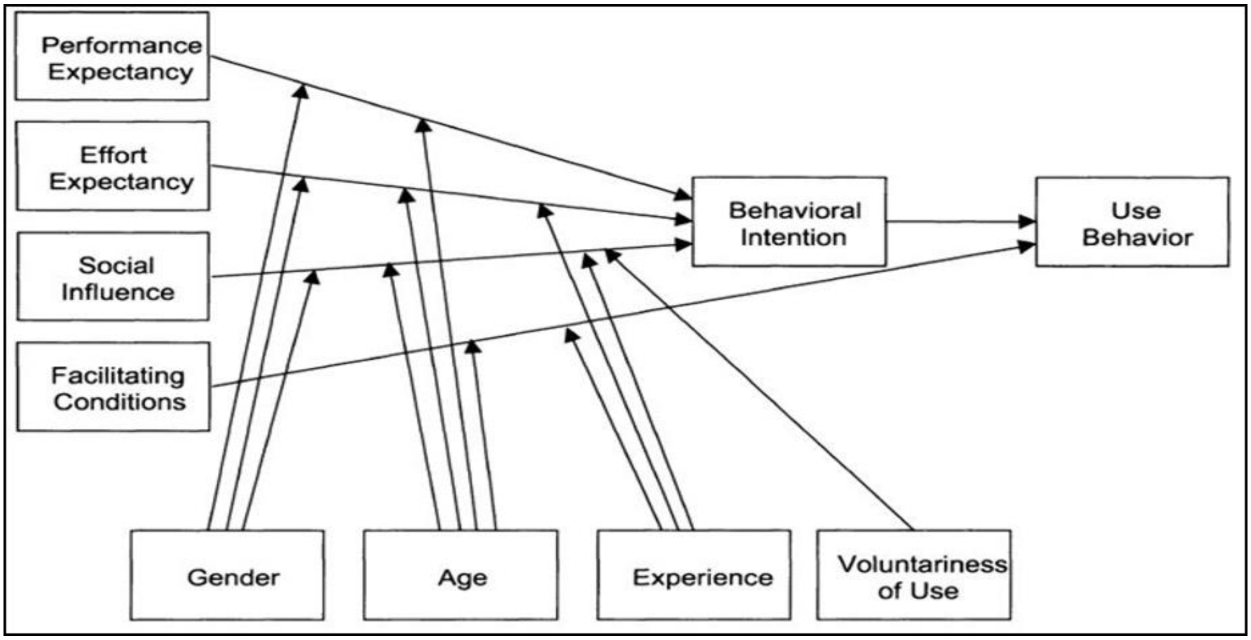
Source: Venkatesh and Davis (2000)

For example, within the context of BI systems, some of the theories that are used are: Diffusion of Innovation (DOI), TAM, TPB, Technology Organisation Environment (TOE) framework, institutional theory, and UTAUT. Among these one of the most frequent theories that has been adopted is DOI (for example Bijker and Hart, 2013; Yoon et al., 2014; Grublješič and Jaklič, 2015; Ahmad et al., 2016; Puklavec et al., 2017; Rouhani et al., 2018; Jaklič et al., 2018; Popovič et al., 2019). UTAUT is another theory that has been used extensively in the technology adoption literature and it will be discussed in the next section.

2.8.1.3 The Unified Theory of Acceptance and Use of Technology

Further reassessments and extensions to TAM and TAM2 have led to the Unified Theory of Acceptance and Use of Technology (UTAUT), which was developed by Venkatesh et al. (2003). Like TAM, UTAUT finds that performance expectancy and effort expectancy (earlier named as perceived usefulness and perceived ease of use in TAM) are variables that influence behavioural intention. However, in this model the effect is direct and attitude is not a mediator (Venkatesh et al., 2003).

Figure 2.4: UTAUT



Source: Venkatesh et al. (2003)

Furthermore, UTAUT has addressed social influence as a factor that impacts behavioural intention. Facilitating conditions, a determinate of whether an existing organisational and technical infrastructure exists to use a technology, has been added as a factor that impacts behavioural intention (Venkatesh et al., 2003). Variables moderating the impact on behavioural intention and use behaviour have also been added, two of which are demographic: age and gender. The other two are experience and voluntariness of use (Venkatesh et al., 2003). The UTAUT model is shown in figure 2.4.

Researchers that have adopted UTAUT for studying BI include Hou (2014), Grublješič and Jaklič (2015), Kester and Preko (2015), and Jaklič et al. (2018). In comparison to the DOI, the use of UTAUT is limited and this research will contribute to the literature in the limited use of UTUAT on BI. Furthermore, this research is focused on the Kuwait banking and telecom sectors, where the BI systems are already in use. Therefore, behavioural intention is not relevant as telecoms and banks have adopted BI. This also leads to the argument on the need for voluntariness of use. However, this research has maintained the moderating role of voluntariness of use to investigate employees' extent of freedom in using BI systems.

2.8.1.4 Critiques of UTAUT

This research chooses to extend the UTAUT model and therefore this section will discuss literature that critiques UTAUT and what justifies its use in information systems literature until today.

Although UTAUT is amongst the most cited models when it comes to technology acceptance and diffusion (Tarhini et al., 2016; Williams et al., 2015), it has received its own share of criticism in information systems research. Whilst Bagozzi (2007) approves of the model, he argues that having a minimum of forty one independent variables to predict intentions and a minimum of eight to predict behaviour will impede technology adoption research. He also suggests that there may be more variables involved that Venkatesh et al. (2003) do not represent in the model.

Furthermore, van Raaij and Schepers (2008) believe that UTAUT's high coefficient of determination (R^2) is due to the moderating impact of age, gender, experience, and voluntariness of use, making the model less parsimonious than the earlier TAM and TAM2. While this may be true when compared to TAM and TAM2, some authors believe that UTAUT still retains a good level of parsimony (Yuen et al., 2010; Tarhini et al., 2016).

Venkatesh et al. (2003) introduction of social influence and facilitating conditions as predicting constructs of the model has been critiqued due to the grouping and labelling of constructs (van Raaij and Schepers, 2008). Social influence groups items of: (1) subjective norm (Ajzen, 1991), perceptions that others believe that the individual should use the system; (2) social factors (Thompson et al. 1991), perceptions that others support using the technology; and (3) image (Moore and Benbasat, 1991), perceptions that system users have higher social status (van Raaij and Schepers, 2008). This grouping of different items into social influence, a single psychological measure, is where van Raaij and Schepers (2008) argue against the presentation of the construct. Similarly, facilitating conditions were found to group items of: (1) perceived behavioural control (Ajzen, 1991) technology-individual work style fit; (2) facilitating conditions (Thompson et al. 1991), availability of assistance; and (3) compatibility (Moore and Benbasat, 1991), availability of required resources (van Raaij and Schepers, 2008). Again, van Raaij and Schepers (2008) disapprove of grouping this variety of items.

The critique of Bagozzi (2007) regarding the great number of variables used in UTAUT, although not explicitly stated, is similar to van Raaij and Schepers's (2008) critique on model parsimony. Though it is lacking when compared to TAM in this perspective, UTAUT's richness in explaining behavioural intention and system use justify its parsimonious sacrifices (Samaradiwakara and Gunawardena, 2014). The items grouped within social influence and facilitating conditions were perceived as 'disparate' by van Raaij and Schepers (2008). This can be argued against since Venkatesh et al. (2003) found similarities in items within each construct. For social influence constructs, subjective norm (Ajzen, 1991), social factors (Thompson et al., 1991), and image (Moore and Benbasat, 1991) behaved similarly when tested against the same moderators (Venkatesh et al. 2003), thus indicating a notion of association. The same similarities in construct behaviour exist for facilitating conditions where perceived behavioural control (Ajzen, 1991), facilitating conditions (Thompson et al., 1991), and compatibility (Moore and Benbasat, 1991) were found to perform similarly when tested against intention (Venkatesh et al., 2003). Construct labelling was critiqued by van Raaij and Schepers (2008) with no rigor to the particular case of labelling; however, grouping and labelling arguments were discussed simultaneously and the number of constructs underlying social influence and facilitating conditions were found difficult to be presented in each single construct (van Raaij and Schepers, 2008). Venkatesh et al. (2003) suggest that labels used for every construct are independent of any theoretical perspective and that they are used as a description to the essence of each construct (Venkatesh et al., 2003). This is more of a perspective matter on how the papers in discussion view the purpose of construct labelling.

Other elements of UTAUT were also criticised. The omission of attitude whilst acceptance is in itself an attitude has been criticised (Renaud and van Biljon, 2008; Kiwanuka, 2015). However, empirical results show that the significance of attitude is only important when performance and effort expectancies are not present (Venkatesh et al., 2003). Kiwanuka (2015) suggests that UTAUT does not consider individual characteristics and cultural aspects that are crucial for technology acceptance. Certain individual characteristics including self-efficacy and personal innovativeness in IT are thought to be influential in predicting use behaviour (Chomchaloa and Naenna, 2013; Dwivedi et al., 2017). Although it is true, this research views UTAUT as an acceptance model that relates more to behavioural beliefs. Both individual characteristics and cultural aspects are object-based beliefs that provoke behavioural beliefs (Grublješič and Jaklič 2015). Since many researchers find rationale behind integrating external variables to UTAUT (Williams et al. 2015), individuals characteristics, cultural aspects, and other object-based beliefs can be integrated to address the limitations suggested by Kiwanuka (2015).

2.8.2 Object-based beliefs

This section will cover individual characteristics, system and information characteristics, and organisational factors. The final section under object-based beliefs will provide literature critique on object-based beliefs in BI system use.

2.8.2.1 Individual characteristics

The use of any system is affected by certain individual characteristics (or personal traits) that are specific to the individual (Chomchaloa and Naenna, 2013; Grublješič and Jaklič, 2015). Chomchaloa and Naenna (2013) have suggested four individual characteristics as external constructs that extend TAM, affecting perceived ease of use and perceived usefulness: self-efficacy, personal innovativeness in IT, social influence, and facilitating conditions. However, social influence and facilitating conditions are UTAUT constructs and are categorised by Grublješič and Jaklič (2015) under behavioural beliefs and attitudes rather than object-based beliefs. This paper argues against the suggestion that social influence and facilitating conditions are object-based beliefs believing that the use of TAM instead of UTAUT may have led to a displacement of the constructs in Chomchaloa and Naenna (2013).

In addition to self-efficacy and personal innovativeness in IT, a third individual characteristic must be considered and may be very important in the case of BI: readiness to change. Grublješič and Jaklič (2015) view readiness to change as one of the most important individual characteristics linked to BI system use. Employees must be ready for change as BI alters their work processes and has an impact upon their jobs (Wixom and Watson, 2010). In a study focusing on ERP implementation, Kwahk and Lee (2008) found that readiness to change affects both perceived usefulness and perceived ease of use. Consequently, this paper shall test the same correlations.

2.8.2.2 System and information characteristics

For systems to be used in the BI context, both system quality and information quality are vital (Popovič et al., 2014). System quality and information quality have both been investigated in information system literature for some time. In DeLone and McLean's (1992) Information Systems Success Model, system quality and information quality are posited as constructs that influence the success of information systems. Petter et al. (2013) define system quality as the 'desirable characteristics of an information system' while they define information quality as 'desirable characteristics of the system outputs (content, reports, dashboards)' (p. 11). The measures of system quality are accessibility, reliability, response time (speed), flexibility, and integration (Nelson et al., 2005; Popovič et al., 2014). Information quality measures are accuracy, completeness, currency, format, and relevance (Popovič et al., 2014).

Frameworks have been developed where information quality and system quality were indirect influencers of intention and use. For example, Daradkeh and Al-Dwairi (2017) studied the intention to use BI based on information quality, system quality, and analysis quality with perceived usefulness and perceived ease-of-use. The relationship of information quality and system quality on intention to use was indirect. Another research by Wixom and Todd (2005) studied the impact of information quality and system quality on usefulness and ease-of-use, which impact attitude and intention. This is a further evidence of an indirect relationship. Gaardboe et al. (2017) studied the success of BI in healthcare information systems. They examined the direct effect of information quality and system quality on use and user satisfaction. They found system quality to impact use, but did not find direct impact of information quality on use. Most studies that tested the direct impact of information quality and system quality on use are based on initial system adoption and do not focus on continued use where information quality and system quality impact on use is mostly indirect.

Although BI system quality generally follows the same measures as any other information system, BI information quality may require further investigation. To rationalise this, we must refer back to the architecture of BI systems and realise that the core BI database is the DWH which gathers its data from different sources (Wixom and Watson, 2010). Given that the BI database collects its data from different source systems, the information quality of BI systems depends on the combined information quality of the source systems. Hence, when discussing BI information quality, one must understand the underlaying effect of the information quality of source systems.

2.8.2.3 Organisational factors

Grublješič and Jaklič (2015) have emphasised the importance of organisational factors in influencing BI system use. Top management support and information culture were amongst the elements predicted to be very influential; however, the authors have not linked those object-based beliefs with specific behavioural beliefs (Grublješič and Jaklič, 2015). Top management support is the existence of senior support for information systems, along with a favourable attitude in general towards information systems (Sabherwal et al., 2006). Some researchers agree that top management support is a determinant of behavioural beliefs such as social influence and facilitating conditions, and have drawn links with UTAUT-based constructs (Sabherwal et al., 2006; Ahmad et al., 2013). This research finds these links important, as top management support may positively impact facilitating conditions and can also influence employees to use BI systems.

Information culture is a subset of organisational culture that deals with information (Curry and Moore, 2003; Popovič et al., 2014). Information culture is defined as a 'culture in which the value and utility of information in achieving operational and strategic success is recognised, where information forms the basis of organisational decision making and Information Technology is readily exploited as an enabler for effective Information Systems' (Curry and Moore, 2003: p. 94). Choo et al. (2008) adopt the following six information behaviours and values (IBVs) that characterise information culture within the organisation and were earlier suggested by Marchand et al. (2001): information integrity, information formality, information control, information sharing, information transparency, and information proactiveness. Grublješič and Jaklič (2015) have highlighted the importance of information transparency and information proactiveness in the specific case of BI. Although the path has not been tested, it may be likely that information culture would influence BI use through facilitating conditions.

2.8.2.4 Critiquing object-based belief influences on BI system use

The Information Systems Success model proposed by DeLone and McLean (1992) and their updated version (2002) mention specific object-based beliefs such as information, system, and service quality. However, this direct causal link has been criticised by researchers suggesting that object-based beliefs are limited in directly impacting use behaviour (Davis, 1993; Kang and Lee, 2010). That said, researchers found that object-based beliefs are more influential to corresponding behavioural beliefs than the use of the object itself (Davis, 1993; Kang and Lee 2010). For instance, system quality influences an individual's belief about the system's ease of use more strongly when compared to the direct influence of system quality on system use. This means that behavioural beliefs are better utilised as mediators between object-based beliefs and system use. Therefore, this paper finds that the integration of object-based and behavioural beliefs first formed by Wixom and Todd (2005) would better explain BI system use.

Wixom and Todd (2005) view user satisfaction as an object-based attitude that a user has regarding an information system. Their model highly mediates object-based beliefs and behavioural beliefs by two user satisfaction constructs: system satisfaction and information satisfaction (Wixom and Todd, 2005). In a different approach, Chomchaloa and Naenna (2013) have proposed a model that omits the mediating role of user satisfaction and proposes a direct link between object-based beliefs and behavioural beliefs. This may be due to the fact that user-satisfaction, being an attitude, becomes less significant in the presence of behavioural beliefs regarding ease of use and usefulness as argued by Venkatesh et al. (2003) and discussed earlier.

The object-behaviour belief integration proposed by Wixom and Todd (2005) and adopted by Grublješič and Jaklič (2015) leads to more construct additions, and therefore less model parsimony. Again, the dilemma between model parsimony and explanatory richness in what influences BI system use is put into question. Nevertheless, the integration is required to investigate the root drivers of BI system use through studying what influences behavioural beliefs.

2.9 Literature gap

This section discusses the gaps in the literature. It discusses the gap of an empirically tested holistic framework, the gap of developing the causal links between constructs, and other gaps in the literature. This is followed by discussing the contextual gap.

2.9.1 The lack of an empirically tested holistic framework

Conceptual frameworks drawn from qualitative studies have provided a multidimensional view on BI use. Grublješič and Jaklič (2015) have conceptualized a framework combining individual characteristics, system characteristics, organisational factors, and macro-environmental characteristics. They suggest that each of these groups contains respective object-based beliefs and attitudes that affect behavioural beliefs and in turn those behavioural beliefs and attitudes affect BI system use (Grublješič and Jaklič, 2015). Though this may be true, it has not been tested empirically.

2.9.2 The lack of causal links between constructs

While Grublješič and Jaklič (2015) have provided an aggregated understanding that different object-based beliefs impact different behavioural beliefs, they do not illustrate which object-based beliefs affect which behavioural beliefs. Therefore, it is not clear how different individual characteristics, system and information quality characteristics, and organisational factors impact behavioural beliefs. Hence, a gap in the literature opens new opportunities to draw the cause-and-effect links of each object-based belief towards its corresponding behavioural belief. This is important to understand how different dimensions, or rather object-based beliefs, affect behavioural beliefs, which ultimately impact BI system use. This research extends previous behavioural-based perspectives by incorporating object-based perspectives to develop a holistic understanding and analyse behavioural and preceding object-based beliefs that determine BI system use.

2.9.3 Other gaps in the literature

The importance of individual characteristics has been highlighted by many authors (Ain et al., 2019; Grublješič and Jaklič, 2015; Morville et al., 2015). While focusing on the importance of users to IT, Morville et al. (2015) describe users as powerful, complex, and unpredictable. However, literature has revealed that there is limited research on the individual characteristics and IT competencies of BI system users (Ain et al., 2019). This research addresses this gap since it includes and empirically tests the indirect effect of different individual characteristics pertaining IT competencies on BI system use.

System and information quality characteristics, and organisational factors have been relevant constructs when discussing system use both in general and in the context of BI (Nelson et al., 2005; Popovič et al., 2014). Behavioural beliefs comprising of performance expectancy, effort expectancy, social influence, and facilitating conditions, although studied widely in information systems literature, have gained less attention when discussing BI. While behavioural beliefs are about 'using' the systems, object-based beliefs are about 'the system' itself (Al-Natour and Benbasat, 2009; Grublješič and Jaklič, 2015), and are under-researched with regards to BI.

A database search using Scopus and querying business intelligence in the title field found 2,670 results. A similar search on Web of Science found 1,713 results. However, out of the 2,670 Scopus search results, there are 1,444 conference papers and 893 articles. For the 1,713 Web of Science search results, there are 996 proceeding paper and 574 articles. Other publications were book chapters, editorials contents, reviews, that did not necessarily contribute to the literature review. The business intelligence search (in the title field) was further combined with using UTAUT as a keyword in the title, abstract, and keywords fields. Searches on Scopus and Web of Science resulted in one document each: Yusof, et al. (2020) on Scopus and Hou and Gao (2018) on Web of Science. Both studies adopted the UTAUT framework in combination with other frameworks. The study by Hou and Gao (2018) combined UTAUT with the Task-Technology Fit (TTF). The study by Yusof et al. (2020) combined UTAUT with the Information System Continuance Model (ISCM). Both these studies, however, do not adopt a model that is specific towards BI systems use. In addition to these two citation databases, a search for business intelligence was also carried out in other prominent digital libraries: ScienceDirect, ProQuest, and Emerald. The ScienceDirect search in title field found 211 results. However, a combination of UTAUT in the search within title, abstract, and author-specified keywords did not yield any results. On ProQuest the search produced 1,611 results and a combination with UTAUT in all fields except full text provided three results. All these three were dissertations or theses. Finally, the Emerald search for business intelligence in the title field found 124 results. UTAUT was added to the search in the abstract search field; however, this yielded no results.

2.9.4 The contextual gap

There is a significant amount of research on BI system use conducted in the context of the banking industry. However, a significant yet lesser amount of research was conducted in the telecom industry (Ahmad et al., 2020a; Ain et al., 2019). Most of these studies were in Asia, followed by Europe, the USA, Africa, South America, and Australia (Ahmad et al., 2020a). Despite a focus on Asia, no research that investigates BI system use in the telecom and banking industries of Kuwait has been identified. It is important to address this contextual gap since: telecom operators and banks have large volumes of data; and 51% of Kuwaiti businesses, as discussed earlier, reported substantial increases in data volumes (CAIT 2016). Hence, the context of investigating BI system use in Kuwait's telecom and banking industries addresses a contextual gap.

Chapter 3: Conceptual framework development

3.1 Introduction

This chapter discusses the development of the conceptual framework. The two foundational models that are used in conceptualizing the framework are Grublješič and Jaklič (2015) BIEUM and UTAUT developed by Venkatesh et al. (2003). This chapter will discuss the constructs including the dependent variable, the mediators, the independent variables, and the moderators. This will be followed by presenting the developed conceptual framework and the hypotheses.

3.2 Constructs used in conceptual framework development

3.2.1 Business intelligence system use (BISU) – the dependent variable

BISU has been developed by adopting Venkatesh et al., (2003) use behaviour construct and altering it to the context of BI. Use behaviour measures an individual's frequency of using a technology (Wu et al., 2012). The earlier TAM by Davis et al. (1989) uses the term 'actual use'. Venkatesh et al. (2003) do not explicitly state why they choose to use the term use behaviour. However, from examining the instruments used in measuring use behaviour and the emphasis on frequency of use, we can clearly understand why the term 'behaviour' is vital.

BISU is essential in understanding employee use towards BI systems. In the case of this research, the subject of use is the BI system, and the user is the employee using the system. Both the subject and user have specific characteristics and generic theoretical positions may not apply. For example, if the subject system was a technology used by a consumer, then certain habits and price would be factors to study. In that case Venkatesh et al.'s (2012) UTAUT2 would be appropriate to study. However, since the user is the employee, the use of UTAUT is reasonable.

3.2.2 Performance expectancy (PE) – mediator

Venkatesh et al. (2003) have defined performance expectancy as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (p. 447). This idea combines five elements developed in earlier theories: perceived usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectations (Venkatesh et al., 2003). Many studies have found that performance expectancy is one of the most, if not the most, important constructs in technology use (Alraja, 2015; Benbasat and Barki, 2007; Venkatesh et al., 2003).

BI systems are systems used for analysis and their use is may or may not be mandatory. To attain greater user adoption rates, employees must perceive BI systems to have an impact on their individual performance (Grublješič and Jaklič, 2015). Hou (2012) has found that individual performance increases with increased usage of BI systems. However, the expectancy of an individual regarding the potential impact of BI use on their performance is a belief and does not necessarily reflect reality.

3.2.3 Effort expectancy (EE) – mediator

Effort expectancy is "the degree of ease associated with the use of the system" (Venkatesh et al., 2003: p. 450). Formulation of the factor in UTAUT is drawn from three factors in earlier research: perceived ease of use, ease of use, and complexity – the inverse of ease of use (Venkatesh et al., 2003). While testing UTAUT, effort expectancy has been found to be vital during the early stages of adoption, specifically after the user is trained to use the systems and with time significance of the construct decreases (Venkatesh et al., 2003). Ease of access and navigation have been as indicators of effort expectancy (Volery and Lord, 2000).

However, when it comes to BI systems, employees may find that effort expectancy is much more than mere accessibility and navigation. Finding business-driven information and result-oriented information is the main goal of BI systems (Bach et al., 2016). The ability to complete such a goal using BI systems may form employee beliefs regarding effort expectancy.

3.2.4 Social influence (SI) – mediator

Venkatesh et al. (2003) define social influence as "the degree to which an individual perceives that important others believe he or she should use the new system" (p. 451). Subjective norm, social factors, and image are all constituent elements of social influence (Venkatesh et al. 2003). In a business context, employees' intention to use certain information systems is impacted by their peers and managers (Khechine et al., 2016). Eckhardt et al. (2009) study the role of social influence from different and referent groups, both hierarchal groups (managers) and departmental ones. They found that managers are the greatest influencers on information system use, whilst the IT department is the weakest (Eckhardt et al., 2009). It is surprising to find that the implementers of an information system – the IT department – is the weakest group at influencing others to use the system.

For BI systems, social influence is vital to the expansion and penetration of system use (Grublješič and Jaklič, 2015). Moreover, Grublješič and Jaklič (2015) believe that after perceptions on performance, social influence comes second in increasing the adoption rates of BI systems. Social influence to use BI systems becomes an effective factor when peers and supervisors believe that the BI system is useful, as this may affect the degree to which the individual intends to use the system (Yoon et al., 2014).

3.2.5 BI system and information quality characteristics – independent variables

In this section, the system quality and information quality with regards to BI systems will be discussed.

3.2.5.1 BI system quality (SQ)

Though system quality emphasises the characteristics of the system itself, some researchers have indicated that ease of use or effort expectancy is a measure of system quality (Petter et al., 2013). However, this may be disputed given that effort expectancy is a behavioural belief, while system quality is an object-based belief. Behavioural beliefs are results of object-based beliefs (Grublješič and Jaklič, 2015; Wixom and Todd, 2005), and not the other way around. This research adopts Nelson et al. (2005) dimensions for system quality which include:

- Accessibility: 'the degree to which a system and information it contains can be accessed with relatively low effort' (p. 206).
- Reliability: 'the degree to which a system is dependable (i.e., technically available) over time' (p. 206).
- Response time: 'the degree to which a system offers quick (or timely) responses for information or action' (p. 206).
- Flexibility: 'the degree to which a system can adapt to a variety of user needs and to changing conditions' (p. 206).
- Integration: 'the degree to which a system facilitates the combination of information from various sources to support business decisions' (p. 206).

Both accessibility and reliability are categorised as system-related characteristics, while response time, flexibility, and integration are task-related characteristics (Nelson et al., 2005). Grublješič and Jaklič (2015) classify system quality as an important predictor for the intensity and extent of BI system use.

3.2.5.2 BI information quality (IQ)

Information quality concerns outputs of the system such as content, reports, and dashboards that enhance decision making and lead to positive outcomes (Petter et al., 2013). Grublješič and Jaklič (2015) find information quality to be a very important factor in the intensity of BI use and of significant importance when it comes to the extent of BI use. The information quality dimensions used in this research have been derived from Popovič et al. (2014) and Nelson et. al (2005), and are as follows:

- Accuracy: 'the degree to which information is correct, unambiguous, meaningful, believable, and consistent' (Nelson et al., 2005: p. 204).
- Completeness: 'the degree to which all possible states relevant to the user population are represented in the stored information' (Nelson et al., 2005: p. 204).
- Currency: 'the degree to which information is up-to-date, or the degree to which information precisely reflects the current state of the world that it represents' (Nelson et al., 2005: p. 204).
- Format: 'the degree to which information is represented in a manner that is understandable and interpretable to the user and thus aids in the completion of a task' (Nelson et al., 2005: p. 204).
- Relevance: 'the degree to which information is easily applicable to the problem at hand' (Popovič et al., 2014: p. 7).

Popovič et al. (2014) have considered information relevance in addition to Nelson et al.'s (2005) dimensions due to the specific importance of information relevance in the context of BI. This may be because BI systems have a variety of information integrated from different sources and the importance of finding information relevant to the current need represents a challenge to users.

3.2.6 BI individual characteristics – independent variables

In this section, self-efficacy, personal innovativeness in IT, and readiness to change will be discussed with regards to BI systems.

3.2.6.1 Self-efficacy (SE)

An individual's perception of their own self-efficacy is defined as "beliefs in one's capabilities to organise and execute the courses of action required to manage prospective situations" (Bandura, 1995: p. 2). It has been proven that self-efficacy is not a direct determinant of behavioural intention or system use; however, it has an indirect effect on intention to use mediated by effort expectancy (Venkatesh, 2000; Venkatesh et al., 2003). Chomchaloa and Naenna (2013) confirm the relationship, suggesting that with increased self-efficacy, individuals are more likely to use complex information systems. They have found self-efficacy to be the most significant construct affecting effort expectancy (Chomchaloa and Naenna, 2013).

Grublješič and Jaklič (2015) confirm that self-efficacy is an individual characteristic that is important to the intensity of BI system use. However, they suggest that the importance of self-efficacy for BI system use is lower than individual characteristics of personal innovativeness in IT and readiness to change (Grublješič and Jaklič, 2015). Nevertheless, this has not been empirically tested.

3.2.6.2 Personal innovativeness in IT (PIIT)

Personal innovativeness in IT is "a user's determination or willingness to try out new Information Technology" (Chomchaloa and Naenna, 2013: p. 885). Individuals with high levels of innovativeness are more likely to develop optimistic beliefs about a technology (Lu et al., 2005). People with high levels of innovation are prone to risk-taking and the acceptance of uncertainty (Agarwal and Prasad, 1998). Personal innovativeness in IT was conceived by Agarwal and Prasad (1998) and subsequent research has found it as a determinant of effort expectancy (Agudo-Peregrina et al., 2014; Chomchaloa and Naenna, 2013).

For BI system use, personal innovativeness in IT is particularly important for transitioning from infrequent usage to habitual usage (Grublješič and Jaklič, 2015). Its importance in the context of BI is because BI systems are research-oriented and identifying information needs with BI is less established than operational systems (Grublješič and Jaklič 2015). Therefore, personal innovativeness in IT may be very helpful in making use of the complex datasets within BI systems.

3.2.6.3 Readiness to change (RTC)

Kwakh and Lee (2008) define readiness to change as "the extent to which organisational members hold positive views about the need for organisational change, as well as their belief that changes are likely to have positive implications for them and the organisation" (p. 475). If employees are informed about the positive impact of a system, this influences their perception of usefulness. Moreover, their technological readiness impacts their effort expectancy (Kwahk and Lee, 2008).

Grublješič and Jaklič (2015) find readiness to change important to the intensity, extent, and embeddedness of BI system use and their qualitative study suggests that it may be the most important individual characteristic for BI system use. The voluntary use of BI systems may explain the importance of employee readiness to change. If employees are unwilling to use BI systems, there is usually no mandate forcing them to do so (Grublješič and Jaklič, 2015).

3.2.7 BI organisational factors – independent variables

In this section, BI organisational factors of top management support, and information culture will be discussed.

3.2.7.1 Top management support (TMS)

Top management support is characterised by motivation driven by management to use a system (Costa et al., 2016). Costa et al. (2016) have linked management support as a direct determinant of system use. However, the existence of management support is more of an object-based belief than a behavioural belief. Therefore, the relationship with the intention to use or the actual usage of a system is mediated by behavioural constructs. Top management support impacts social influence as seen in Ahmad et al. (2013). This may be due to the authority managers have on their subordinates.

Grublješič and Jaklič (2015) realised that management support is a very critical factor when it comes to deep and structural use of BI systems. They find that support from management is one of the most important organisational factors when it comes to BI system use (Grublješič and Jaklič 2015). However, the links between top management support on one hand and social influence on the other are yet to be tested in the BI context.

3.2.7.2 Information culture (IC)

Information systems literature has focused on the impact of culture on information technology and information systems (Leidner and Kayworth, 2006). However, we are more interested in one aspect of culture that deals with information. One may look at information culture through the information behaviour values (IBVs) adopted by Choo et al. (2008):

- Information integrity: 'the use of information in a trustful and principled manner at the individual and organisational level' (p. 3).
- Information formality: 'the willingness to use and trust institutionalized information over informal sources' (p. 3).
- Information control: 'the extent to which information about performance is continuously presented to people to manage and monitor their performance' (p. 3).
- Information sharing: 'the willingness to provide others with information in an appropriate and collaborative fashion' (p. 3).
- Information transparency: 'openness in reporting and presentation of information on errors and failures, thus allowing members to learn from mistakes' (p. 3).
- Information proactiveness: 'the active concern to think about how to obtain and apply new information in order to respond quickly to business changes and to promote innovation in products and services' (p. 3).

Although there is no empirical evidence that information culture impacts social influence, the link should be tested to understand whether a specific subset of organisational culture that deals with information is an influencing organisational factor. Construct instrumentalization is through using the IBVs presented by Choo et al. (2008).

3.2.8 Moderators (gender, age, experience, voluntariness of use)

Demographic variables of gender, age and experience moderate the relationships of UTAUT, in addition to voluntariness of use (VU). This research tests the moderation of gender between PE and BISU, EE and BISU, SI and BISU. It tests the moderation of age between PE and BISU, EE and BISU, SI and BISU. Experience moderates the relationship between EE and BISU and SI and BISU. VU moderates the relationship between SI and BISU. Voluntariness of use is important since it explains the degree to whether BI systems are voluntary to use or on the other hand are a mandate. BI systems in specific are analytical systems that are not necessarily mandatory to use and are different from operational systems such as customer relationship management (CRM) systems or enterprise resource planning (ERP) systems that are operational and mandatory to use.

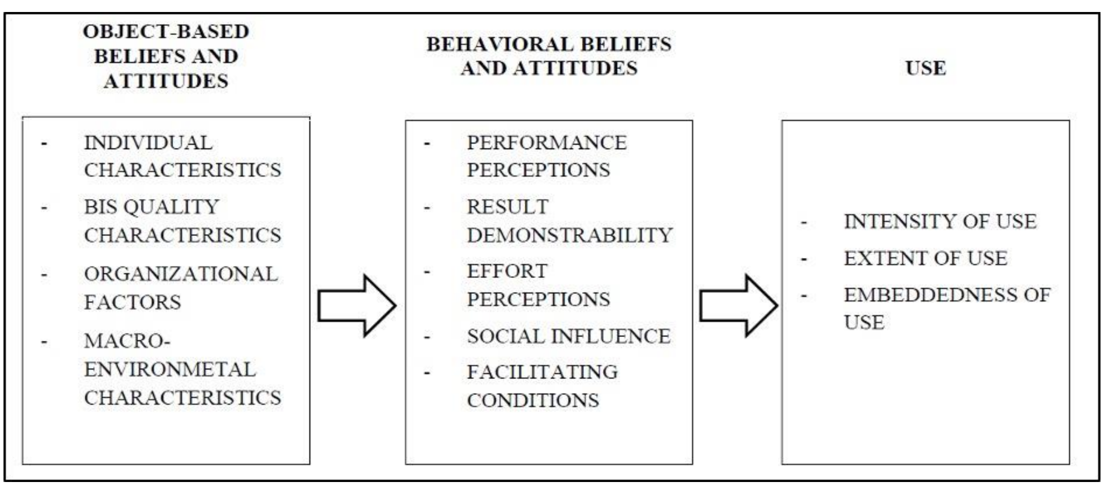
3.3 Conceptual framework

This research uses constructs from the UTAUT model as the foundation to study BI system use. The UTAUT model can be used to understand use intention and actual use. The model proposes that a higher behavioural intention will lead to actual use. However, this research has excluded behavioural intention in its examination of the telecommunications and banking industries of Kuwait as BI systems have already been implemented. Two studies related to BI system use and UTAUT have been identified through Scopus and Web of Science search results (Huo and Gao, 2018 and Yusof et al., 2020). Both these are relatively recent studies. Huo and Gao (2018) investigated the managerial use of mobile BI through semi-structured interviews with seven senior managers. A more recent study by Yusof et al. (2020) in manufacturing organisations used a survey to understand the ongoing use of BI, excluding behavioural intention.

Huo and Gao (2018) combined UTAUT with task-technology fit (TTF) whereas Yusof et al. (2020) combined UTAUT with the information system continuance model (ISCM). Similarly, this study links UTAUT constructs with external constructs from another model. In addition to the UTAUT factors, Huo and Gao (2018) used constructs such as mobile IT (functionality, adaptability, user interface, and network), managerial tasks (time criticality, interdependence, non-routineness, mobility), and individual factors (position experience, cognitive style, and computer self-efficacy). Yusof et al. (2020) have also enhanced the UTAUT model by combining it with the ISCM model that studies perceived usefulness, confirmation, and satisfaction as determinants to IS continuance intention. This is similar to this research, where the UTAUT model is integrated with the BI extended use model (BIEUM) developed by Grublješič and Jaklič (2015).

The proposed conceptual framework aims at studying BI use. The model is initially derived from Grublješič and Jaklič (2015) BI extended use model (BIEUM) depicted in figure 3.1.

Figure 3.1: BIEUM

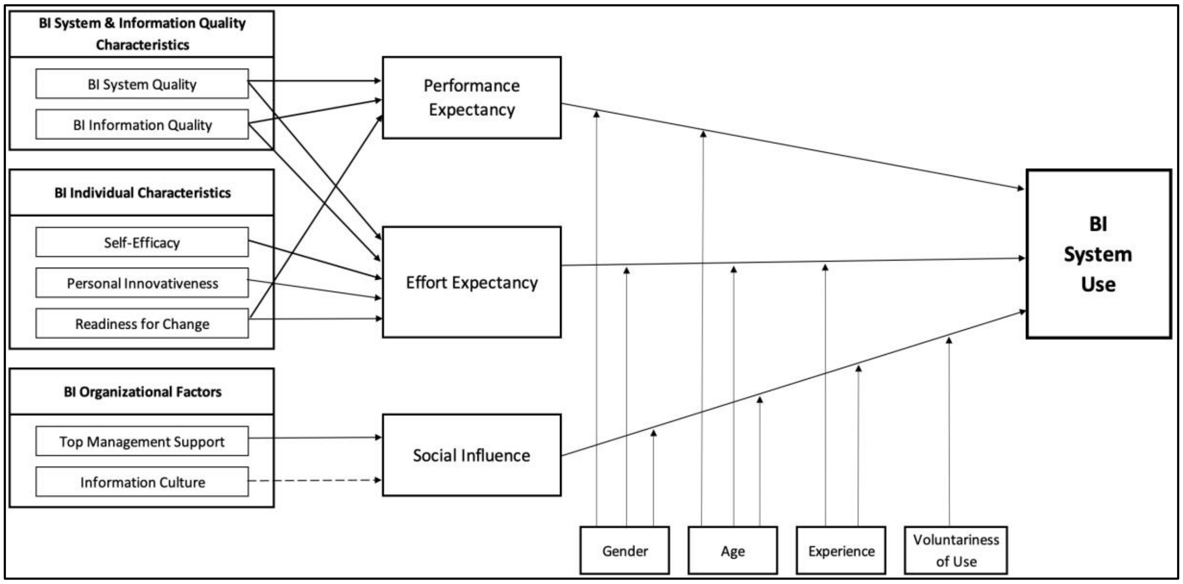


Source: Grublješič and Jaklič (2015)

This research proposes a model that links object-based beliefs with behavioural beliefs. The integration has been done with Venkatesh et al. (2003) UTAUT model. The UTAUT constructs remain unchanged except for the omission of behavioural intention and facilitating conditions. Behavioural intention has been omitted since we are studying the continued use of BI systems and since BI systems are already implemented in this research's context. Facilitating conditions has been omitted since it combines multiple psychometric constructs into one construct as discussed earlier in the literature review. Furthermore, van Raaij and Schepers (2008) agree to the narrative that facilitating conditions combines many constructs into one and perceive that those constructs are disparate in nature. Object-based beliefs comprising of individual characteristics, system and information quality characteristics, as well as organisational factors have been linked to performance expectancy, effort expectancy, and social influence.

This research has integrated UTAUT with BIEUM developed by Grublješič and Jaklič (2015), which is more specific to the context of BI systems. Grublješič and Jaklič's (2015) model is the outcome of qualitative research and therefore it has not been studied empirically. In addition, BIEUM is divided into three categories that consist of various factors (see figure 3.1).

Figure 3.2: Conceptual framework



The BIEUM model first groups individual characteristics, BIS quality, organisational factors, and macro-environmental characteristics into object-based beliefs and attitudes which impact the second group of behavioural beliefs and attitudes consisting of five factors (performance perceptions, result demonstrability, effort perceptions, social influence, and facilitating conditions). The behavioural beliefs and attitude then further impact the BI use which is made up of three factors (intensity of use, the extent of use, and embeddedness of use). The limitation of BIEUM is that it does not study the causal relationship between the variables that contribute to BI system use. Hence, the proposed conceptual framework draws the causal links between variables. The conceptual framework does not study macro-environmental characteristics due to the ambiguity of the construct and since macro-environment characteristics are indefinite. As for result demonstrability, this construct has been dropped in UTAUT since Perceived Usefulness fulfils the result of demonstrability of the system; that is, if a system is perceived to be useful then it has demonstrated its results. Figure 3.2 depicts the conceptual framework that will be tested.

3.4 Hypotheses

Following are the hypotheses of this research, each with a reference to the articles where the corresponding theoretical link is justified. Every hypothesis is accepted or rejected based on the empirical results.

First, the model examines the influence of SQ, IQ, and RTC on PE. Following are the related hypotheses:

H_1: Performance expectancy	H_{1a}: BI system quality has a significant positive impact on performance expectancy (Chomchaloa and Naenna, 2013).
	H_{1b}: BI information quality has a significant positive impact on performance expectancy (Chomchaloa and Naenna, 2013; Bach et al., 2016).
	H_{1c}: Readiness to change has a significant positive impact on performance expectancy (Kwahk and Lee, 2008).

The relationship in H_{1a} is justified by Chomchaloa and Naenna (2013). Their research extended TAM to investigate system traits and personal traits impact on perceived usefulness (performance expectancy) and perceived ease of use (effort expectancy). H_{1b} is justified by Chomchaloa and Naenna (2013) and Bach et al. (2016). Bach et al. (2016) also extended TAM, however, their research investigated BI systems in specific. H_{1c} is justified by Kwahk and Lee (2008). The authors also extended TAM to investigate the intention to use ERP systems.

Second, the model studies the influence of SQ, IQ, SE, PIIT, and RTC on EE. Following are the hypotheses for EE:

H_2: Effort expectancy	H_{2a}: BI system quality has a significant positive impact on effort expectancy (Chomchaloa and Naenna, 2013; Costa et al., 2016).

H_{2b}: BI information quality has a significant positive impact on effort expectancy (Chomchaloa and Naenna, 2013).
H_{2c}: Self-efficacy has a significant positive impact on effort expectancy (Chomchaloa and Naenna, 2013).
H_{2d}: Personal innovativeness in IT has a significant positive impact on effort expectancy (Lu et al. 2005; Chomchaloa and Naenna, 2013; Agudo-Peregrina et al., 2014).
H_{2e}: Readiness to change has a significant positive impact on effort expectancy (Kwahk and Lee, 2008).

H_{2a} is also investigated by Chomchaloa and Naenna (2013). It is further investigated by Costa et al. (2016) where the context is regarding ERP use and user satisfaction. Both justify the relationship. H_{2b} and H_{2c} are also justified by Chomchaloa and Naenna (2013). H_{2d} is justified by Lu et al. (2005) where the context is regarding the adoption of mobile technology wireless internet services. It is further justified by Agudo-Peregrina et al. (2014) where their research extended TAM to investigate the acceptance of e-learning systems. In addition, Chomchaloa and Naenna (2013) also confirm the relationship. H_{2e} is justified by Kwahk and Lee (2008) in the context of ERP systems.

Third, the model studies the influence of TMS and IC on SI. Following are the hypotheses for SI:

H_3: Social influence

H_{3a}: Top management support has a significant positive impact on social influence (Ahmad et al., 2013).
H_{3b}: Information culture has a significant positive impact on social influence (theoretical link established in this research).

H_{3a} is justified by Ahmad et al. (2013). The research extended TAM to investigate ITIL acceptance and use behaviour of IT service management systems. The relationship in H_{3b} is not found in the existing body of literature. However, Choo et al. (2008) explored the link between information culture and information use and emphasised the importance of IBV's. This research tests the impact of information culture on social influence using the IBV's adopted from Choo et al. (2008).

Fourth, the framework studies the influence of PE, EE, and SI on BISU. Following are the hypotheses for BISU:

H_4: BI system use	H_{4a}: Performance expectancy has a significant positive impact on BI system use (Venkatesh et al., 2003). H_{4b}: Effort expectancy has a significant positive impact on BI system use (Venkatesh et al., 2003). H_{4c}: Social influence has a significant positive impact on BI system use (Venkatesh et al., 2003).

H_{4a}, H_{4b}, and H_{4c} are adopted from Venkatesh et al. (2003) UTAUT. However, in UTAUT, PE, EE, and SI are investigated against intention to use and not actual usage. Grublješič and Jaklič (2015) BIEUM view these constructs as direct antecedents of use. Hence, the relationship is justified and directed towards BISU.

The model also investigates gender, age, experience, and voluntariness of use as moderators. Following are the hypotheses for the moderators.

H_5: Gender as moderator	H_{5a}: Gender affects the relationship between performance expectancy and BI system use (Venkatesh et al., 2003). H_{5b}: Gender affects the relationship between effort expectancy and BI system use (Venkatesh et al., 2003). H_{5c}: Gender affects the relationship between social influence and BI system use (Venkatesh et al., 2003).

H_6: Age as moderator	H_{6a}: Age affects the relationship between performance expectancy and BI system use (Venkatesh et al., 2003). H_{6b}: Age affects the relationship between effort expectancy and BI system use (Venkatesh et al., 2003). H_{6c}: Age affects the relationship between social influence and BI system use (Venkatesh et al., 2003).
H_7: Experience as moderator	H_{7a}: Experience affects the relationship between effort expectancy and BI system use (Venkatesh et al., 2003). H_{7b}: Experience affects the relationship between social influence and BI system use (Venkatesh et al., 2003).
H_8: Voluntariness as moderator	H_8: Voluntariness of use affects the relationship between social influence and BI system use (Venkatesh et al., 2003).

The roles of gender (H_5), age (H_6), experience (H_7), and voluntariness of use (H_8), are justified in Venkatesh et al. (2003) UTAUT, moderating relationships towards either behavioural intention or actual use.

Chapter 4: Methodology

4.1 Introduction

This chapter discusses the research methodology adopted in this research. The discussion will begin with research philosophy, discussing the positivist stance taken. This discussion then moves on to the research approach, research method, research strategy, research type, and time horizon. This is followed by a discussion on data collection, validity and reliability, the pilot survey, and the sample. The final section provides the data analysis methods that are used in this research.

4.2 Research Philosophy

Research philosophy is the foundation mindset that incubates scientific and logical methods used in selecting strategies to acquire new reliable knowledge significant to the research through gathering and analysing information (Žukauskas, Vveinhardt, and Andriukaitienė, 2019).

4.2.1 Research Paradigms

Research philosophical paradigms are categorised into ontology, epistemology, and axiology. Each of which are discussed in this section.

4.2.1.1 Ontology

Ontology refers to the nature of reality and the view of the assumptions that shape the view of the researcher towards the organisation, management, individuals, and events (Dawson, 2018). In brief, this reflects to the researcher's own view of how the nature of reality is defined, which could be either subjective, revolving around the existence of humans, or objective and independent of humans and their social interactions.

4.2.1.2 Epistemology

Epistemology is about how knowledge about the world is acquired, the assumption related to the knowledge, and how that knowledge can be communicated to others (Boadu and Sorour, 2015). It is based on how reality is viewed, and how knowledge could be defined accordingly. Epistemology can be developed in two opposing ways, deductively through testing theories based on assumption, or inductively through the observation and the development of theories based on real events.

4.2.1.3 Axiology

Axiology refers to the use of ethics and values in the research process (Ihuah and Eaton, 2013). It is applicable to both research participants and collected data. It is important for the researcher to communicate the importance of the use of the data clearly to ensure that the results are credible (Ihuah and Eaton, 2013).

4.2.2 Research philosophies

There are five research philosophies, which are, interpretivism, positivism, pragmatism, and realism. Each of which will be discussed in this section. Table 4.1 provides a summary of the viewpoints.

4.2.2.1 Interpretivism

Interpretivism focuses on interpreting and developing meaning from the perspectives people attach to their actions. The argument by interpretivists is that human beings and the social worlds cannot be viewed in the same way as physical objects. Interpretivists are therefore concerned with the meanings attached to human beings (Park et al., 2020).

4.2.2.2 Positivism

Positivism refers to producing knowledge where the researcher relies on the empirical data and facts based on which the organisation and other social entities are viewed by the researcher as physical objects and a natural phenomenon (Greener and Martelli, 2018).

4.2.2.3 Pragmatism

Pragmatism emphasises that "concepts are only relevant where they support action" (Saunders et al., 2016; p. 143). Pragmatism is based on theories, concepts, hypothesis, and findings of the research which are instruments of thought and action that are relevant to practical consequences and in specific contexts.

4.2.2.4 Realism

Realism refers to what is seen and experienced related to the observable events. Critical realist dependent strongly on philosophical consideration and structured layout. Such researchers argue that with the philosophical context, reality is most important (Clark and Ivankova, 2017).

Table 4.1: Summary of Research Viewpoints

	Interpretative	Positivism	Pragmatism	Realism
Ontology	Things are socially constructed leading to subjective reasoning which may change with multiple realities	Emphasises that researcher is external, objective and independent of that study	Researcher is external, multiple, and the view is that chosen to best answer the research questions	Researcher is objective and exists independently of human mind but interpreted out of social situation
Epistemology	Toward subjective meanings of social phenomena, looking at details and realities behind it with motivating actions	Things are observed to prove credibility to facts, focusing on causality and law generalisations thereby reducing phenomena to simplest elements	Either subjective or objective meanings can provide facts to a research question; focus on practical application to issues by merging views to help interpret data	Belief that observing an event proves credibility of facts; scarce data, facts creates imprecision and misinterpretations; focus only within context or contexts for explanations
Axiology	The research is value bound; such that the researcher is part of what is being studied, not isolated from the studied and will be subjective	The research is value free, hence independent of the data and objective in the analysis of the data	Values play a vital role to interpret results using subjective and objective reasoning	The research is value laden; hence, the researcher is biased by world views, culture, values, experiences and will affect the results/research

Source: Ihuah and Eaton (2013)

It is important for researchers to have good skills with regards to understanding participants and using the collected data to ensure credibility of the research. In addition to this, the process of collecting the data should also be justifiable. This refers to either using quantitative, qualitative, or secondary data, and the tools used in collecting the data (Saunders et al. 2016).

4.2.3 Research philosophy used in this research

This research is positivist as the role of the researcher is to measure the antecedents of business intelligence system use. Therefore, the researcher depends on empirical data to apply measurements. Thus collecting and interpreting the data in an objective manner, resulting in a positivist philosophy discussion with intentions to focus on causal links between constructs. This would start with a theory linking constructs that the researcher would then test empirically to accept or reject a hypothesis.

Aliyu et al. (2014) state that a ‘positivist investigator has an idea or notion that the universe or world conforms to permanent and unchanging laws and rules of causation and happenings; that there exist an intricacy and complexity that could be overcome by reductionism; and with the intention of asserting an importance and emphasis on impartiality, measurement, objectivity and repeatability’ (pp. 81–2). The key features of positivism are arguably its weaknesses. For example, in a positivist approach, the researcher is independent and rarely interacts with the participants during data collection. This lack of in-depth involvement by the researcher in data collection can be a limitation. However, the choice of research approach and researcher involvement depends upon the problem statement, the research objectives, and the research questions.

This research aims to demonstrate the causal relationship between variables based on a framework developed using existing literature. It employs a deductive approach where the data collected is statistically analysed to establish the causality. In other words, the generalisation is achieved through statistical probability. To achieve generalisation, the researcher is required to collect data from a significant population. The researcher relies on the empirical data and facts where the organisation and other social entities are viewed, by the researcher, as physical objects and natural phenomena.

4.3 Research approach

The research approach may be deductive, inductive, or abductive. An inductive approach is a bottom-up approach, while a deductive approach is a top-down approach. Abductive is a combination of deductive and inductive (Cramer-Petersen et al., 2018). This section discusses each approach and the approach of this research.

4.3.1 The inductive approach

The inductive approach is conducted bottom-up, relying on data to develop theories. This is because the researcher does not rely on existing theories as there may be a lack of appropriate theories that could be applied in the research context or where the phenomenon has to be explored rather than empirically experimented (Saunders et al., 2016). The researcher contributes to existing literature through developing theories via identifying themes inherited in data.

In the present instance, a deductive approach is most appropriate to develop hypotheses and therefore, the discussion in this section will be limited to deductive reasoning.

4.3.2 The deductive approach

In the deductive approach, the researcher relies on existing theories with the aim of testing theory in the research context. The literature review provides the researcher with the approaches that other studies have used and assists in identifying the various factors to be investigated. Based on the theories and literature evidence, the researcher moves to collect the empirical data (Lautenbach et al., 2017). The deductive approach draws logical consequences from the premises and assumptions with the aim of providing conclusions and recommendations. The deductive approach is based on hypotheses that are evaluated and tested, where the hypotheses are refined based on other plausible environments. Causal relationships are established between the studied variables based on a framework using existing theories (Kase et al., 2011).

4.3.3 Approach of this research

The deductive approach is applicable in this research as it primarily extends and uses UTAUT to test the use of BI systems in the telecom and banking industries. This research has also provided evidence on other theories that are related to the development of UTAUT. Furthermore, this research deduces information and derives knowledge from Grublješič and Jaklič's (2015) BIEUM by developing causal links between constructs and testing these links empirically.

The approach deduces information on reviewed BI and technology acceptance literature taking Venkatesh et al. (2003) UTAUT and Grublješič and Jaklič's (2015) BIEUM as base models. The purpose of the deductive approach is to arrive at conclusions regarding employee use behaviour towards BI and to analyse the different individual characteristics, system and information characteristics, and organisational factors impact on BI system use.

Deductive reasoning is mainly associated with a positivist research paradigm (Creswell, 2013; Mertens, 2014; Saunders et al., 2016) and therefore a quantitative research method, which is discussed in the next section. As discussed, the objective of this research is to demonstrate causality and provide generalisations based on data gathered from a number of BI users. Therefore, the research uses existing theories and studies in BI and system use to identify and measure that antecedents of BI system use.

4.4 Research methods

Research methods include quantitative methods, qualitative methods, and mixed methods. Each of which will be discussed in this section, followed by the method used in this research.

4.4.1 Quantitative methods

A quantitative method is a research method that relies on the collection of numerical data and analysis using statistical and mathematical methods to test the effect of different variables and their correlation in order to determine the validity of given assumed theories (Yilmaz, 2013).

The strengths of quantitative methods are data reliability based on statistical analyses, less time required in collecting data, and the ease of collecting data from large number of respondents. However, Choy (2014) points out that the strengths of quantitative research can also be its weakness. For example, effective quantitative research usually requires a large sample size. In some cases, acquiring data from the required sample size may not be possible as it depends on the agreement to participate by potential respondents. Another limitation that Dudwick et al. (2006) describe is the potential lack of expertise on the part of the researcher to conduct a full evaluation of quantitative data. Further, since researchers are not usually part of the data collection process, they must design a data collection tool and distribute it effectively. Quantitative methods allow researchers to obtain a broad and generalisable set of findings and present them succinctly and parsimoniously. However, since they require a deductive approach and predetermined sets of standardised responses based on theory, they fail to provide insight into the participants' individual or personal experiences. They do not let the respondents describe their feelings, thoughts, frames of reference, and experiences with their own words. Quantitative researchers should play a neutral role in the research process. Therefore, the meaning participants ascribe to the phenomenon studied is largely ignored in quantitative studies (Patton, 2002).

4.4.2 Qualitative methods

A qualitative method is a research method that relies on the researcher's observation, collection of information through self interaction with sources, and the interpretation of experiences, views, and phenomena to provide answers to the questions that have been raised to validate given assumed theories (Harwell, 2011).

Qualitative methods strengths are in exploring, getting an in-depth understanding of the phenomena, behaviours, assumptions, and beliefs (Greener and Martelli, 2018). The weaknesses are that these findings are independent, could not be verified objectively, and require extensive skills from the researcher in collecting data. The data collection process can consume time, therefore limiting the researcher in the process. There is also emphasis on the participation and involvement of the researcher in the data collection process.

4.4.3 Mixed methods

Mixed methods are used when a combination of quantitative and qualitative research is necessary to answer complicated research questions, and when an independent research method would lead to difficulty in analyzing gathered information. In such case, the researcher may require to obtain a deep understanding of the elaboration of certain information in addition to assess the patterns of gathered numerical data (McCusker and Gunaydin, 2015).

4.4.4 Method used in the research

The method of choice for this research is quantitative. Empirical data is collected from participants whom are users of BI systems in Kuwait's telecom and banking industries. This method is chosen in order to test the conceptual framework and to accept or reject hypotheses on the bases of numerical data.

4.5 Research type

Research types include exploratory, descriptive and explanatory research (Ihuah and Eaton, 2013). This section discusses each and further discusses the research type used in this research.

4.5.1 Exploratory research

Exploratory research is where the researcher is driven towards understanding the research problem. Exploratory research is particularly useful when studying a relatively new topic and when there is limited literature and academic studies in this area (Ihuah and Eaton, 2013). The nature of exploratory research therefore is associated with an inductive approach and qualitative methods (Saunders et al., 2016).

4.5.2 Descriptive research

Descriptive research portrays events and situations (Saunders et al., 2016). The emphasis here is on illustrating the data in a descriptive manner as with descriptive statistics. In addition, descriptive research can be associated with both deductive approach and quantitative methods as well as an inductive approach and qualitative methods. It is also widely used in mixed methods.

4.5.3 Explanatory research

Explanatory research examines why the data behaves as it does and attempts to identify the key variables affecting data values (Ihuah and Eaton, 2013). Explanatory research is associated with a deductive approach and quantitative methods as this research type uses statistical analyses to explain relationships between variables (Greener, 2008). This establishes a causal relationship between independent variables and a dependent variable. The results will explain how the dependent variable is influenced by independent variables.

4.5.4 Research type used in this research

This research is mainly explanatory as it attempts to explain the relationships between factors influencing business intelligence system use. It explains how system and information quality characteristics, individual characteristics, and organisational factors influence behavioural beliefs, which in turn impact business intelligence system use. In a marginal manner, it is descriptive since it describes the results of respondents ahead of explaining them. For instance, the demographic factors such as gender, age, work, job role, business unit, and years of experience describe the research sample.

4.6 Research strategy

Saunders et al. (2009) provide different research strategies for collecting data, such as, "experiment, survey, case study, action research, grounded theory, ethnography, and archival research" (p. 141). Experiments and surveys fall under the positivist and objectivist philosophies. On the other hand, case studies, action research, grounded theory, and archival research fall under the interpretivist and constructivist philosophies (Yin, 2009). This research is based on positivist philosophy; therefore, the strategy choices are experiments and surveys.

According to Saunders et al. (2009), experiment research is strong in psychology based social science research. Saunders et al. (2009) suggest that experiments fall under the "exploratory and explanatory research to answer 'how' and 'why' questions" (p. 142). Nonetheless, researchers conduct experiments in controlled environments and not in the field. The purpose of this research is to collect data from BI users working in the telecom and banking industries. These employees are required to be present in the workplace regularly which makes conducting an experiment in a controlled environment difficult.

Alternatively, a survey allows the researcher to collect the data from participants with minimal interaction.. Surveys are more popular in quantitative research and allow a large amount of data to be collected using consistent and relatively inexpensive methods (Dawson, 2018). Therefore, this research has used a survey as a mean to collect primary data. Researchers using surveys ask questions in a written format which is then either mailed, handed over personally, or electronically delivered (Neuman, 2007). In this research, surveys were self-administered and delivered in hard copies to ensure that participants are actually BI system users.

The choice of research strategy depends on the data collection and is related to the research approach and what is required to answer the research questions. This research has used a survey based on the positivist and deductive approach that is aimed investigating causality of constructs. A survey does not require the researcher to be heavily involved with the data collection. Furthermore, choosing a survey allows for the efficient collection of data from most of the BI users in the telecom and banking industries in Kuwait.

4.7 Time horizon

Time horizons are classified into cross-sectional and longitudinal. This section discusses both and further discusses the time horizon adopted in this research.

4.7.1 Longitudinal time horizon

Longitudinal time horizons have been used in different information system studies. Li et al. (2013) studied the post-acceptance phase of IS use behaviours. They state that researchers employ a "longitudinal research design to examine the process through which and the reasons why employees choose to routinise a certain type of innovative IS use but not to incorporate others as part of their normal work" (Li et al., 2013: p. 31). One of the studies that are used to develop the conceptual framework is by Grublješič and Jaklič (2015), which is a qualitative cross-sectional study. They recommend the use of a longitudinal study to establish the causal relationship of the variables and how the relationships unfold over time. This requires repeated data collection and a long-term involvement of participants. The limitation of longitudinal studies is that they require a long period of time to complete as data from several time periods must be compared. An additional limitation is the risk associated with participants' long-term involvement as they may voluntarily or involuntarily end their participation.

4.7.2 Cross-sectional time horizon

A cross-sectional time-horizon involves collecting different samples at a single point in time. Greener (2008) states that cross-sectional data cannot be applied for time series. It may rather examine causal inferences of variables at a given point in time. In addition to this, the cross-sectional studies would require observing different samples. Ihuah and Eaton (2013) indicate that cross-sectional data can be used in both qualitative and quantitative methods but recommend the use of statistical software such as NVivo (for qualitative data analysis) and SPSS (for quantitative data analysis).

4.7.3 Time horizon used in this research

This research uses a cross-sectional time horizon. The use of a cross-sectional time horizon allows for data collection from BI users at a single point of time. Furthermore, data is collected from two industries, banking and telecom. This choice has been made to avoid long-term involvement risks and to ensure that the research can be conducted efficiently.

4.8 Data Collection

The data collection of this research is acquired through self-administered questionnaires. Questionnaires require the researcher to use pre-constructed standardised instruments or pre-determined response categories into which the participants' perspectives and experiences are expected to fit. They commonly demand randomly selected, large representative samples from which the researcher generalises findings. The major advantage of using a questionnaire is that it allows one to measure the responses of several participants to a limited set of questions, thereby facilitating comparison and statistical aggregation of data (Yilmaz, 2013).

In a questionnaire, an individual is asked to respond to a series of questions, often in a predetermined order (Ragab and Arisha, 2018). Questionnaires are typically used to collect primary data from large samples over short periods of time (Dawson, 2018). They are also useful in collecting data from samples that are geographically dispersed. Data collected through a questionnaire can be statistically analysed to study from different perspectives (De Vaus, 2002; Bailey, 2008). Authors such as Evans and Mathur (2005) also observe convenience as another benefit. That means that respondents can answer questionnaires at their own convenience. Questionnaires can fulfill two research types, namely, descriptive and explanatory research (Gill and Johnson, 2010).

There are two types of questions in a questionnaire - open-ended and closed-ended. Open-ended questions do not provide a choice to the respondents and therefore, require respondents to provide their own responses. Close-ended questions on the other hand are designed providing choices that respondents select from. Open-ended questionnaires provide respondents with the ability of providing their own answers, but according to Albudaiwi and Allen (2018), the answers can lead to unpredictable directions. The issues are in providing incorrect answers that do not meet the research subject. The time required to answer open-ended questions can also be longer. Close-ended questions on the other hand, can be easily be answered and take little time to complete, making a questionnaire most efficient. The questions in this research’s questionnaire are close-ended.

Questionnaires do not require the researcher to interact with participants and can be administered through hard copy – delivered in person or by post – or electronically, using simple means like email or through an online survey platform (Saunders et al. 2016). This research uses self-administered, hard copy questionnaires that were delivered in person to employees in Kuwait's telecom and banking industries. The choice of distributing paper-based questionnaires instead of electronic versions was to ensure that the correct sample (BI users) are the only ones that take part in the research. To ensure this, the researcher visited each company and worked with the BI department to distribute the questionnaire to the BI users. In doing so, this research ensured that the distribution was to the intended sample.

It can thus be understood that the objective of descriptive research in relation to the questionnaire is to provide expressive information about respondents and their views. On the other hand, the purpose of explanatory research is to use the data collected via the questionnaire to study the relationship between variables through various analytical processes. It is in relation to this that Ghauri and Grønhaug (2005) state that the questionnaire should identify the variables that are studied and the questions should reflect what is being studied, based on which the data should be collected.

This requires the researcher to have a good understanding of the questionnaire design. Saunders et al. (2016) indicate this requirement of the researcher and recommend the use of literature sources to design the questionnaire. The questionnaire should be able to capture respondent opinions (their perspective), actions (behavioural aspects), and attributes (respondent characteristics). Another recommendation provided by Saunders et al. (2016) is for quantitative studies to have close-ended questions and restrict or limit the use of open-ended questions as followed by this research.

Demographic questions are designed using multiple options and variable items are designed using a five-point Likert scale (see Appendix 1) because Likert scales are universal when it comes to collecting data. As the questionnaire is self-administered, the researcher must ensure that the questionnaire is understandable and applicable to the study.

4.8.1 Pilot survey

Validity and reliability are key measures recommended in the use of questionnaires in quantitative studies. However, it is also recommended that the questionnaire be tested before distributing it to the target sample (De Vaus, 2002; Saunders et al., 2016).

A pilot survey is the use of the questionnaire with a small sample of respondents. The chosen sample should have similar characteristics of the intended target sample. Pilot testing is part of the validity and reliability steps, where Saunders et al. (2016) state that "the purpose of the pilot test is to refine the questionnaire so that respondents will have no problems in answering the questions and there will be no problems in recording the data" (Saunders et al., 2016: p. 473). The feedback received from the selected pilot samples can also provide the researcher with information required in assessing the questionnaire. The pilot sample should also provide feedback on the understandability of the questionnaire and the ease of answering it. The pilot survey is therefore the preliminary step that the researcher takes in ensuring the validity and reliability of the questionnaire (Saunders et al., 2016).

Bell and Waters (2014) indicate some of the measures that the researcher should aim to observe in the pilot survey. These are the length of the questionnaire, time taken in completing the questionnaire, clarity, any part of the questionnaire that is difficult to understand, any part of the questionnaire that is difficult to answer, any major omissions, attractiveness of the layout, and any other comments to improve the questionnaire. The pilot survey feedback is provided in table 4.2.

Table 4.2: Pilot Survey Feedback

Sample		**Responses**
Pilot Survey Sample	11	From telecom operators
No changes	3	These participants indicated satisfaction with the questionnaire
Recommendations	8	These participants indicated satisfaction and recommended additions or changes to the questionnaire

Following are significant pilot survey recommendations. One respondent recommended the addition of two more demographic questions regarding the role of the respondent (staff, vendor, and contractor) and job role (team member, supervisor, manager, and other). The need for job role was also pointed out by two other pilot survey respondents. The recommendations were added in the questionnaire alongside the existing demographic questions: gender, age, business unit, and years of experience. One of the participants happens to be an academic professor, and suggested that to comprehensively study a construct, there is a need for every variable having a minimum of three items: preferably around four to six items. Based on this, the number of items per variable was ensured to be three or more.

4.8.2 Sampling and sample

Sampling refers to studying small groups, also referred to as cases or target population. These samples represent larger populations. Sampling is important as it is often not feasible for the researcher to survey an entire population (Neuman, 2007). Therefore, researchers must select samples that are representative of the entire population. Sampling also allows the researcher to complete research within the time and budget limits. By focusing on the selected sample, the researcher can repurpose the time to design an effective questionnaire in order to collect rich data and carry out detailed analyses (Saunders et al., 2016).

The sampling design process is structured into five steps (Malhotra et al., 2004):

1. Defining the population,
2. Determining the sampling frame,
3. Selecting the appropriate sampling technique,
4. Determine the sample size; and finally,
5. Executing the sampling process.

The sample population consists therefore of individuals that hold information that the researcher requires to answer the research questions. Saunders et al. (2016) categorise sampling into probability and non-probability sampling techniques. Probability sampling is part of the quantitative survey method and is categorised into simple, random, systematic random, stratified random, and cluster random.

This research collects data only from BI users in the telecom and banking industries in Kuwait. The questionnaire was distributed to all BI users in both the telecom and banking companies selected based on their availability at a given time of the data collection. The hardcopy questionnaires were distributed to all the users. The completed questionnaires were then collected after few days. Multiple visits were made to remind the BI users to provide their time and knowledge by answering the questionnaire and to collect completed surveys. Table 4.3 provides the details of the responses.

Table 4.3: Questionnaire distribution

Questionnaire distribution	Total	Response rate	Respondents by industry
Total distributed	400		
Responses received (total)	211	52.75%	
Responses received (telecom)	124		58.77%
Responses received (banking)	87		41.23%

Distribution targeted BI system users within the telecom and banking industries in Kuwait which were estimated at 400. The sample targeting the whole population is acceptable for a 95% confidence rate and a 5% margin of error. The recommended sample size of a minimum of 197 was surpassed by having 211 respondents.

4.9 Data analysis

The data analysis software used is the SmartPLS 3 and SPSS version 23. There are different steps that have been carried out to ensure validity and reliability.

SmartPLS and SPSS are used to study quantitative data. Owusu (2017) also used SmartPLS and SPSS in their study of BI systems in the banking sector. SmartPLS was used for inferential statistics and SPSS was used for studying respondent profiles. Another analogue may be observed in another study by Al-Eisawi et al. (2021) on BI system efficiency and organisational efficiency. These authors first used SPSS to enter the data and then uploaded it to SmartPLS. This research also first entered the data in SPSS and then converted the data to CSV format which is required to be uploaded to SmartPLS. Further, these authors used SmartPLS for testing the validity, reliability, and testing the relationships and hypotheses. This is similar to the present research. Jaklic et al. (2009) studied the impact of BI system on information quality improvement, where the quantitative data was analysed using both SmartPLS and SPSS. According to Jaklic et al. (2009) SmartPLS is effective for studying small and large sample sizes. In addition to that, PLS is argued to be effective in studying complex relationships as with the conceptual model of this research.

Prior to entering the data into SmartPLS and SPSS, the questionnaires were examined to ensure that the data entry is complete. This examination revealed that some items were without responses. Eekhout et al. (2014) recommend two methods in handling missing data. One method pertains to <50% missing entries for a single construct and the other pertains to handling missing data when >50% data is missing in s single construct. Missing data was found in demographic items and also in five-point Likert scale items.

4.9.1 Missing Data

The responses received from the 211 participants had a few missing data related to certain variables. This section outlines the process taken in handling the missing data.

Method 1: In cases where, for a single participant, a construct had <50% missing entries amongst its respective questions, the mean of the answered items for this single participant substitutes the missing item, which is referred to as person mean substitution (Eekhout et al., 2014). This is then rounded to the nearest scale value.

Method 2: In cases where, for a single participant, a construct had >=50% missing entries amongst its respective questions, the mean of responses of all participants for each missing item is calculated and replaces the missing values of the items, this is referred to as item mean substitution (Eekhout et al., 2014). This is then rounded to the nearest scale value. This method is always used for demographic information. Details on how missing data has been handled is shown in the descriptive analysis.

Table 4.4 (for demographics) and table 4.5 (for studied variables) provide an overview of the missing data.

Table 4.4: Missing data for demographics

Demographics	Missing data	Method used
Gender	6	2
Age	3	2
Years of Experience	5	2
Working as	5	
Job Role	17	
Business Unit	16	

The missing data is handled only for gender, age, and years of experience. The other demographics (working as, job role, and business unit) are not part of the model; consequently, the missing data does not impact studying the model. Therefore, not any of the methods are used to replace these missing data.

Table 4.5: Missing data for studied variables

Variables	Items	Number of missing data	Variables	Items	Number of missing data
Service quality (6 items)	SQ1	2	Information quality (5 items)	IQ1	2
	SQ2	1		IQ2	2
	SQ3	1		IQ3	2
	SQ4	1		IQ4	2
	SQ5	1		IQ5	3
	SQ6	4			
Self-Efficacy (4 items)	SE1	2	Personal innovativeness in IT (4 items)	PIIT1	2
	SE2	2		PIIT2	2
	SE3	2		PIIT3	2
	SE4	2		PIIT4	3
Readiness to change (4 items)	RTC1	1	Top management support (3 items)	TMS1	2
	RTC2	1		TMS2	2
	RTC3	0		TMS3	3
	RTC4	2			
Information culture (6 items)	IC1	2	Performance expectancy (4 items)	PE1	2
	IC2	4		PE2	1
	IC3	1		PE3	1
	IC4	2		PE4	1
	IC5	1			
	IC6	2			
Effort expectancy	EE1	1	Social influence (4 items)	SI1	2
	EE2	2		SI2	2
	EE3	2		SI3	2
	EE4	2		SI4	2

BI system use	BISU1	1	Voluntariness of use	VU1	0
	BISU2	1		VU2	0
	BISU3	1		VU3	1
	BISU4	1			

Details on how the missing data is handled are provided in chapter 4. Following are the different types of data analysis that are carried out in this research based on the completed survey received from telecom and banking BI system users.

4.9.2 Validity and reliability

The validity and reliability of the data collected from questionnaires are vital. In this quantitative research, the task is to establish a 'representation' of what BI users think about the use of the BI system. Therefore, Barnham (2015) adds that it is essential to establish behavioural and mental facts. When data is intended as a reflection of a reality, then it is important to know whether the representation is a true one. This leads us into issues of validity and reliability (Barnham, 2015).

Assessing the validity of the data collected from the questionnaire pertains to examining what it is measuring and its appropriateness to what is being studied. The researcher must ensure that the validity of the questionnaire is verified by experts on the research topic. They should also be able to understand and evaluate the questionnaire in relation to the research topic (Saunders et al., 2016).

Reliability means consistency or the degree to which a research instrument measures a given variable consistently every time it is used under the same condition with the same subjects. It is important to note that reliability applies to data not to measurement instruments (Barnham, 2015). Reliability refers to the repeatability of the questionnaire; that is, it should be designed so that it could produce consistent findings in the context that it is applied and studied (Saunders et al., 2016). Reliability of the data collected is verified statistically using the Cronbach's Alpha and Composite Reliability using the SmartPLS software.

4.9.3 Statistical analyses

SmartPLS The data is first studied for validity and reliability using the convergent and discriminant validity tests:

- **Outer loadings** studies the validity of each item with a cut-off value of 0.70 (Hair et al., 2017). Items that have outer loading below this cut-off are excluded from the respective variable.
- **Average variance extracted (AVE)** studies the validity of each variable where the cut-off value is maintained at 0.50 (Hair et al., 2017).
- **Cronbach's Alpha and composite reliability** study the internal consistency (reliability) of the variable which is maintained with a cut-off value of 0.70 (Hair et al., 2017).
- **Cross-loading** studies the validity of the item in the latent variable in relation to items in the other variables.
- **Fornell-Larcker criterion** studies the square-root of AVE and compares the value with other variables.
- **Heterotrait-monotrait ratio (HTMT)** studies the 'ratio of the between-trait correlations to the within-trait correlations' (Hair et al., 2017: p. 140).
- **Common Method Bias** is also used to study whether there are bias related issues and to study if there are any multicollinearity issues.
- **Structured equation modelling (SEM)** provides the direct and indirect effects of variables that answer the hypotheses.

SPSS

- **Descriptive statistic**s study the demographics and summarise the responses received from 211 respondents to understand their viewpoints.

Chapter 5: Data analysis and findings

5.1 Introduction

This chapter analyses the empirical data that was collected from BI users in Kuwait's telecom and banking industries. A total of 211 responses were collected and analysed using SmartPLS and SPSS. This chapter begins with analysing the demographics. It then moves to assessing the convergent validity, discriminant validity and conducting a common method bias test. It further discusses the descriptive analysis, the structured equation modelling and ends with accepting or rejecting hypotheses based on analyses and findings.

5.2 Demographics

There are six demographics that are collected through the questionnaire. These are gender, age group, working as (employee, vendor, contractor), job role, business unit, and years of experience.

Table 5.1: Demographics – gender and age group

Gender	Freq.	%
Male	**167**	**79%**
Female	44	21%

Age Group	Freq.	%
20–29 years old	43	20%
30–39 years old	**111**	**53%**
40–49 years old	49	23%
50 and above	8	4%

Since gender and age are part of the framework, the missing data was calculated using Method 2 and the values are entered in the respective records. Six respondents did not provide gender information. For gender, the value calculated through Method 2 is male. And for age, three records were missing for which the value calculated through Method 2 is 30–39 years old.

Table 5.1 provides the results for gender and age group. There is higher participation from male respondents (79%) and from age group between 30–39 years (53%).

Table 5.2: Number of employed people in Kuwait from 2012 to 2015, by gender

Year	Male		Female		Total
	N	%	N	%	N
2012	1,615,182	71%	649,918	29%	2,265,100
2013	1,645,666	72%	639,042	28%	2,284,708
2014	1,718,545	72%	661,649	28%	2,380,194
2015	1,765,386	73%	656,673	27%	2,422,059

Source: statistia.com (2020)

There is a significant difference between male and female participants, and this corresponds to the employee profile in the telecom and banking sectors in Kuwait. The statista.com (2020) website provides a distribution of the male and female working population in Kuwait. The information is not by business sector but provides understanding into the distribution of working population by gender. Data available is between 2012 and 2015 (see table 5.2). There is a large difference between male and female work populations. This is similar to the gender distribution in table 5.1.

Table 5.3: Demographics: Working as and job role

Working as	Freq.	%
Employee	**176**	**83%**
Vendor	9	4%
Contractor	21	10%
Missing	*5*	*2%*

Job Role	Freq.	%
Team Member	**96**	**45%**
Supervisor/ Team Lead	33	16%
Manager	60	28%
Director	5	2%
Missing	*17*	*8%*

Table 5.3 provides the results for working as and job role. There is a higher participation from employees (83%) and team members (45%). Five (2%) participants did not provide information for their employment status and there are 17 (8%) missing records for job role. The responses show that most participants are team members, with less participants higher up the organisational structure. Moreover, most responses were from employees when compared to vendors and contractors.

Table 5.4: Demographics: Business Unit and Years of Experience

Business Unit	**Freq.**	**%**
IT	47	22.3%
Marketing	35	16.6%
Finance	**65**	**30.8%**
Network	1	0.5%
Sales	20	9.5%
Customer Care	9	4.3%
Human Resources	1	0.5%
Other	17	8.1%
Missing	*16*	*7.6%*

Years of Experience	**Freq.**	**%**
Less than 1 year	6	2.8%
1–5 years	35	16.6%
6–10 years	**62**	**29.4%**
11–15 years	52	24.6%
16–20 years	35	16.6%
Above 20 years	16	7.6%
Missing	*5*	*2.4%*

Table 5.4 provides the results for business unit and years of experience. The findings indicate a higher response rate from participants working in Finance (30.8%) and Marketing (16.6%). This is common within the telecom and banking industries where the number of BI users is typically higher in finance and marketing departments. The 8.1% who responded with 'other' are likely to be within an organisation that has a centralised Management Information Systems (MIS) department that dealt with BI requirements. Furthermore, most of the respondents were mid-career, with 29.4% having 6–10 years of experience and 24.6% having 11–15 years of experience. Business unit has 16 missing records and years of experience has 5 missing records.

Experience is part of the model and had 5 missing entry records. The Method 2 was used to calculate the average and based on the calculation, value 4 was entered for missing records.

5.3 Convergent validity

In this section, the outer loadings, average variance extracted (AVE), and internal consistency tests are used to study the convergent validity.

5.3.1 Outer loadings

Outer loadings study the validity of the items. This is similar to the confirmatory factor analysis (CFA) that is carried out using SPSS. Hair et al. (2017) advise a cut-off value of 0.70 for item validity.

Table 5.5: Outer loadings

BI SQ and IQ characteristics	Outer loading 1	Outer loading 2
SQ1	0.822	0.821
SQ2	0.843	0.844
SQ3	0.827	0.827
SQ4	0.862	0.864
SQ5	0.841	0.841
SQ6	0.801	0.799
IQ1	0.785	0.783
IQ2	0.844	0.843
IQ3	0.777	0.776
IQ4	0.794	0.797
IQ5	0.870	0.869
BI individual characteristics	**Outer loading 1**	**Outer loading 2**
SE1	0.796	0.796
SE2	0.822	0.822
SE3	0.783	0.783

SE4	0.809	0.809
PIIT1	0.882	0.882
PIIT2	0.773	0.773
PIIT3	0.902	0.902
PIIT4	0.851	0.851
RTC1	0.860	0.861
RTC2	0.824	0.820
RTC3	0.755	0.754
RTC4	0.836	0.839

BI organisational factors	**Outer Loading 1**	**Outer Loading 2**
TMS1	0.918	0.918
TMS2	0.939	0.939
TMS3	0.895	0.895
IC1	0.701	0.720
IC2	0.777	0.783
IC3	0.789	0.818
IC4	0.783	0.811
IC5	0.622	Removed
IC6	0.766	0.758

UTAUT	**Outer Loading 1**	**Outer Loading 2**
PE1	0.875	0.900
PE2	0.922	0.945
PE3	0.914	0.927
PE4	0.661	Removed
EE1	0.831	0.831
EE2	0.868	0.868
EE3	0.878	0.878
EE4	0.876	0.876
SI1	0.830	0.831
SI2	0.841	0.842
SI3	0.909	0.910
SI4	0.773	0.771
BISU1	0.895	0.896

BISU2	0.935	0.935
BISU3	0.917	0.917
BISU4	0.819	0.818

Table 5.5 provides the outer loadings for each item related to the variable. One item related to information culture (IC05) has cross loading of 0.622 and another item (PE04) in performance expectancy also has an outer loading value of 0.661. Both are below the cut-off value of 0.70. Therefore, the following analyses will be carried out without these two items related to the information culture (IC) and performance expectancy (PE).

5.3.2 Average variance extracted (AVE)

The AVE studies the validity of the variable. Hair et al. (2017) recommend a cut-off value of 0.50 or above for establishing the validity.

Table 5.6: Validity Analysis

Variables		**AVE**
BI SQ and IQ characteristics	BI system quality	0.694
	BI information quality	0.663
BI individual characteristics	Self-efficacy	0.644
	Personal innovativeness	0.728
	Readiness to change	0.671
BI organisational factors	Top management support	0.841
	Information culture	0.606
UTAUT	Performance expectancy	0.855
	Effort expectancy	0.746
	Social influence	0.705
	BI system use	0.797

Table 5.6 provides the AVE results and all the variables have values that are higher than the expected cut-off of 0.50. Therefore, AVE establishes the validity of the studied variables.

5.3.3 Internal consistency

The internal consistency studies the reliability of the variables. Two analyses are used here, and these are Cronbach's Alpha and Composite Reliability (CR). Although either one is sufficient to study the reliability, both are presented here. Hair et al. (2017) state that for reliability the Cronbach's Alpha or CR should have value above 0.70.

Table 5.7: Reliability analysis

Variables		**Cronbach's Alpha**	**Composite reliability**
BI SQ and IQ characteristics	BI system quality	0.912	0.931
	BI information quality	0.873	0.908
BI individual characteristics	Self-efficacy	0.822	0.879
	Personal innovativeness	0.876	0.914
	Readiness to change	0.840	0.891
BI organisational factors	Top management support	0.906	0.941
	Information culture	0.837	0.885
UTAUT	Performance expectancy	0.915	0.946
	Effort expectancy	0.886	0.921
	Social influence	0.860	0.905
	BI system use	0.914	0.940

Table 5.7 provides the Cronbach's Alpha and CR which is studied based on the threshold of 0.70. The results show that for both Cronbach's Alpha and composite reliability, all variables have values above 0.70; therefore, all variables maintain the required reliability.

5.4 Discriminant validity assessment

The discriminant validity will be studied using cross-loading, Fornell-Larcker criterion, and Heterotrait-Monotrait ratio (HTMT) to ensure that constructs reflect their indicators.

5.4.1 Cross-loadings

Cross-loading studies the value of the item related to the variable in relation to other items related to the latent variables. Hair et al. (2017) add that 'an indicator's outer loading on the associated construct should be greater than any of its cross-loading (correlation) on other constructs' (p. 139).

Table 5.8: Cross-loadings

	BISU	EE	IC	IQ	PE	PIIT	RTC	SE	SI	SQ	TMS
BISU1	0.896	0.451	0.255	0.316	0.498	0.149	0.071	0.475	0.494	0.379	0.206
BISU2	0.935	0.464	0.293	0.322	0.516	0.213	0.098	0.452	0.487	0.358	0.221
BISU3	0.917	0.472	0.298	0.307	0.450	0.197	0.108	0.458	0.439	0.360	0.204
BISU4	0.818	0.519	0.353	0.390	0.472	0.296	0.200	0.535	0.486	0.475	0.347
EE1	0.546	0.831	0.283	0.425	0.569	0.249	0.211	0.506	0.470	0.473	0.250
EE2	0.378	0.868	0.306	0.463	0.436	0.294	0.247	0.452	0.469	0.498	0.363
EE3	0.472	0.878	0.376	0.498	0.357	0.260	0.195	0.534	0.513	0.593	0.406
EE4	0.436	0.876	0.308	0.438	0.492	0.292	0.196	0.476	0.428	0.476	0.392
IC1	0.263	0.243	0.720	0.366	0.247	0.345	0.301	0.349	0.312	0.379	0.264
IC2	0.201	0.244	0.783	0.403	0.225	0.398	0.423	0.284	0.311	0.299	0.469
IC3	0.272	0.309	0.818	0.443	0.171	0.267	0.380	0.390	0.387	0.396	0.452
IC4	0.291	0.362	0.811	0.421	0.253	0.247	0.348	0.447	0.347	0.495	0.421
IC6	0.276	0.274	0.758	0.454	0.187	0.274	0.284	0.372	0.369	0.390	0.413
IQ1	0.177	0.341	0.408	0.783	0.280	0.228	0.210	0.413	0.266	0.637	0.447
IQ2	0.305	0.426	0.381	0.843	0.309	0.216	0.228	0.436	0.366	0.623	0.373
IQ3	0.264	0.419	0.409	0.776	0.203	0.207	0.171	0.415	0.345	0.545	0.405
IQ4	0.395	0.429	0.458	0.797	0.384	0.309	0.246	0.531	0.425	0.514	0.389
IQ5	0.350	0.515	0.519	0.869	0.351	0.323	0.349	0.528	0.453	0.680	0.548
PE1	0.471	0.509	0.281	0.357	0.900	0.282	0.229	0.371	0.375	0.360	0.249
PE2	0.508	0.472	0.245	0.318	0.945	0.210	0.185	0.310	0.344	0.375	0.176
PE3	0.527	0.507	0.239	0.383	0.927	0.190	0.193	0.366	0.411	0.375	0.202
PIIT1	0.223	0.224	0.367	0.232	0.185	0.882	0.566	0.314	0.250	0.299	0.362
PIIT2	0.171	0.211	0.337	0.262	0.101	0.773	0.455	0.302	0.208	0.214	0.358
PIIT3	0.198	0.278	0.312	0.284	0.220	0.902	0.544	0.317	0.235	0.296	0.345
PIIT4	0.223	0.333	0.320	0.302	0.285	0.851	0.463	0.314	0.308	0.308	0.269
RTC1	0.138	0.235	0.371	0.287	0.220	0.544	0.861	0.298	0.227	0.300	0.338
RTC2	0.098	0.155	0.396	0.231	0.170	0.437	0.820	0.218	0.207	0.219	0.460
RTC3	0.094	0.155	0.343	0.238	0.098	0.482	0.754	0.135	0.179	0.262	0.444
RTC4	0.102	0.232	0.357	0.234	0.195	0.471	0.839	0.215	0.220	0.293	0.350

SE1	0.493	0.600	0.407	0.536	0.330	0.388	0.295	0.796	0.428	0.600	0.440
SE2	0.457	0.414	0.312	0.438	0.319	0.220	0.149	0.822	0.363	0.387	0.235
SE3	0.376	0.349	0.385	0.391	0.312	0.212	0.182	0.783	0.370	0.384	0.300
SE4	0.363	0.390	0.416	0.438	0.237	0.297	0.218	0.809	0.307	0.462	0.415
SI1	0.387	0.423	0.308	0.273	0.302	0.173	0.096	0.347	0.831	0.258	0.261
SI2	0.420	0.469	0.326	0.339	0.322	0.189	0.153	0.396	0.842	0.402	0.330
SI3	0.600	0.516	0.390	0.428	0.402	0.291	0.220	0.457	0.910	0.423	0.373
SI4	0.355	0.415	0.457	0.488	0.327	0.326	0.366	0.350	0.771	0.508	0.474
SQ1	0.393	0.541	0.381	0.607	0.312	0.280	0.270	0.499	0.432	0.821	0.445
SQ2	0.321	0.516	0.397	0.610	0.356	0.241	0.247	0.466	0.424	0.844	0.471
SQ3	0.375	0.462	0.448	0.570	0.319	0.269	0.282	0.501	0.372	0.827	0.395
SQ4	0.412	0.468	0.489	0.615	0.398	0.278	0.286	0.478	0.351	0.864	0.407
SQ5	0.362	0.486	0.417	0.632	0.310	0.293	0.255	0.566	0.426	0.841	0.415
SQ6	0.344	0.489	0.397	0.642	0.301	0.299	0.315	0.458	0.401	0.799	0.504
TMS1	0.303	0.344	0.489	0.470	0.213	0.369	0.481	0.384	0.397	0.502	0.918
TMS2	0.259	0.393	0.496	0.542	0.245	0.381	0.465	0.423	0.412	0.507	0.939
TMS3	0.193	0.385	0.450	0.453	0.159	0.300	0.339	0.422	0.386	0.443	0.895

Table 5.8 provides the cross-loadings for each item related to the variables. Similar to the other analyses, IC05 and PE04 are not part of the analysis based on the low outer loading results. The results indicate that all the items have values higher than the item values of latent variables. For example, the value of BISU1 (0.896) is higher than values of other items in the same line. Another example is EE1 that has a cross-loading value of 0.831, which is higher than values of other items in the same line. Similar results are found for all other items related to the studied variables.

5.4.2 Fornell-Larcker criterion

The Fornell-Larcker criterion studies the square root of the average variance extracted (AVE) and compares them to the latent variables. The value of the studied variable should be greater than the that of the latent variables (Hair et al. 2017).

Table 5.9: Fornell-Larcker criterion

	BISU	EE	IC	IQ	PE	PIIT	RTC	SE	SI	SQ	TMS
BISU	0.893										
EE	0.535	0.864									
IC	0.337	0.370	0.779								
IQ	0.375	0.529	0.539	0.814							
PE	0.544	0.537	0.275	0.382	0.924						
PIIT	0.241	0.316	0.388	0.320	0.245	0.853					
RTC	0.134	0.245	0.445	0.303	0.218	0.591	0.819				
SE	0.539	0.573	0.476	0.576	0.377	0.365	0.275	0.803			
SI	0.536	0.546	0.446	0.464	0.408	0.299	0.256	0.466	0.840		
SQ	0.442	0.593	0.506	0.736	0.400	0.332	0.331	0.593	0.482	0.833	
TMS	0.275	0.408	0.522	0.534	0.225	0.382	0.468	0.446	0.434	0.528	0.917

Table 5.9 provides the Fornell-Larcker criterion results. The values of the studied variables are higher than the latent variables and therefore establishes the discriminant validity. For example, the Fornell-Larcker criterion value of BISU (0.893) is higher than that of other variables. Similar results are also found for other variables.

5.4.3 Heterotrait-monotrait ratio (HTMT)

HTMT studies “the ratio of the between-trait correlations to the within-trait correlations” (Hair et al., 2017: p. 140). Hair et al. (2017) indicate that values of the studied variables should be below 1 to establish the HTMT. It is also suggested that values that are close to 1 may also have issues.

Table 5.10: HTMT

	BISU	EE	IC	IQ	PE	PIIT	RTC	SE	SI	SQ	TMS
BISU											
EE	0.589										
IC	0.383	0.425									
IQ	0.409	0.593	0.622								
PE	0.593	0.596	0.319	0.419							
PIIT	0.266	0.348	0.464	0.355	0.260						
RTC	0.149	0.275	0.533	0.343	0.238	0.692					
SE	0.603	0.633	0.565	0.652	0.427	0.407	0.300				
SI	0.590	0.619	0.517	0.516	0.454	0.329	0.289	0.535			
SQ	0.483	0.656	0.577	0.825	0.437	0.366	0.373	0.656	0.535		
TMS	0.301	0.456	0.595	0.596	0.247	0.438	0.553	0.499	0.485	0.580	

Table 5.10 provides the HTMT results. All variables have values below 1; therefore, as per the HTMT results, the discriminant validity is established.

5.5 Common method bias

Common method bias (CMB) happens when “the estimates of the relationships between two or more constructs are biased because they are measured with the same method” (Jordon and Troth, 2020; p. 5). It is necessary to understand CMB to reduce the negative effects that arise from single sources of data, which according to Chaubey and Sahoo (2021) can be a threat that instruments are causing response variations instead of predispositions. Several BI researches have conducted CMB using different types of analyses (for example, Chaubey and Sahoo, 2021; Elbashir et al., 2021). In accordance with Passlick et al. (2020) and Youssef and Mahama (2021), this research uses the PLS Collinearity Variance Inflation Factor (VIF) to study common method bias issues.

Table 5.11: Collinearity VIF values

	BISU	EE	IC	IQ	PE	PIIT	RTC	SE	SI	SQ	TMS
BISU											
EE	**1.713**										
IC									**1.374**		
IQ		**2.347**			**2.199**						
PE	**1.442**										
PIIT		**1.653**									
RTC		**1.588**			**1.133**						
SE		**1.721**									
SI	**1.464**										
SQ		**2.450**			**2.242**						
TMS									**1.374**		

Garson (2016) states that so long as the VIF value is maintained below 4.0, there are no CMB issues. Barajas-Portas (2017) argues that best results are available when the VIF value is below 3.3. Results in table 5.11 show that all causal relationship in the framework have values below 3.3, therefore, the data does not have any common method bias issues.

5.6 Descriptive analysis

Descriptive analysis is used to understand the raw data and interpret the numbers to create meaning (Gill and Johnson 2010). The objective of this research is to study the factors that impact BI system use. To understand this in the context of the Kuwaiti telecom and banking industries, the data has been collected from participants using BI systems in organisations operating in these sectors. Responses have been collected from 211 participants and the descriptive analysis will provide an overall understanding of the responses received for each variable using the five-point Likert scale.

5.6.1 BI system and information quality characteristics

The BI system and information quality characteristics will be discussed using BI system quality (SQ) and BI information quality (IQ).

Figure 5.1: SQ and IQ (percentage averages)

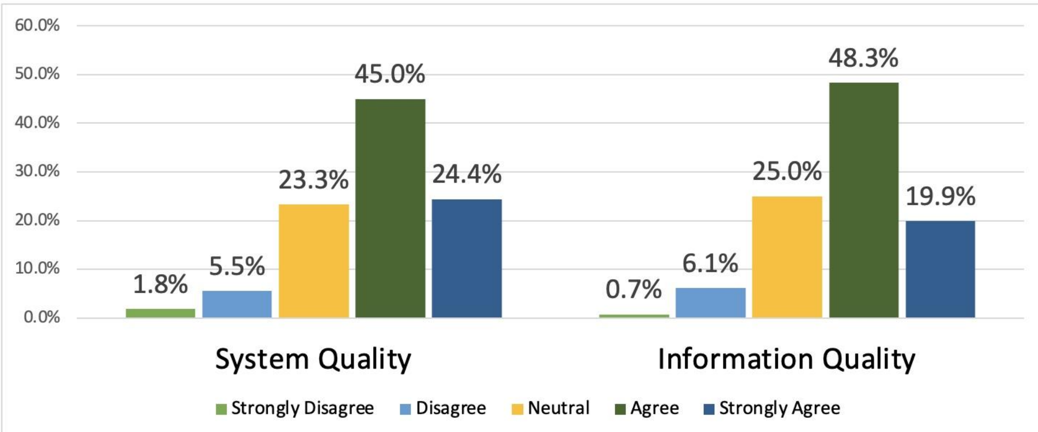


Figure 5.1 provides an overview of the descriptive results for SQ and IQ. For both these variables, higher responses are in the agree scale, with a considerable amount of responses in the strongly agree and neutral scales. This means that the respondents perceive that the BI system and the information are of quality. The descriptive tables below provide further descriptive details.

Table 5.12: Descriptive for SQ

System Quality	SD	D	N	A	SA	Mean	SD
The BI system operates reliably.	1.4%	6.2%	24.6%	47.4%	20.4%	3.791	0.886
The BI system can be adapted to meet a variety of needs.	0.9%	4.3%	22.7%	46.0%	26.1%	3.919	0.861
The BI system effectively integrates data from different areas of the company.	0.9%	4.7%	19.4%	47.9%	27.0%	3.953	0.861

The BI system allows information to be readily accessible to me.	1.4%	2.8%	21.8%	44.1%	29.9%	3.981	0.873
It does not take long for the BI system to respond to my requests.	3.8%	9.0%	27.5%	38.9%	20.9%	3.640	1.030
In terms of system quality, I would rate the BI system highly.	2.4%	5.7%	23.7%	46.0%	22.3%	3.801	0.930
Average	**1.8%**	**5.5%**	**23.3%**	**45.0%**	**24.4%**	**3.848**	**0.907**

Note on missing data:

- Participant 52: SQ1 was unanswered. Method 1 is used to enter the missing data.
- Participant 63: SQ6 was unanswered. Method 1 is used to enter the missing data.
- Participant 93: SQ6 was unanswered. Method 1 is used to enter the missing data.
- Participant 131: SQ1, SQ2, SQ3, SQ4, SQ5, SQ6. Method 2 is used to enter the missing data.
- Participant 134: SQ6. Method 1 was used to enter the missing data.

Table 5.12 provides the descriptive results for SQ. The mean values are above 3.6 and the SD values range between 0.861 to 1.030, indicating the data distribution along the 5-point scale for the SQ items. SQ has six items and all of them showed positive responses. The descriptive findings show that the BI system provides information to be readily accessible (agree = 44.1% and strongly agree = 29.9%). The results also indicate the effectiveness of data integration (agree = 47.9%; strongly agree = 27.0%). 46.0% agree and 26.1% strongly agree that the BI system in is flexible in adopting to use needs. There are also high positive responses for high system quality of the BI system, its reliability, and that it does not take long for BI system to respond to user requests.

Table 5.13 Descriptive for IQ

Information Quality	SD	D	N	A	SA	Mean	SD
The BI system provides me with a complete set of information.	0.0%	8.1%	22.3%	51.2%	18.5%	3.801	0.833
The BI system produces correct information.	0.5%	4.7%	28.0%	47.9%	19.0%	3.801	0.815
The information provided by the BI system is well formatted.	1.4%	8.1%	27.0%	47.9%	15.6%	3.682	0.883

The BI system provides me with the most recent information.	0.5%	4.7%	21.8%	49.8%	23.2%	3.905	0.823
Overall, I would give the information provided by the BI system a high rating in terms of quality.	0.9%	4.7%	26.1%	45.0%	23.2%	3.848	0.865
Average	**0.7%**	**6.1%**	**25.0%**	**48.3%**	**19.9%**	**3.808**	**0.844**

Note for missing data:

- Participant 99: IQ5 was unanswered. Method 1 is used to enter the missing data.
- Participant 131: IQ1, IQ2, IQ3, IQ4, IQ5. Method 2 is used to enter the missing data.
- Participant 134: IQ1, IQ2, IQ3, IQ4, IQ5. Method 2 is used to enter the missing data.

The descriptive results for IQ (table 5.13) are also mostly in the agree, neutral and strongly agree scales. The descriptive results for information quality indicate that BI system provides the most recent information (agree = 49.8%; strongly agree = 23.2%), correct information (agree = 47.9%; strongly agree = 19.0%); complete set of information (agree = 51.2%; strongly agree = 18.5%), and information being well formatted (agree = 47.9%; strongly agree = 15.6%). Therefore, the majority of respondents rate BI highly in terms of quality.

5.6.2 BI individual characteristics

The BI individual characteristics are studied through (1) self-efficacy (SE), (3) personal innovativeness in IT (PIIT), and (3) readiness to change (RTC).

Figure 5.2: SE, PIIT, and RTC (percentage averages)

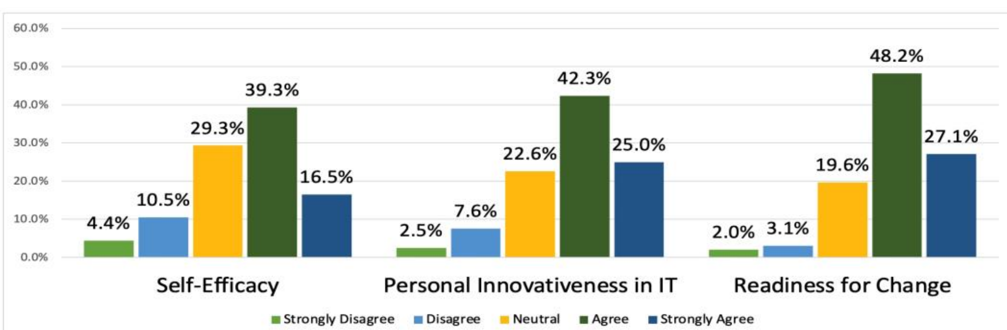


Figure 5.2 provides the summary for SE, PIIT, and RTC. RTC has higher responses in agree compared to SE and PIIT. RTC also has higher responses in strongly agree compared to SE and PIIT, suggesting that RTC is of more importance. To understand these responses, the responses for each of these variables will be discussed below.

Table 5.14: Descriptive results for SE

Self-Efficacy	SD	D	N	A	SA	Mean	SD
I could do my job using the BI system if there is no one around me to tell me what to do as I go.	5.7%	12.3%	19.4%	41.7%	20.9%	3.597	1.119
I could do my job using the BI system if I could call someone for help if I get stuck.	3.3%	8.1%	32.2%	39.3%	17.1%	3.588	0.974
I could do my job using the BI system if I had a lot of time to complete the job for which the system was provided.	3.3%	10.9%	36.0%	36.5%	13.3%	3.455	0.967
I could do my job using the BI system if I had just the built-in help facility for assistance.	5.2%	10.9%	29.4%	39.8%	14.7%	3.479	1.039
Average	**4.4%**	**10.5%**	**29.3%**	**39.3%**	**16.5%**	**3.530**	**1.025**

Note for missing data:

- Participant 131: SE1, SE2, SE3, SE4. Method 2 is used to enter the missing data.
- Participant 134: SE1, SE2, SE3, SE4. Method 2 is used to enter the missing data.

Table 5.14 provides the descriptive results for self-efficacy (SE). On average, SE has 39.3% responses in the agree and 16.5% responses in the strongly agree points of the scale. The findings show that the BI system can be used by individuals without assistance or instructions from others. However, there are people that provide assistance to operate the BI system when needed. Furthermore, 56% of the participants (39.8% agree and 14.7% strongly agree) indicate that a 'built-in help facility for assistance' would be sufficient in executing their tasks using the BI system. Another factor relates to time, as 49.8% of the respondents (36.5% agree and 13.3% strongly agree) stated the need for more time to complete their jobs. The users of BI have the confidence in the system. However, factors related to time and availability of assistance, whether via the system or a technical expert, have a role to play regarding their use behaviour.

Table 5.15: Descriptive results for PIIT

Personal innovativeness in IT	SD	D	N	A	SA	Mean	SD
When I hear about a new Information Technology, I look for ways to experiment with it.	1.9%	7.1%	22.3%	42.2%	26.5%	3.844	0.961
Among my peers, I am usually the first to explore new information technologies.	2.4%	14.7%	35.5%	31.8%	15.6%	3.436	1.000
I like to experiment with new information technologies.	2.4%	6.2%	17.1%	49.3%	25.1%	3.886	0.934
In general, I am not hesitant to try out new information technologies.	3.3%	2.4%	15.6%	46.0%	32.7%	4.024	0.938
Average	**2.5%**	**7.6%**	**22.6%**	**42.3%**	**25.0%**	**3.797**	**0.958**

Note for missing data:

- Participant 35: PIIT4 was unanswered. Method 1 is used to enter the missing data.
- Participant 99: All four items were answered. Method 2 is used to enter the missing data.
- Participant 134: PIIT1, PIIT2, PIIT3, PIIT4. Method 2 is used to enter the missing data.

The results for personal innovativeness in IT (table 5.15) indicate that most of the respondents are willing to experiment with new IT, especially when they hear about new developments and innovations in the field of IT. Although the majority (31.8% agree and 15.6% strongly agree) of participants indicated a behaviour of exploring new IT, 35.5% were neutral, indicating that they may or may not (indecisive) try out new IT innovations. It could also be argued that the choice of using the new systems is not entirely theirs. This can be further conceived in the voluntariness of use variable.

Table 5.16: Descriptive results for RTC

Readiness to change	SD	D	N	A	SA	Mean	SD
I look forward to changes at work.	2.4%	0.9%	16.1%	46.9%	33.6%	4.085	0.863
I find most change to be pleasing.	2.4%	5.2%	23.2%	46.4%	22.7%	3.820	0.924
Other people think that I support change.	1.9%	3.8%	25.6%	47.4%	21.3%	3.825	0.874
I am inclined to try new ideas.	1.4%	2.4%	13.3%	52.1%	30.8%	4.085	0.812
Average	**2.0%**	**3.1%**	**19.6%**	**48.2%**	**27.1%**	**3.954**	**0.868**

Note for missing data:

- Participant 50: RTC4 was unanswered. Method 1 is used to enter the missing data.
- Participant 115: RTC4 was unanswered. Method 1 is used to enter the missing data.
- Participant 134: RTC1, RTC2. Method 1 is used to enter the missing data.

Readiness to change (table 5.16) indicates the level and degree of change that the individual is willing to make in work and using the BI system. Most respondents indicated that they look forward to changes at work and that they are inclined to trying out new ideas. However, change may not always be welcome or pleasing. According to 69.1% (46.4% agree and 22.7% strongly agree), they find most change to be pleasing. However, 23.2% could not agree or disagree to this (neutral scale). Further, the view of others in supporting change is also essential. It is also found that 68.7% (47.4% agree and 21.3% strongly agree) of the participants perceive that others support their view of change. However, 25.6% indecisive responses were also there in the neutral scale. Change is not easy and, in some situations, it requires lots of time and effort. This is true for the implementation and use of BI systems. Overall, the majority of participants reported that they are willing to change to accommodate the needs of working with the BI system.

5.6.3 BI organisational factors

The BI organisational factors that are discussed are top management support (TMS) and information culture (IC).

Figure 5.3: TMS and IC (percentage averages)

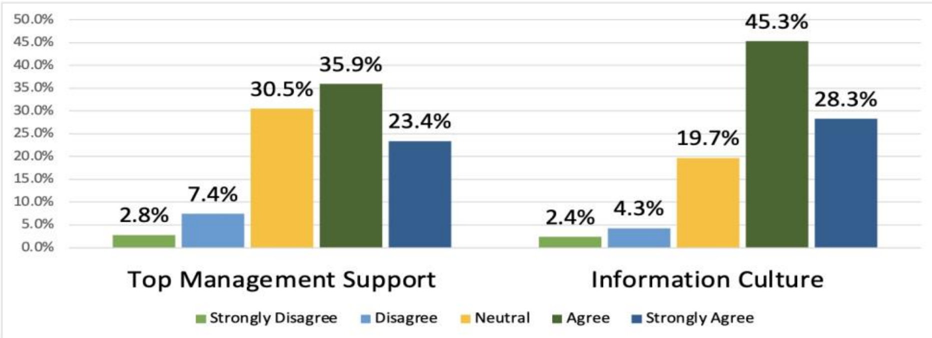


Figure 5.3 provides a summary for top management support (TMS) and information culture (IC). These are organisational factors. The responses for TMS are mainly between agree, neutral, and strongly agree, suggesting that many are neutral when it comes to top management support for BI. Data for IC shows that most of the responses are in the agree scale, followed by strongly agree and neutral scales, indicating perceived existence of information culture. Each of the two variables will be discussed below separately to have a clearer view.

Table 5.17: Descriptive results for TMS

Top management support	SD	D	N	A	SA	Mean	SD
Top management demonstrates continuous enthusiasm and interest in the BI system.	2.4%	7.6%	32.7%	30.3%	27.0%	3.720	1.020
I think highly of the overall level of management support towards the BI system.	2.8%	6.6%	29.4%	37.4%	23.7%	3.725	0.991
Personal involvement of upper-level managers in matters related to the BI system exist.	3.3%	8.1%	29.4%	39.8%	19.4%	3.640	0.992
Average	**2.8%**	**7.4%**	**30.5%**	**35.9%**	**23.4%**	**3.695**	**1.001**

Note for missing data:

- Participant 50: Out of three items for TMS, two were not answered (TMS1 and TMS3). Since Method 1 cannot be used to calculate average, Method 2 is used to enter the missing data.

- Participant 99: All three items for TMS were unanswered. Therefore, Method 2 is used to enter the missing data.
- Participant 115: Out of the three items, two were unanswered (TMS2 and TMS3). Therefore, Method 2 is used to enter the missing data.

The BI system integrates with every function of the organisation (table 5.17). Management has an important role in supporting the implementation and use of BI system to bring about better employee and organisational performance. Findings for TMS indicate that 57.3% (30.3% agree and 27% strongly agree) of the respondents believe that their top management demonstrated continuous enthusiasm and interest in the BI system. 32.7% were neutral, indicating that many employees were indecisive regarding the amount of support by management for the BI system in their organisation. Similar responses were also received for personal involvement of upper-level managers in matters related to the BI system. The overall findings indicate that the participation, enthusiasm, and involvement of the top management needs to be enhanced as many employees are indecisive towards their top managements' support.

Table 5.18: Descriptive results for IC

Information culture	SD	D	N	A	SA	Mean	SD
I often exchange information with the people with whom I work regularly.	2.8%	2.8%	8.5%	49.8%	36.0%	4.133	0.895
I actively seek out relevant information on changes and trends going on outside my organisation.	3.3%	3.8%	19.0%	46.9%	27.0%	3.905	0.951
Managers and supervisors of my work unit encourage openness.	2.4%	3.3%	19.9%	47.9%	26.5%	3.929	0.900
Among the people I work with regularly, it is common to distribute information to justify decisions already made.	2.4%	5.2%	21.8%	47.4%	23.2%	3.839	0.922

I trust formal information sources (i.e. reports) more than I trust informal sources (i.e. colleagues).	0.9%	6.2%	27.0%	34.1%	31.8%	3.896	0.955
I receive information about the performance of my organisation.	2.4%	4.3%	22.3%	46.0%	25.1%	3.872	0.919
Average	**2.4%**	**4.3%**	**19.7%**	**45.3%**	**28.3%**	**3.929**	**0.924**

Note for missing data:

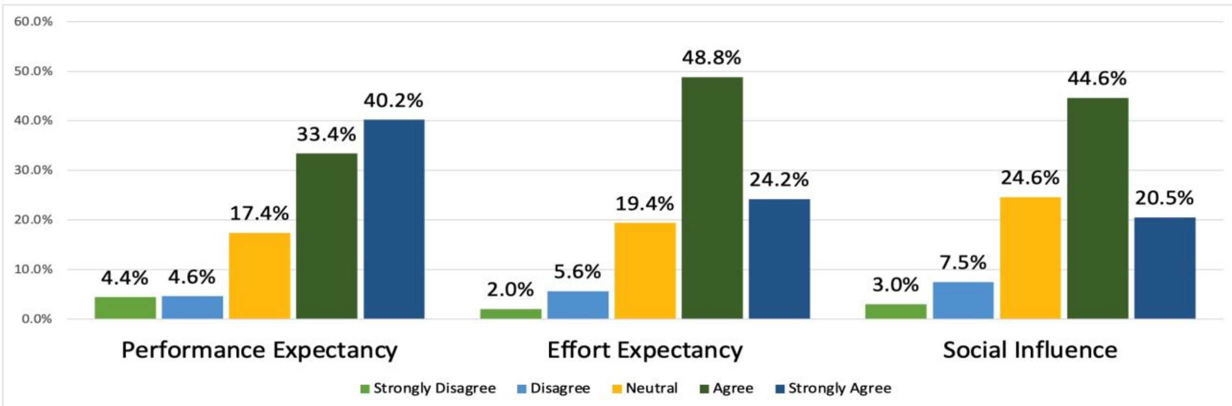
- Participant 5: IC2 was unanswered. Method 1 is used to enter the missing data.
- Participant 31: Only IC2 was answered and all others unanswered. Therefore, Method 2 was used to enter the missing data.
- Participant 82: IC2 was unanswered. Method 1 was used to enter the missing data.
- Participant 99: Only IC1 was answered. Therefore, Method 2 is used to enter the missing data.
- Participant 115: IC4 was unanswered. Method 1 is used to enter the missing data.
- Participant 124: IC6 was unanswered. Method 1 is used to enter the missing data.
- Participant 184: IC1, IC2, IC3, IC4, IC5, IC6. Method 2 is used to enter the missing data.

Information culture (IC) has six items (table 5.18). Strong positive responses were received for employees exchanging information with colleagues. This also refers to knowledge sharing practices which are essential for a strong work environment. Moreover, 65.9% (34.1% agree and 31.8% strongly agree) of the participants state that they trust formal information sources, such as reports, compared to information shared by colleagues (informal sources), which may imply trust in information coming from the BI system. External sources of information are vital to know what competitors, partners, and suppliers are doing. It is in-line with this fact that 73.9% (46.9% agree and 27.0% strongly agree) indicated that they actively seek out relevant information on changes and trends going on outside their organisations. Results also indicate that employees receive information about the performance of their organisations. Data suggests that managers and supervisors encourage openness in sharing information. Information is also shared to justify already made decisions. This benefits employees in understanding why certain decisions are made. The findings for information culture indicate that most employees believe in the existence of information culture in their working environments.

5.6.4 Mediating variables adopted from UTAUT

The UTAUT framework has several variables. This section discusses the mediating variables, which are performance expectancy, effort expectancy, and social influence.

Figure 5.4: UTAUT variables (percentage averages)



The variables discussed here are only part of the UTAUT framework. Three variables are provided in the graph (figure 5.4). Based on the response comparison, most of responses are in the agree point for effort expectancy followed by the strong agree point. However, performance expectancy has most responses in the strongly agree point, followed by responses in the agree point. This means that most of the employees find the BI system useful in enhancing their performance. For social influence, most of the responses were on the agree point, followed by the, neutral, and strongly agree points. The following descriptive tables for each of the three variables provide better understanding of the responses.

Table 5.19: Descriptive results for PE

Performance expectancy	SD	D	N	A	SA	Mean	SD
I find the BI system useful in my job.	2.4%	0.9%	12.8%	37.0%	46.9%	4.251	0.888
Using the BI system enables me to accomplish my tasks more quickly.	2.8%	1.9%	12.3%	36.0%	46.9%	4.223	0.937

Using the BI system increases my productivity.	2.4%	4.3%	13.7%	36.5%	43.1%	4.137	0.969
If I use the BI system, I will increase my chances of getting a raise.	10.0%	11.4%	30.8%	24.2%	23.7%	3.403	1.244
Average	**4.4%**	**4.6%**	**17.4%**	**33.4%**	**40.2%**	**4.004**	**1.009**

Note for missing data:

- Participant 10: PE1 was unanswered and this was completed using Method 1.
- Participant 209: PE1, PE2, PE3, PE4 was unanswered, and this was completed using Method 2.

The findings of PE show that the majority of respondents find BI systems to be useful in their jobs and that BI systems enable them to accomplish tasks more quickly. Most of the participants also state that the BI system increased their productivity. However, they believe that the use of the BI system is not necessarily going to increase the chances of them getting a raise. The mean value for this statement is 3.40 and the SD value is 1.24, indicating a high data distribution. Although 47.9% (24.2% agree and 23.7% strongly agree) supported the idea that the use of the BI system would increase their chances of getting a raise, 30.8% of responses were neutral, while 11.4% of respondents disagreed, and 10.0% strongly disagreed. Responses indicate that BI was beneficial for better job performance, but it did not necessarily impact earnings directly.

Table 5.20: Descriptive results for EE

Effort expectancy	SD	D	N	A	SA	Mean	SD
My interaction with the BI system is clear and understandable.	2.8%	2.8%	21.3%	46.4%	26.5%	3.910	0.919
It is easy for me to become skilful at using the BI system.	1.4%	6.2%	18.5%	47.9%	26.1%	3.910	0.903
I find the BI system easy to use.	2.4%	7.6%	19.0%	48.3%	22.7%	3.815	0.951
Learning to operate with the BI system is easy for me.	1.4%	5.7%	19.0%	52.6%	21.3%	3.867	0.863
Average	**2.0%**	**5.6%**	**19.4%**	**48.8%**	**24.2%**	**3.876**	**0.909**

Note for missing data:

- Participant 131: EE1, EE2, EE3, EE4 was unanswered, and this was completed using Method 2.

- Participant 210: EE2, EE3, EE4 was unanswered, and this was completed using Method 2.

The descriptive results (table 5.20) for effort expectancy (EE) indicate that all four items have mean values above 3.8 and that responses are largely in scales of agree and strongly agree, respectively. A mean of 3.91 is derived for two items: interactions with the BI system being clear and understandable, and ease of becoming skilful in using the BI system. 48.3% agreed and 22.7% strongly agreed that the BI system was easy to use while 52.6% agreed and 21.3% strongly agreed that learning to operate with the BI system required minimal effort. The overall responses indicate that most of the participants believe that the BI system is relatively easy to use.

Table 5.21: Descriptive results for SI

Social influence	SD	D	N	A	SA	Mean	SD
People who influence my behaviour think that I should use the BI system.	3.8%	8.1%	31.8%	44.1%	12.3%	3.531	0.943
People who are important to me think that I should use the BI system.	3.8%	10.0%	29.9%	39.8%	16.6%	3.555	1.005
Senior management has encouraged the use of the BI system.	3.3%	6.2%	19.4%	46.0%	25.1%	3.834	0.984
In general, the organisation has supported the use of the BI system.	0.9%	5.7%	17.1%	48.3%	28.0%	3.967	0.875
Average	**3.0%**	**7.5%**	**24.6%**	**44.6%**	**20.5%**	**3.722**	**0.952**

Note for missing data:

- Participant 131: SI1, SI2, SI3, SI4 was unanswered, and this was completed using Method 2.
- Participant 209: SI1, SI2, SI3, SI4 was unanswered, and this was completed using Method 2.

The findings for social influence indicate high means for two items (table 5.21). The response for organisational support towards the use of the BI system has a mean value of 3.967 and SD value of 0.875, as 76.3% (48.3% agree and 28.0% strongly agree) support this statement. The mean value of 3.834 and SD value of 0.984 as 71.1% (46.0% agreed ad 25.1% strongly agree) that senior management has encouraged the use of the BI system. This is followed by positive responses 56.4% (39.8% agree and 16.6% strongly agree) for participants thinking that people important to them believe that they should use the system. Moreover, most participants believe that people that influence their behaviour think that they should use the BI system 56.4% (44.1% agree and 12.3% strongly agree). The findings indicate that social influence from various individuals has a positive impact on the use of the BI system.

5.6.5 Business intelligence system use

This section discusses the dependent variable which is the BI system use (BISU). The descriptive results are provided in table 5.22.

Table 5.22: Descriptive results for BISU

Business Intelligence system use	SD	D	N	A	SA	Mean	SD
I depend on the BI system to achieve my work tasks.	5.7%	7.6%	19.4%	42.2%	25.1%	3.735	1.094
I have used the BI system a lot in the past 4 weeks.	9.5%	4.7%	17.1%	36.0%	32.7%	3.777	1.224
I have been using the BI system regularly in the past 4 weeks.	10.0%	5.2%	15.2%	34.6%	35.1%	3.796	1.254
I create my own analyses using the BI system.	9.5%	9.0%	17.5%	34.6%	29.4%	3.654	1.253
Average	**8.7%**	**6.6%**	**17.3%**	**36.9%**	**30.6%**	**3.741**	**1.206**

Note for missing data:

- Participant 131: BISU1, BISU2, BISU3, BISU4 was unanswered, and this was completed using Method 2.

The responses for BI system use indicate that the majority of the respondents (34.6% agree and 35.1% strongly agree) have been using BI system regularly over the past 4 weeks. A majority (36.0% agree and 32.7% strongly agree) also indicate that they have used the BI system a lot in the past 4 weeks. Furthermore, users create their own analyses using BI systems (34.6% agree and 29.4% strongly agree). The dependency on BI systems to achieve work tasks is supported by most users (42.2% agree and 25.1% strongly agree). Actual utilisation is analysed through the BI system use responses.

5.6.6 Voluntariness of use

Voluntariness of use (VU) is a moderator with three items.

Table 5.23: Voluntariness of use

Voluntariness of use	SD	D	N	A	SA	Mean	SD
My use of the BI system is optional.	40.3%	17.5%	14.2%	20.4%	7.6%	2.374	1.383
My supervisor does not require me to use the BI system.	45.0%	27.5%	10.9%	10.4%	6.2%	2.052	1.239
Although it might be helpful, using the BI system is certainly not compulsory in my job.	39.3%	23.7%	11.8%	15.6%	9.5%	2.322	1.377
Average	**41.5%**	**22.9%**	**12.3%**	**15.5%**	**7.8%**	**2.249**	**1.332**

Note for missing data:

- Participant 36: VU3 was not answered, and this was completed using Method 1.

The average responses for voluntariness of use (table 5.23) indicate higher responses for strongly disagree (41.5%) and disagree (22.9%). This means that most employees believe that using the BI system is mandatory and that it is not up to them to make the decision. The strongest negative response is received for supervisors not requiring employees to use BI system (27.5% disagree and 45.0% strongly disagree). Employee views on whether BI system use is optional show negative responses (17.5% disagree and 40.3% strongly disagree). It is also understood that many disagree (23.7%) and even more strongly disagree (39.3%) to the use of BI system not being compulsory. Data from the overall responses indicate that using the BI system is a mandate enforced by organisations. Hence, the descriptive results show that voluntariness is very limited when it comes to BI system use.

5.7 Structured equation modelling

The different analysis provided above studied the validity and reliability to ensure that the framework can be studied. The SEM will provide the direct effects and moderation effects.

Figure 5.5: SEM

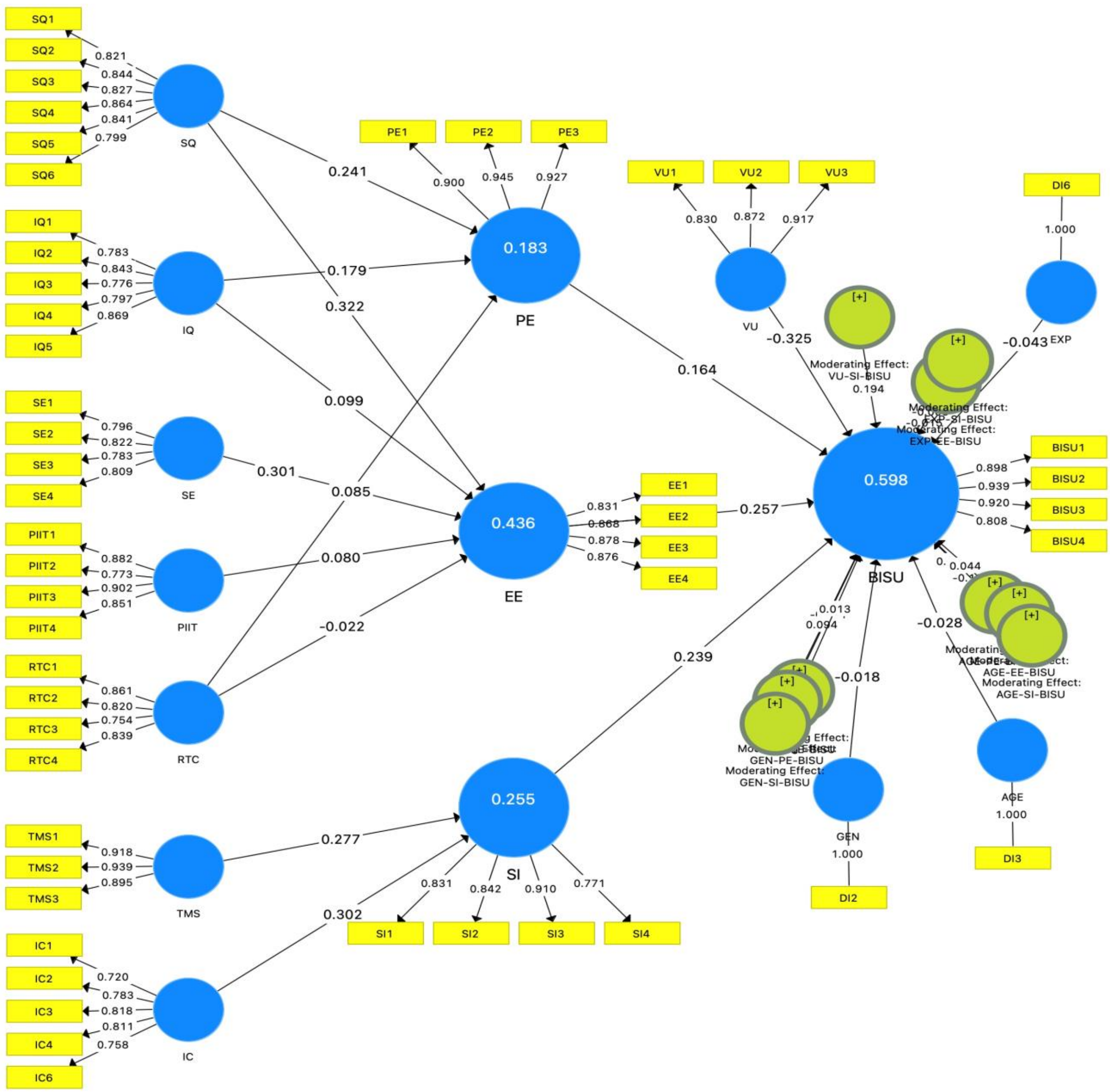


Figure 5.5 depicts the entire framework and the various values. The values between yellow rectangles (items) and the blue circles (variables) are the outer loading values that are discussed earlier. The values inside the blue circles are the R-squared (R^2) values that indicate the predictive power of and variance of the model. A higher variance indicates a better explained model. The values between the blue circles are the original sample values that indicate the impact of the variables.

5.7.1 Direct effects

This section will present the direct effects and discuss the hypotheses results.

Table 5.24: Direct effects

	Original sample (O)	**P-values**	**Hypotheses results**
Performance expectancy			**R^2: 18.3%**
SQ → PE	0.241	0.013	H_{1a}: Accepted
IQ → PE	0.179	0.073	H_{1b}: Rejected
RTC → PE	0.085	0.228	H_{1c}: Rejected
Effort expectancy			**R^2: 43.6%**
SQ → EE	0.322	0.000	H_{2a}: Accepted
IQ → EE	0.099	0.282	H_{2b}: Rejected
SE → EE	0.301	0.000	H_{2c}: Accepted
PIIT → EE	0.080	0.264	H_{2d}: Rejected
RTC → EE	-0.022	0.760	H_{2e}: Rejected
Social influence			**R^2: 25.5%**
TMS → SI	0.277	0.004	H_{3a}: Accepted
IC → SI	0.302	0.001	H_{3b}: Accepted
BI system use			**R^2: 59.8%**
PE → BISU	0.164	0.031	H_{4a}: Accepted
EE → BISU	0.257	0.001	H_{4b}: Accepted

SI → BISU	0.239	0.002	H_{4c}: Accepted

Table 5.24 provides the direct effect results. The framework studies four direct effects. The first is the role of BI system quality (SQ), BI information quality (IQ), and readiness to change (RTC) on performance expectancy (PE). The R^2 of 18.3% indicates the model variance. The p-value indicates that only SQ is significant with PE (p-value = 0.013). IQ (p-value = 0.073) and RTC (p-value = 0.228) have values higher than the required significance value of 0.050, therefore they are not significant. The path coefficient (original value) of 0.241 for SQ indicates positive impact on PE. Therefore, hypothesis **H_{1a} is accepted** and hypotheses **H_{1b} and H_{1c} are rejected**.

The second direct effect studies the role of SQ, IQ, self-efficacy (SE), personal innovativeness in IT (PIIT), and readiness to change (RTC) on effort expectancy (EE). The R^2 of 43.6% indicates good variance between the studied variables. The p-value indicates significance of SQ (p-value = 0.000) and SE (p-value = 0.000) on EE. IQ (p-value = 0.282), PIIT (p-value = 0.264), and RTC (p-value = 0.760) are not significant. The path coefficient (original sample) values indicate that both SQ (O = 0.322) and SE (O = 0.301) have a positive impact on EE with stronger impact from SQ. The results confirm that **hypotheses H_{2a} and H_{2c} are accepted**, whereas **hypotheses H_{2b}, H_{2d}, and H_{2e} are rejected**.

The third direct effect is that of top management support (TMS) and information culture (IC) on social influence (SI). The R^2 indicates a model variance of 25.5% between the studied variables. The p-value indicates that both TMS (p-value = 0.004) and IC (p-value = 0.001) are significant. The path coefficient (original sample) indicates that both have positive impact on SI with stronger impact from IC (O = 0.302), followed by TMS (O = 0.277). Therefore, **hypotheses H_{3a} and H_{3b} are accepted.**

The fourth direct effect is that of PE, EE, and SI on BI system use (BISU). The R^2 of 59.8% indicates good variance between the studied variables. The p-value indicates that all three variables have values below 0.050, therefore, they are significant. The path coefficient (original sample) indicates that PE (O = 0.164), EE (O = 0.257), and SI (0.239) have positive impact with the strongest impact on BISU from EE, followed by SI and PE, respectively. Therefore, **hypotheses H_{4a}, H_{4b}, and H_{4c} are accepted**.

5.7.2 Moderating effects

This section will discuss the moderating effects of gender, age, experience, and voluntariness of use.

Table 5.25: Moderators

	Original sample (O)	P-values	Hypotheses results
Gender			
GEN → BISU	-0.018	0.715	
GEN → PE → BISU	0.001	0.985	H_{5a}: Not supported
GEN → EE → BISU	0.013	0.868	H_{5b}: Not supported
GEN → SI → BISU	0.094	0.343	H_{5c}: Not supported
Age			
AGE → BISU	-0.028	0.640	
AGE → PE → BISU	0.080	0.306	H_{6a}: Not supported
AGE → EE → BISU	0.044	0.668	H_{6b}: Not supported
AGE → SI → BISU	-0.182	0.082	H_{6c}: Not supported
Experience			
EXP → BISU	-0.043	0.484	
EXP → EE → BISU	-0.015	0.858	H_{7a}: Not supported
EXP → SI → BISU	-0.003	0.976	H_{7b}: Not supported
Voluntariness			
VU → BISU	-0.325	0.000	
VU → SI → BISU	0.194	0.001	H_8: Supported

Table 5.25 describes the moderating effect of gender, age, experience, and voluntariness of use. The framework studies the role of gender between (1) PE and BISU, (2) EE and BISU, and (3) SI and BISU. The p-values for all three are higher than 0.050, therefore gender does not moderate the relationship between any of the studied variables. The result also indicates that **hypotheses H_{5a}, H_{5b}, and H_{5c} are rejected**.

The next relationship is that of age as a moderator between PE and BISU, EE and BISU, and SI and BISU. The p-values for all three are higher than 0.050. Therefore, age does not moderate the relationship between any of the studied variables, hence **hypotheses H_{6a}, H_{6b}, and H_{6c} are rejected**.

The next relationship is that of experience as moderator between EE and BISU and SI and BISU. The p-values for both are higher than 0.050. Therefore, experience does not moderate the relationship between any of the studied variables. **Hypotheses H_{7a} and H_{7b} are rejected**.

The final moderation is that of voluntariness of use (VU) between SI and BISU. The p-value of 0.000 indicates that VU moderates the relationship between SI and BISU with original sample of 0.194. This indicates that the moderating impact is positive and **hypothesis H_8 is accepted**.

5.8 Hypotheses summary

To accept or reject the hypotheses suggested in Chapter 3, the PLS-SEM results are followed. Listed below are the hypotheses results:

5.8.1 Hypothesis result for performance expectancy

- H_{1a}: that BI system quality has a significant positive impact on performance expectancy is **supported** with a path coefficient of 0.241.

- H_{1b}: that BI information quality has a significant positive impact on performance expectancy is **not supported** as it has a p-value of 0.073, which is higher than the accepted p-value of 0.050 (95% or higher confidence level).
- H_{1c}: that readiness to change has a significant positive impact on performance expectancy is **not supported** as it has a p-value of 0.228, which is higher than the accepted p-value of 0.050 (95% or higher confidence level).

5.8.2 Hypothesis result for effort expectancy

- H_{2a}: that BI system quality has a significant positive impact on effort expectancy is **supported** with a path coefficient of 0.322.
- H_{2b}: that BI information quality has a significant positive impact on effort expectancy is **not supported** as it has a p-value of 0.282, which is higher than the accepted p-value of 0.050 (95% or higher confidence level).
- H_{2c}: that self-efficacy has a significant positive impact on effort expectancy is **supported** with a path coefficient of 0.301.
- H_{2d}: that personal innovativeness in IT has a significant positive impact on effort expectancy is **not supported** as it has a p-value of 0.264, which is higher than the accepted p-value of 0.050 (95% or higher confidence level).
- H_{2e}: that readiness to change has a significant positive impact on effort expectancy is **not supported** as it has a p-value of 0.760, which is higher than the accepted p-value of 0.050 (95% or higher confidence level).

5.8.3 Hypothesis results for social influence

- H_{3a}: that top management support has a significant positive impact on social influence is **supported** with a path coefficient of 0.277.
- H_{3b}: that information culture has a significant positive impact on social influence is **supported** with a path coefficient of 0.302.

5.8.4 Hypothesis result for BI system use

- H_{4a}: that performance expectancy has a significant positive impact on BI system use is **supported** with a path coefficient of 0.164.
- H_{4b}: that effort expectancy has a significant positive impact on BI system use is **supported** with a path coefficient of 0.257.
- H_{4c}: that social influence has a significant positive impact on BI system use is **supported** with a path coefficient of 0.239.

5.8.5 Hypothesis result for gender as moderator

- H_{5a}: that gender affects the relationship between performance expectancy and BI system use is **not supported** as gender is not significant (p-value = 0.985).
- H_{5b}: that gender affects the relationship between effort expectancy and BI system use is **not supported** as gender is not significant (p-value = 0.868).
- H_{5c}: that gender affects the relationship between social influence and BI system use is **not supported** as gender is not significant (p-value = 0.343).

5.8.6 Hypothesis result for age as moderator

- H_{6a}: that age affects the relationship between performance expectancy and BI system use is **not supported** as age is not significant (p-value = 0.306).
- H_{6b}: that age affects the relationship between effort expectancy and BI system use is **not supported** as age is not significant (p-value = 0.668).
- H_{6c}: that age affects the relationship between social influence and BI system use is **not supported** as age is not significant (p-value = 0.082).

5.8.7 Hypothesis result for experience as moderator

- H_{7a}: that experience affects the relationship between effort expectancy and BI system use is **not supported** as experience is not significant (p-value = 0.858).
- H_{7b}: that experience affects the relationship between social influence and BI system use

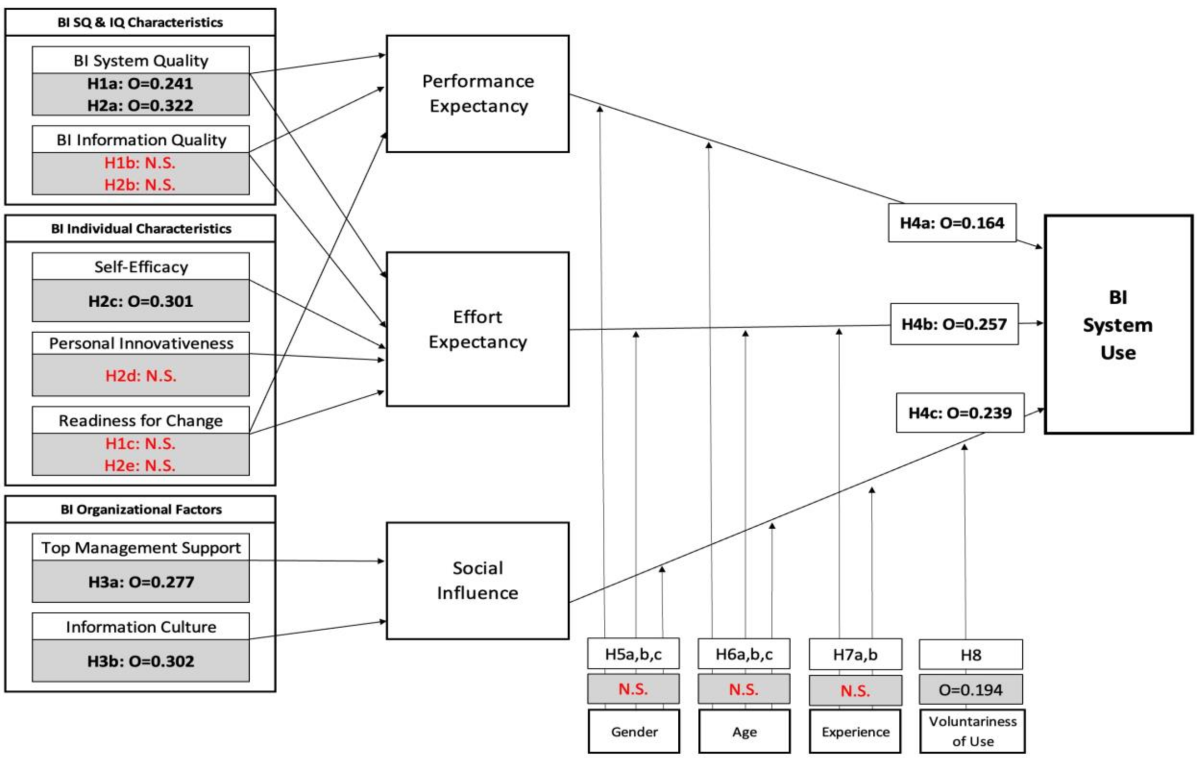
is **not supported** as experience is not significant (p-value = 0.976).

5.8.8 Hypothesis result for voluntariness as moderator

- H_8: that voluntariness of use affects the relationship between social influence and BI system use is **supported** with a path coefficient of 0.194.

Figure 5.6 provides the summary of the results in the framework.

Figure 5.6: Final model with hypotheses results



Chapter 6: Discussion

6.1 Introduction

This research has developed a framework to study the use of BI by moving beyond behavioural beliefs and understanding how object-based beliefs play a role in BISU. This research has investigated BISU in Kuwait's telecom and banking industries and has developed a framework based on BIEUM and UTAUT to identify and assess important factors affecting BISU.

Grublješič and Jaklič (2015) have indicated the need to study BI based on object-based beliefs and attitudes, behavioural beliefs and attitudes, and use. The object-based beliefs and attitudes comprise individual characteristics, BIS quality characteristics, organisational factors, and macro-environmental characteristics. The behavioural beliefs and attitudes comprise performance perceptions, result demonstrability, effort perceptions, and social influence. The outcome comprises the intensity of use, the extent of use, and embeddedness of use. This research has disregarded macro-environment characteristics due to ambiguity and variety.

Since the context of this research focuses on the telecom and banking industries, it is important to understand that both of these industries process large volumes of data, and therefore are important industries when it comes to BI. The telecom market in Kuwait is shared between three major operators. Zain, a Kuwaiti-based company, the other two: Ooredoo and STC (formerly Viva), are regionally owned and operated companies. The banking industry in Kuwait is largely limited to local banks with a few foreign banks. There is a combination of Islamic and conventional banks in Kuwait. Both telecom and banking businesses have substantial amounts of data that need to be analysed and transformed to produce intelligent and business actionable knowledge that businesses can utilise.

As discussed in chapter 2, behavioural intention and facilitating conditions have been omitted. The omission of behavioural intention was due to the fact the BI systems were already in place in this research's context. Facilitating conditions has been omitted due to grouping of multiple constructs into one (van Raaij and Schepers, 2008). Therefore, the three constructs that were studied in direct effect to BISU are: performance expectancy (PE), effort expectancy (EE), and social influence (SI).

By combining UTAUT and BIEUM, a framework was developed to study BI system use in the telecom and banking industries. The data was collected through a survey using self-administered questionnaires and analysed using SmartPLS and SPSS. The BIEUM is the result of a qualitative method which provides in-depth knowledge; however, it also lacks in establishing causal relationships between variables. Through drawing the causal links, this research addresses this gap and the findings contribute to the existing body of literature. This research also investigates BISU using a quantitative method, thus empirically investigating the cause and effect relationships between variables.

The next sections discusses the predictive power of the model towards BISU, the determinants of performance expectancy and effort expectancy, the determinants of social influence, and the determinants of BISU, respectively.

6.2 Conceptual framework predictive power

The degree to which BISU is explained by its determinants for this research model is 59.8% (R^2=0.598). This is considered acceptable for purposes of research. UTAUT explains intention at 70% (R^2=0.7) and use at 47% (R^2=0.47) (Venkatesh et al., 2003). Furthermore, this research's model is compared well to Grublješič et al. (2017) study on BI acceptance which focused on individualistic considerations and socio-organisational considerations towards the intention to use BI systems with a predictive power of 28.4% (R^2=0.284). It also compares well against Gaardboe et al. (2017) model that studies whether user satisfaction impacts BISU with a predictive power of 56% (R^2=0.56). Hence, given the R^2 value achieved, this research model is considered to explain BISU well. Effort expectancy is also explained well by its determinants with a predictive power of 43.6% (R^2=0.436). Social influence (R^2=0.255) and performance expectancy (R^2=0.183) were less explained by their determinants.

6.3 Determinants of performance expectancy and effort expectancy

The model begins with the role of BI quality characteristics which is made up of BI system quality (SQ) and BI information quality (IQ) on performance expectancy (PE) and effort expectancy (EE). SQ and IQ characterise the information system through which the user experiences different levels of satisfaction and sense of achievement in using the system (Gaardboe et al., 2017). Several authors have studied the role of SQ and IQ on PE (for example, Zhao et al., 2012; Popovič et al., 2014; Bouchana and Idrissi, 2015; Grublješič and Jaklič, 2015; Gonzales et al., 2015; Mudzana and Mahraj, 2015; Gaardboe et al., 2017). The quality of information is based on the outputs which are primarily related to the content, reports, and dashboards. The role of IQ on system adoption and utilisation has been identified as important in various studies (for example, Zhao et al., 2012; Foshay et al., 2014; Bouchana and Idrissi, 2015; Bischoff et al., 2015; Bach et al., 2016; Nofal and Yusof, 2016; Visinescu et al., 2017). These studies, however, are in different settings from this research.

The role of performance expectancy on BI system use is studied using system quality, information quality, and readiness to change. This research established the positive impact of system quality on performance expectancy and effort expectancy. However, the role of information quality and readiness to change on both performance expectancy and effort expectancy were not significant. While information quality is essential when it comes to BI, there is reason as to why it may not have played a role in impacting performance and effort expectancies. The data stored in BI systems is considered to be secondary data that is derived from primary source system databases. Thus, the information quality of BI systems is dependent on the information quality of other source systems.

The impact of system quality (SQ) on performance expectancy was found to be significantly positive. One of the strongest qualities of the BI system is its organisation-wide integration which allows accessibility of information to users. The effectiveness of the BI system for users is based on the accessibility and availability of relevant data across the organisation for effective decision making. The reliability of BI systems is in its effectiveness and operations. Other studies have also found similar relationships; however, they differ in many ways. For example, Zhao et al. (2012) studied system quality of BI systems based on multiple attributes such as completeness of the BI solution, quality of the software code, ease of testing, and quality of the BI software. Another difference is that this research extended the UTAUT framework as opposed to the TAM model used by Zhao et al. (2012).

The descriptive findings for information quality (IQ) showed that BI systems produce correct, up to date and complete sets of information. The information produced by BI systems is complete, and therefore the information quality of the BI system was given a high rating. The research by Bach et al. (2016) adopted TAM in studying BI implementation. They investigated the influence of information quality on perceived usefulness and perceived ease of use, and found a positive impact. The study by Bischoff et al. (2015) is more closely related to this research as its emphasis was on the continued use of BI systems. However, they based the development of the framework on TAM. In addition to this, the role of information quality towards continued use of BI was studied through trust and perceived usefulness. Information quality was found to have a positive role on continued use of BI. However, this research found that information quality does not play a role in impacting performance and effort expectancies. As discussed earlier, this may be because BI systems are secondary sources of data, and that quality of information is mainly determined by primary sources. For instance, if the BI system processes data from a customer relationship management (CRM) system, the quality of data mainly depends on the CRM. Gaardboe et al. (2017) studied the role of system quality on use satisfaction and found a positive impact. Gaardboe et al. (2017) used the DeLone and McLean's IS Success Model.

Zhao et al. (2012) recommend the use of TAM, whereas Gaardboe et al. (2017) recommend the DeLone and McLean's IS Success Model to study BI system use. It can therefore be concluded that different models could be adopted in investigating the role of BI system quality on achieving effective BI adoption and use through performance expectancy and effort expectancy.

In addition to this, the impact of RTC on PE and EE was studied. Kwakh and Lee (2008) provide a definition of RTC which emphasises the readiness of employees to have a positive perspective on organisational change, with the belief that the change will bring about a positive impact for the individual and the organisation. This means that individuals should intend to adopt and use the system. Grublješič and Jaklič (2015) suggest that change is vital for the success of BI systems and for individuals in implementing and using new technologies. They also state that individuals who voluntarily use BI systems will show a stronger intention to adopt and use the system. This also means that individuals that show stronger RTC can be expected to put more effort into using BI systems.

The findings for RTC showed that BI systems require users to be prepared and adapt to changes. The responses for readiness to change showed that BI users looked forward to and were optimistic regarding changes and saw a similar positive attitude amongst others as well. The inclination towards new ideas and readiness to change promotes the use of BI systems. Using new technologies in a changing business environment requires users to adapt to the changes to ensure effective utilisation. The findings of this research indicate that RTC did not have significant impact on PE or EE.

These findings differ from earlier studies (for example Kwahk and Lee, 2008; Grublješič and Jaklič, 2015) that found RTC to be essential in playing a role towards PE and EE. The difference in findings between this research and existing literature is due to certain reasons. Kwahk and Lee (2008) research was investigating use intention, whereas the current research is based in contexts where BI systems are already implemented and in use. In other words, the employees who have participated in this survey are used to BI, and therefore may have changed their perspectives towards BI and changed their work routines in accordance to BI. In addition to this, the study by Kwahk and Lee (2008) focuses on ERP implementation intention and not continued BI system use. Furthermore, Grublješič and Jaklič (2015) carried out a qualitative research that investigated the role of RTC, while this research has drawn causal links and quantitatively investigated the impact of RTC on PE and EE.

Moreover, this research studies the role of SE and PIIT on EE. The findings for SE showed that BI users were confident about using the BI system on their own, but their confidence level needed improvement. Users require more time and effort to operate the BI system, therefore, this research recommends training based on user needs. In brief, the self-efficacy of BI users requires improvement. SE emphasises the belief in oneself in carrying out specific tasks. In this research, SE refers to using BI based on the confidence and ability individuals have about themselves. In earlier research, SE has been found to have a substantial impact on behavioural intention and the study by Venkatesh (2000) found that EE mediates the relationship between SE and intention to use. Other studies such as Hou (2013; 2014), Grublješič et al. (2017), and Hou and Gao (2018) have also pointed to the role of SE in adoption and use of information systems. Chomchaloa and Naenna (2013) have also found that stronger SE leads to stronger behavioural intentions and increases the likelihood of the individual trying out complex information systems.

PIIT is the determination of the individual in trying out new technologies (Chomchaloa and Naenna, 2013). This means that individuals that are attracted to innovation and new technology are more tempted to use new technologies. Personal innovativeness in IT is often studied in adoption (for example, Wang, 2014; Popovič et al., 2019). PIIT emphasises that new technologies are seen as opportunities to learn more through experimentation and that PIIT is a mean to exploring new technologies. The responses show that BI users are eager to learn more about new technologies which implies interest towards the use of BI systems.

This research established the positive impact of SE on EE; however, PIIT was not a significant determinant of EE. This means that the self-efficacy of the BI user to carry out specific tasks is important in determining the effort needed towards effective use of BI. Grublješič et al. (2017) studied the acceptance of BI and stressed on the ability of users to use new systems. One of the closest studies in relation to this research is that of Hou and Gao (2018) on mobile BI use based on the UTAUT model in addition to the Task-Technology Fit (TTF) theory. There are three differences between Hou and Gao's work and this research. First, their research is qualitative; second, it is limited to managers as the users; and third, it is in the specific context of mobile BI. In other words, although there are a few similarities related to the use of UTAUT, there are also methodological and contextual differences. As with Hou and Gao (2018), the study by Grublješič and Jaklič (2015) was also qualitative and failed to establish causal relationships. This research identified the causal relationship of SE on EE in the context of BI and contributes to the existing body of literature by determining the effect..

Individuals that are attracted to innovation and developments in technology should be attracted towards their use. As stated above, PIIT did not significantly impact EE. The reason that PIIT does not play a role in the continued use of BI could be because PIIT focuses on the innovativeness of the individual, which may not be applicable in organisations where employees are expected to use the system for specific tasks and where innovation is limited. Organisations in the telecom and banking industries may give more importance to the self-efficacy of employees when using the system rather than their PIIT.

6.4 Determinants of social influence

This research also addresses to the role of TMS and IC in impacting SI. The role of TMS towards SI has been identified in earlier literature. The support and motivation provided by top management creates a supportive environment for BI system adoption and use (Kohnke et al., 2011; Ravasan and Savoji, 2014; Audzeyeva and Hudson, 2015; Nofal and Yusof, 2016; Puklavec et al., 2017; Lautenbach et al., 2017). The findings for TMS show that top management play an essential role in the continued use of BI systems. According to BI users, the participation and enthusiasm of top management is essential for BI system success. Overall, the role and participation of top management can promote BI system use. The study by Costa et al. (2016) has shown that TMS had a direct influence on system use. Ahmad et al. (2013) have added that TMS impacts social influence based on the authority of managers. In addition, Sabherwal et al. (2006) and Ahmad et al. (2013) have suggested that TMS influences the existence of facilitating conditions. Galal et al. (2016) studied BI in banking and discussed top management within the business-driven, top-down approach. In that approach, the top managers decide what needs to be carried out and the employees have to follow. Other authors (for example, Audzeyeva and Hudson, 2015; Nofal and Yusof, 2016; Lautenbach et al., 2017) have discussed the important role of TMS on SI. Those studies were similar as they were based on post-implementation contexts and have used quantitative methods, where the causal relationships between variables were studied. Lautenbach et al. (2017) applied the Technology-Organisation-Environment (TOE) framework and found that TMS has the strongest influence on BI system use when compared to other factors that were studied. A similar finding was found by Nofal and Yusof (2016) who have studied BI using critical success factors (CSFs). Moreover, Audzeyeva and Hudson (2015) emphasise that the decision making role of senior management in long-term commitment to BI is particularly important for the continued use of BI.

This research contributes to literature by establishing a relationship between IC and SI. Organisations that depend strongly on information technology should have a culture that supports information use. This is supported by Leidner and Kayworth (2006). IC reflects the organisation values, norms, and practices based on which the information is perceived, created, and used. IC also promotes innovation in products and services (Choo et al., 2008; Hwang et al., 2013) which is essential for organisations to gain competitive advantages. The overall findings for IC showed that BI users exchange information on a regular basis and this is based on the openness that is encouraged by managers. Based on this, the users actively seek out relevant information on changes and trends both internally and outside the organisation. BI users also receive information about organisational performance.

This research mirrors Skyrius et al. (2018) in its emphasis on BI culture and the importance of information sharing and the creation of an intelligence community. This is related to social influence, social networking, and social cohesion. Another similarity lies in the investigation of the role of information and BI culture on social influence. However, Skyrius et al. (2018) do not indicate the use of a particular theory or model. This research, on the other hand, empirically proved that IC influences SI and therefore, IC becomes important to the continued use of BI systems.

6.5 Determinants of BI system use

UTAUT has been widely used in several studies where it has identified the role of performance expectancy, effort expectancy, and social influence on use behaviour directly and indirectly. The overall findings for BI system use indicate that users depend on the BI system to achieve tasks and conduct analysis. Their usage of BI systems is regular and often increases, demonstrating dependency on BI systems. As stated earlier, this research has excluded facilitating conditions and behavioural intention. The analysis therefore investigates the direct impact of PE, EE, and SI on BISU. All three variables were found to significantly and positively impact BISU.

Performance expectancy refers to the individual's perception of and expectations from the BI system. In addition to this, the degree to which the employee's job performance is improved while using the system is perceived by the employee. Several examples have indicated the positive impact of PE on behavioural intention towards use (for example, Alraja 2015; Benbasat and Barki, 2007; Venkatesh et al., 2003). In addition to this, Grublješič and Jaklič (2015) and Hou (2012) also state that higher expectations regarding the performance of the BI system will lead to higher intention to use. The findings for PE showed that the BI users found the system to be useful to their job as it enables them to accomplish their tasks quickly, leading to increased productivity.

Effort expectancy refers to the ease of using and working with the BI system. New systems require a certain degree of effort that needs to be applied by the user. Venkatesh et al. (2003) developed the concept of effort expectancy from various factors. EE is considered vital during the initial stages of adoption as users are required to put considerable effort into learning the new system. If individuals are required to expend effort, they might be demotivated to use the system. On the other hand, when the information system is easy to understand – reducing effort in learning – then users will be motivated in using such systems. This is the ease of access, ease of navigation, and overall ease of use (Volery and Lord, 2000; Bach et al., 2016). The findings for EE showed that BI systems are easy to operate and therefore minimal efforts are required when using BI systems.

Social influence refers to the individual's acceptance of the system based on the actions of others. The findings for SI show that the employees receive support from people who are important to them, be it peers or managers. Khechine et al. (2016) have identified the influence of peers and managers as the influencers. Other researchers have found a similar influence of superiors and those in the employee's same department as influencers (Eckhardt et al., 2009). These authors also pointed out that the weakest influencers are the implementers of the system. This could be because implementers may be biased about the system that they are implementing and, therefore, users neglect their opinions. The influence of SI on the use of BI systems has also been pointed out by authors such as Grublješič and Jaklič (2015), who have stated that the positive influence of people in the social circle, such as peers and superiors, could increase the use of BI systems.

Venkatesh et al. (2003) developed UTAUT which is generic in context and does not demonstrate the direct impact of PE, EE, and SI on system use. Studies such as Bischoff et al. (2015) investigated the impact of perceived usefulness and perceived ease of use on continued use of BI using TAM. Grublješič et al. (2017) used UTAUT to study the acceptance of BI. They were able to identify the positive role of PE, EE, and SI on behavioural intention but did not use these factors to study BI system use directly. However, this research has investigated the direct impact of PE, EE, and SI on BISU.

6.6 The role of moderators

With regards to the moderating impact on BISU, this research finds that gender, age, and experience are not significant. BI systems depend on other core IT systems such as the customer relationship management (CRM), enterprise resource planning (ERP), etc. These are online transactional processing (OLTP) systems that are mandatory to use. BI is an online analytical processing (OLAP) system that derives data from OLTP platforms to carry out queries and provide results. BI applications include activities relative to decision support systems (DSS), query and reporting, statistical analysis, forecasting, and data mining (Phillips-Wren et al., 2021). Examples provided by Al-Khowarizmi et al. (2021) are "enterprise search engines, data mining engines and reporting servers" (p. 226). Therefore, the choice of using BI systems, how they are used, and when they are used, depends on managerial needs. The findings therefore indicate the voluntariness and need-based usage of BI systems. The descriptive results for VU indicate that usage is not based on individual voluntariness. In other words, the usage is not optional and using BI systems is part of the participants' jobs. However, the moderating impact showed that VU significantly and positively moderates the relationship between SI and BISU. This could be explained in such a way that SI would be more effective in determining BISU if users believed that BISU was more voluntary. This shows that the use of BI systems depends on whether it is mandatory or optional to use and that this is linked to social influence. In other words, what influential figures in the workplace think about whether the use of BI systems is voluntary or not plays a significant role on BISU, hence the positive role of moderation.

Chapter 7: Conclusion and recommendations

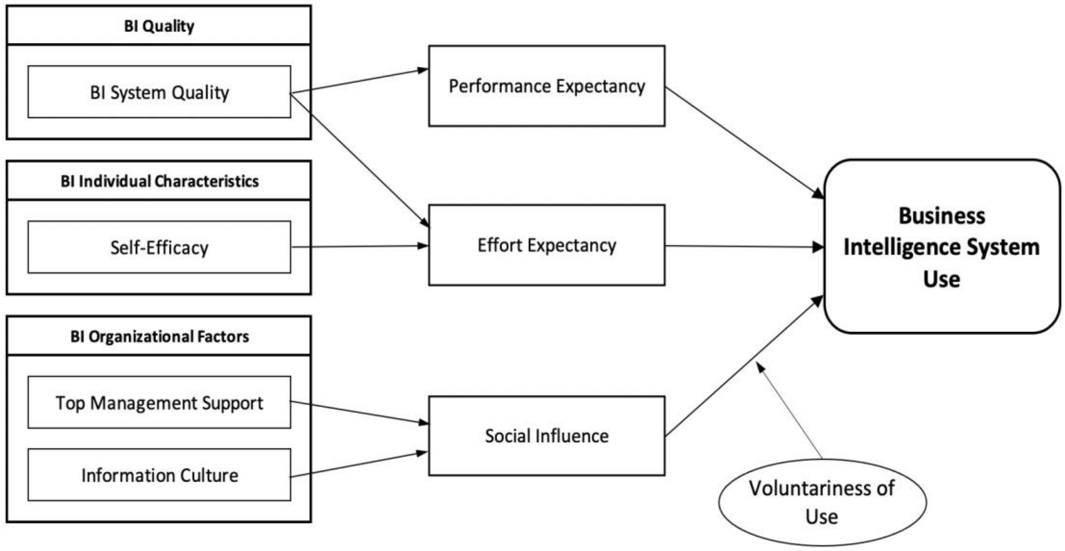
7.1 Introduction

This chapter starts by presenting the revised framework – the Business Intelligence System Use Model (BISUM). This is followed by answering the research questions, discussing the theoretical contributions, the methodological contributions, the managerial recommendations, the limitations, and the future research recommendations.

7.2 The business intelligence system use model (BISUM)

This thesis investigated the antecedents of business intelligence system use (BISU). A conceptual framework was presented based on a thorough review of the literature. The conceptual framework was empirically tested. Consequently, each hypothesis was either accepted or rejected. This process led to revisiting the conceptual framework and presenting a new model – the Business Intelligence System Use Model (BISUM). Figure 7.1 depicts the BISUM.

Figure 7.1: Business intelligence system use model (BISUM)



This proposed model finds that BISU is positively impacted by performance expectancy (PE), effort expectancy (EE), and social influence (SI). One BI quality characteristic, namely BI system quality (SQ) positively impacts both PE and EE. Self-efficacy (SE), an individual characteristic, positively impacts EE. Two organisational factors positively impact social influence, namely, top management support (TMS) and information culture (IC). Furthermore, voluntariness of use (VU) positively moderates the relationship between SI and BISU.

The BISUM identifies critical beliefs regarding system quality, self-efficacy, top management support, and information culture that indirectly impact BISU through their behavioural mediators. It also identifies that voluntariness of use is perceived importantly when addressing BI system use. The model draws the causal relationships that were previously aggregated in Grublješič and Jaklič (2015) BIEUM and emphasises the important antecedents impacting BISU.

7.3 Answering the research questions

Chapter 1 presented three questions that this research aimed at investigating. This section answers each research question independently.

7.3.1 Research question 1

To what degree do different system and information quality characteristics, individual characteristics, and organisational factors influence different behavioural beliefs of employees regarding BI system use?

The emphasis of the question focuses on the degree by which behavioural beliefs of performance expectancy, effort expectancy, and social influence are impacted by their antecedents. These antecedents are grouped into system and information quality, individual characteristics, and organisational factors.

Empirical results demonstrate that out of the two BI system and information quality characteristics, only BI system quality impacts both performance and effort expectancies. However, the degree by which system quality impacts effort expectancy appeared to be higher than that of performance expectancy. The results also reveal that self-efficacy is the only individual characteristic to influence effort expectancy. This impact is slightly lower than the impact of system quality on effort expectancy. Furthermore, both investigated organisational factors: top management support and information culture, impact social influence. The impact of information culture on social influence was higher.

7.3.2 Research question 2

To what degree does performance expectancy, effort expectancy, and social influence affect BI system use?

The question focuses on the degree by which business intelligence system use is influenced by its determinant behavioural beliefs, namely performance expectancy, effort expectancy, and social influence.

The empirical results indicate that performance expectancy, effort expectancy, and social influence all have a positive impact on business intelligence system use. All three behavioural beliefs appear to highly impact business intelligence system use. Effort expectancy has the highest impact on business intelligence system use, this is respectively followed by social influence and performance expectancy.

7.3.3 Research question 3

Does gender, age, experience, and voluntariness of use have a moderating effect between different behavioural beliefs and BI system use?

The question focuses on the role of moderators between different behavioural beliefs and business intelligence system use. The moderators are gender, age, experience, and voluntariness of use.

The empirical results revealed that the only moderator of significance is voluntariness of use. Voluntariness of use positively moderates the relationship between social influence and business intelligence system use. Gender, age, and experience do not play a moderating role. However, it must be noted that this may be due to the fact that the sample does not include many females and certain age groups are minimally represented within the sample. This is further discussed in the research limitations section.

7.4 Theoretical contributions

This research contributes to the literature by investigating the antecedents of business intelligence system use. This research has developed a holistic model combining disparate factors including BI system quality characteristics, individual characteristics, and organisational factors.

Although Grublješič and Jaklič (2015) BIEUM have established the links between BI system quality, individual characteristics, and organisational factors on one side, and behavioural beliefs on the other, they only suggest this in an aggregated manner with no indication of which specific variable impacts the other. This research, however, draws the causal links indicating the cause and effect relationships between variables. It thus illustrates that BI system quality impacts both performance and effort expectancies, self-efficacy impacts effort expectancy, and both top management support and information culture impact social influence.

Furthermore, this research has investigated business intelligence system use in the post-implementation stage, providing an understanding of the continued use of business intelligence systems. The BI users that participated were from organisations that already implemented BI systems, hence, BI system use does not reflect testing the use of a new information system but rather an existing one.

Additionally, this research has highlighted how information culture indirectly impacts business intelligence system use through social influence. Although few studies discuss information culture, this specific relationship is not found in the existing body of literature. However, information culture has resulted in higher impact on social influence when compared to top management support. This can be conceived since information is fundamental in the BI context.

This research has also contributed to literature by investigating the individual characteristics required for BI system use. As suggested by Ain et al. (2019) and addressed in chapter 2, this area is under-investigated.

7.5 Methodological contributions

The BIEUM conceptualised by Grublješič and Jaklič (2015) explored business intelligence system use through qualitative methods. This research, however, used quantitative methods to empirically and holistically investigate business intelligence system use. The direct and indirect antecedents degree in impacting business intelligence system use is therefore known. The insignificant constructs were hence dropped in the revisited model. The empirical investigation has provided the ability to compare how different constructs impact BISU either directly or indirectly. Although BI quality characteristics, individual characteristics, and organisational factors were studied in earlier research, a holistic empirical test of these disparate constructs was missing in the context of BI and has been addressed in this research.

7.6 Contextual contributions

As addressed in contextual gap in chapter 2, no research that investigates BI system use in the telecom and banking industries of Kuwait was identified. This research, however, is conducted in Kuwait's telecom and banking industries. This fills a country and industry relevant gap in literature discussing BI system use. The results can be used for future cross-sectional research focusing on different countries and industries. Although the findings are generalised, it must also be noted that telecom and banking organisations hold substantial amounts of data, making BI systems critical for their success.

7.7 Managerial recommendations

To attain higher levels of BI system use, the BI system should be perceived as useful and should not require much effort to use. Employees must also believe that other organisation members encourage use. These are all behavioural beliefs of performance expectancy, effort expectancy, and social influence. The problem is that management could not directly change behavioural beliefs to increase BI system use unless they address their antecedents. Thus, BI quality characteristics, individual characteristics, and organisational factors are factors that organisations can address, and they consequently would impact the behavioural beliefs of employees that use BI.

From the system perspective, increasing BI system quality would enhance performance and effort expectancies. Managers should utilise their IT department and supporting vendors in ensuring that the BI system is reliable, readily accessible, adapted to meet a variety of needs, effectively integrates data from different source systems, and does not take long to respond to user queries.

The individual characteristics of the user have highlighted the importance of self-efficacy in impacting effort expectancy. The findings have pointed out that BI users feel confident in using BI systems, which is positive. However, dependence on technology is increasing and management demands for data-driven information are increasing and becoming more complex. Therefore, employees required to use the BI system need to be trained on using the system, understanding the different data sources, and conducting meaningful analyses that would support management in decision making.

From the organisational factors, both top management support and information culture are critical in impacting social influence. Top management should continuously show enthusiasm towards using the BI system. They must also involve themselves in BI-related matters emphasising the importance of the BI system to employees. They may also set Key performance indicators (KPIs) related to BI system use, thereby encouraging employees to use the system.

Furthermore, managers must focus on a culture where information is valued. Employees would be more driven to continuously use the BI system if they perceive that their management decisions are based on tangible information rather than mere intuition. Seeking out relevant information, exchanging information, justifying decisions based on information, and trusting formal information sources over informal ones must be supported and embedded in the culture of the organisation.

7.8 Research limitations

This research has collected data from BI users in Kuwait's telecom and banking industries. The aim of this research is to investigate BI system use in an environment where BI systems are already implemented, thus focusing on continued use of BI systems. The findings have provided the factors that directly and indirectly influence BI system use. However, there are limitations that may have affected the results. This section discusses these limitations.

7.8.1 Omission of facilitating conditions

This research has excluded 'facilitating conditions' which is part of the UTAUT model. Facilitating conditions plays a significant role is many UTAUT studies and was found to be the only direct determinant of system use (Venkatesh et al., 2003). However, the grounds of omission were based on the merit that the construct groups many constructs to one as suggested by van Raaij and Schepers (2008). This omission may have had its effect on certain outcomes of this research.

7.8.2 Demographic variance and the sample size

Furthermore, the demographics results have shown significantly higher responses from males (79%) in comparison to females (21%). In addition, the demographic results have indicated a significantly higher number of responses from the age group of 30-39 years (53%) in comparison to age groups of 40-49 years (23%), 20-29 years (20%), and 50 years and above (4%). These two demographical limitations are a result of the sample that has not been demographically distributed. Therefore, having mostly males with a certain age group responding to this research's survey may be a reason to why the demographic moderators of gender and age have not been effective.

In addition, this research collected data from 211 BI users in Kuwait's telecom and banking industries. While this number of respondents is valid for a 95% confidence interval and 5% margin of error, having a larger number of respondents may affect the results and perhaps would have greater demographic variance. This limitation may be addressed by applying the framework to a larger number of organisations in different countries.

7.8.3 The importance of managers

BI systems are intended to enhance the decision making of managers. This research has targeted BI users in different roles. Only 30% of the respondents were managers or held higher positions. A focus on managers who actually make decisions and use BI systems for their decision making would provide a more concentrated perspective that may add value in investigating the use of BI systems.

7.8.4 The time-horizon

It is also important to emphasise that this research is cross-sectional where the data is collected in a single point of time. It does not explain the evolvement of BI system use at different stages after BI system implementation. To understand the use of BI systems over a longer period, a longitudinal research would be required. This would necessitate carrying out repeated data collection and engaging participants for longer periods of time. However, it would be beneficial in providing an understanding into how BI system use would change and evolve over time.

7.9 Future research recommendations

The BISUM focused on important antecedents that impact the use of BI systems. This model may be adopted in future research aiming at investigating BI system use. However, the moderators of gender, age, and experience may be retested with a larger and more variant sample to thoroughly investigate their moderating effect.

Future research may also focus on managers since BI systems are intended for decision makers. The responses from managers may be studied comparatively with other members of the organisation to further understand whether the role of the employee impacts the outcomes of the investigation.

A further recommendation is to conduct research regarding the topic with longitudinal time-horizons. Longitudinal studies would reveal further information with regards to the continued use of BI systems. These studies should focus on how BI system use evolves through different stages from the initial implementation to the stage where BI systems are routinely used and embedded within organisational operations. Repeated data collection at each stage may reveal differences in how different antecedents are perceived by users.

Additionally, future research investigating BI system use can focus on small and medium sized enterprises. As previously suggested in chapter 2, these organisations face challenges with regards to low data volumes (English and Hoffmann 2018; Salisu et al., 2021). These organisations are also less hierarchal in terms of organisational structure and have a smaller number of employees when compared to large corporations investigated in this research.

Research focusing on small and medium sized enterprises could suggest how organisational size impacts the use of business intelligence systems.

These recommendations for future research could result in different findings and may contribute to further extending the BISUM to incorporate constructs that have not been investigated in this research.

References

Abelló, A., Darmont, J., Etcheverry, L., Golfarelli, M., Maz, J.-N., Naumann, F., Pedersen, T., Rizzi, S. B., Trujillo, J., Vassiliadis, P., and Vossen, G. (2013) 'Fusion Cubes: Towards Self-Service Business Intelligence', *International Journal of Data Warehousing and Mining*, 9(2), 66–88.

Agarwal, R., and Dhar, V. (2014) 'Editorial—big data, data science, and analytics: The opportunity and challenge for IS research', *Information Systems Research*, 25(3), 443–8.

Agarwal, R., and Prasad, J. (1998) 'The antecedents and consequents of user perceptions in information technology adoption', *Decision Support Systems*, 22(1), 15–29.

Agudo-Peregrina, Á., Hernández-García, Á. and Pascual-Miguel, F. (2014) 'Behavioural intention use behaviour and the acceptance of electronic learning systems: Differences between higher education and lifelong learning', *Computers in Human Behaviour. 34,* 301–14.

Ahmad, N., Tarek Amer, N., Qutaifan, F. and Alhilali, A. (2013) 'Technology adoption model and a road map to successful implementation of ITIL', *Journal of Ent Info Management*, 26(5), 553–576.

Ahmad, A., Ahmad, R., and Hashim, K. F. (2016) 'Innovation Traits for Business Intelligence Successful Deployment', *Journal of Theoretical and Applied Information Technology*, 89(1), 96–107.

Ahmad, S., Miskon, S., Alkanhal, T.A., and Tlili, I. (2020a) 'Modelling of Business Intelligence Systems Using the Potential Determinants and Theories with the Lens of Individual, Technological, Organisational, and Environmental Contexts-A Systematic Literature Review', *Applied Sciences*, 10(3208), 1–23.

Ahmad, S., Miskon, S., Alkanhal, T.A., and Tlili, I. (2020b) 'Towards Sustainable Textile and Apparel Industry: Exploring the Role of Business Intelligence Systems in the Era of Industry 4.0', *Sustainability*, 12, 2632.

Ahmadi, H., Valipour, H., and Jamali, G. (2021). 'Relationship Between Business Intelligence Components and Financial Reporting Quality in Firms'. *Journal of Optimization in Industrial Engineering*, *4*(2), 155-167.

Ain, N. U., Vaia, G., DeLone, W.J., and Waheed, M. (2019) 'Two decades of research on business intelligence system adoption, utilisation and success – A systematic literature review', *Decision Support Systems*, 125, 113113.

Airinei, D., and Berta, D-A. (2012). 'Semantic Business Intelligence - a New Generation of Business Intelligence'. *Informatica Economică, 16*(2), 72-80.

Ajzen, I. (1991). 'The theory of planned behaviour', *Organisational Behaviour and Human Decision Processes*, 50(2), 179–211.

Alaskar, T. and Efthimios, P. (2015) 'Business Intelligence Capabilities and Strategies', *International Journal of Global Business*, 8(1), 34–45.

Albudaiwi, D. and Allen, M. (2018). *Surveys, Advantages and Disadvantages of in: The SAGE Encyclopedia of Communication Research Methods*. SAGE Publications, Inc. 1735-1736.

Al-Eisawi, D., Serrano, A. and Koulouri, T. (2021). 'The effect of organisational absorptive capacity on business intelligence systems efficiency and organisational efficiency'. *Industrial Management & Data Systems*, *121* (2), 519-544.

Ali, G. and Arýtürk, U. (2014) 'Dynamic churn prediction framework with more effective use of rare event data: The case of private banking', *Expert Systems with Applications*, 1(17), 7889–7903.

Aliyu, A. A., Bello, M. U., Kasim, R., and Martin, D. (2014), 'Positivist and non-positivist paradigm in social science research: Conflicting paradigms or perfect partners?', *Journal of Management and Sustainability*, 4(3), 79–95.

Al-Natour, S., and Benbasat, I. (2009) 'The Adoption and Use of IT Artifacts: A New Interaction-Centric Model for the Study of User-Artifact Relationships', *Journal of the Association for Information Systems*, 10(9), 661–685.

Al-Khowarizmi, Lubis, M., Lubis, A.R., Fauzi, and Nasution, I.R. (2021) 'Model of Business Intelligence Applied the Principle of Cooperative Society in the Business Forums'. *In 2021 10th International Conference on Software and Computer Applications (ICSCA 2021),* February 23–26, 2021, Kuala Lumpur, Malaysia. ACM, New York, NY, USA, 1-5.

Alpar, P., and Schulz, M. (2016) 'Self-Service Business Intelligence', *Business and Information Systems Engineering*. 58(2), 151–155.

Alraja, M. (2015) 'User Acceptance of Information Technology: A Field Study of an E-Mail System Adoption from the Individual Students' Perspective', *Mediterranean Journal of Social Sciences*, 6(6), 19–25.

Ali, Q., Yaacob. H., Parveen, S., and Zaini, Z. (2021). 'Big data and predictive analytics to optimise social and environmental performance of Islamic banks'. *Environment Systems and Decisions, 41*(2021), 616-632.

Ambarwati, R., Harja, Y.D. and Thamrin, S. (2020) 'The Role of Facilitating Conditions and User Habits: A Case of Indonesian Online Learning Platform'. *Journal of Asian Finance, Economics and Business.* 7(10), 481-489.

Araz, O. M., Choi, T. M., Olson, D. L., and Salman, F. S. (2020). 'Role of analytics for operational risk management in the era of big data'. *Decision Sciences, 51*(6), 1320-1346.

Arefin, S., Hoque, R. and Rasul, T. (2020) 'Organisational learning culture and business intelligence systems of health-care organisations in an emerging economy', *Journal of Knowledge Management,* 25(3), 573–594.

Arnott, D., Lizama, F., and Song, Y. (2017) 'Patterns of business intelligence systems use in Organisations', *Decision Support Systems,* 97, 58–68.

Ashraf, S and Khan, S. A. (2015) 'Visualizations-based Analysis of Telco Data for Business Intelligence', *Proceedings of the IEEE International Conference on Software Engineering and Service Sciences,* November, 242–246.

Audzeyeva, A., and Hudson, R. (2015) 'How to get the most from a business intelligence application during the post implementation phase and quest; Deep structure transformation at a UK retail bank', *European Journal of Information Systems,* 25, 29–46.

Awa, H., and Ukoha, K. (2020) 'Studying Enterprise Systems' acceptance using integrated Unified Theory of Acceptance and Use of Technology (UTAUT)', *Journal of Sustainability Science and Management,* 15(5), 98–126.

Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S., and Delen, D. (2019). 'Business analytics and firm performance: The mediating role of business process performance'. *Journal of Business Research, 96*(2019), 228-237.

Bach, M., Čeljo, A. and Zoroja, J. (2016) 'Technology Acceptance Model for Business Intelligence Systems: Preliminary Research', *Procedia Computer Science,* 100, 995–1001.

Bach, M. P., Jakliˇc, J., and Vugec, D.S. (2018). 'Understanding impact of business intelligence to organizational performance using cluster analysis: Does culture matter?' *International Journal of Information Systems and Project Management, 6*(2018), 63-86.

Bagozzi, R. P. (2007) 'The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift', *Journal of the Association for Information Systems*, 8, 244–254.

Bagozzi, R. P., Davis F. D., and Warshaw, P. R. (1992) 'Development and Test of a Theory of Technological Learning and Usage', *Human Relations*, 45, 659–686.

Bailey, K. (2008) *Methods of Social Research*. Fourth Ed. New York: Simon and Schuster.

Baishya, K. and Samalia, H.V. (2020) 'Extending unified theory of acceptance and use of technology with perceived monetary value for smartphone adoption at the bottom of the pyramid', *International Journal of Information Management*, 51, 102036.

Bananuka, J., Mukyala, V., Tumwebaze, Z., Ssekakubo, J., Kasera, M. and Najjuma, M.S. (2020) 'The intention to adopt Islamic financing in emerging economies: evidence from Uganda', *Journal of Islamic Accounting and Business Research*, 11(3), 610–628.

Bandura, A. (1995) *Self-efficacy in Changing Societies*. Cambridge: Cambridge University Press.

Barnham, C. (2015) ‘Quantitative and qualitative research: Perceptual foundations’, *International Journal of Market Research*, 57(6), 837–854.

Barajas-Portas, K. (2017) ‘Analysing Brand Love: Integration of Predictive Validity for PLS Models’. *International Journal of Marketing and Business Communication*. *6* (4), 1-8.

Basole, R. C., Seuss, D. C. and Rouse. W. B. (2013) ‘IT innovation adoption by enterprises: Knowledge discovery through text analytics’, *Decision Support Systems,* 54, 1044–1054.

Basile, L. J., Carbonara, N., Pellegrino, R., and Panniello, U. (2021). ‘The improvement of the clinical decision-making through the Business Intelligence’. *29th Mediterranean Conference on Control and Automation (MED),* (2021), 22-25.

Bell, J. and Waters, S. (2014) *Doing Your Research Project*. Sixth Ed. Maidenhead: Open University Press.

Benbasat, I., and Barki, H. (2007) ‘Quo Vadis, TAM?’, *Journal of the Association for Information Systems*, 8(4), 211–218.

Bhattacharyya, S., Jha, S., Tharakunnel, K. and Westland, J.C. (2011) ‘Data mining for credit card fraud: A comparative study’, *Decision Support Systems*, 50(3), 602–613.

Bhattacherjee, A. (2001) ‘Understanding Information Systems Continuance: An Expectation-Confirmation Model’, *MIS Quarterly*, 25(3), 351–370.

Bijker, M. and Hart, M. (2013) ‘Factors Influencing Pervasiveness of Organisational Business Intelligence’, BUSTECH 2013, *The Third International Conference on Business Intelligence and Technology,* 27 May–1 June, Valencia, Spain. 21–26.

Bischoff, S., Aier, S., Haki, MK, and Winter, R. (2015) ‘Understanding continuous use of business intelligence systems: a mixed methods investigation’, *Journal of Information Technology Theory and Application,* 16(2), 5–38.

Boadu, M., and Sorour, M. K. (2015). ‘Utilizing grounded theory in business doctoral research: Guidance on the research design, procedures, and challenges’. *International Journal of Doctoral Studies, 10* (2015), 143-166.

Bouchana, S., and Idrissi, M. A. J. (2015). ‘Towards an assessment model of end user satisfaction and data quality in business intelligence systems’, *2015 10th International Conference on Intelligent Systems: Theories and Applications (SITA), IEEE*, 1–6.

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

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

Brockhoff, K. (2017). ‘Customer Integration into Continuous Development of IT-based Services’. *The Palgrave Handbook of Managing Continuous Business Transformation,* (2017), 315-334.

Buchwald, A., Urbach, N., and von Entreß-Fürsteneck, M. (2018) ‘Insights into personal ICT use: understanding continuance and discontinuance of wearable self-tracking devices (2018)’, *Proceedings of the 26th European Conference on Information Systems*, Portsmouth, United Kingdom.

Burton-Jones, A. and Straub, D. W. (2006) 'Reconceptualizing System Usage: An Approach and Empirical Test'. *Information Systems Research*, 17(3), 228–246.

Calza, F., Parmentola, A., and Tutore, I. (2020). 'Big data and natural environment How does different data support different green strategies?' *Sustainable Futures, 2*(2020), 100029.

Canhoto, A. I., and Arp, S. (2017). 'Exploring the factors that support adoption and sustained use of health and fitness wearables'. *Journal of Marketing Management*, 33(1–2), 32–60.

Castleberry, A. and Nolen, A. (2018). 'Thematic analysis of qualitative research data: Is it as easy as it sounds?' *Currents in Pharmacy Teaching and Learning*, 10(2018), 807-815.

Central Agency for Information Technology (2016) *Consolidated Kuwait National ICT Indicators Report*. Kuwait.

Central Bank of Kuwait (2020) *The 47th Economic Report for the Year 2018*.

cbk.com (2021a) 'Conventional Banks'. Retrieved from: https://www.cbk.gov.kw/en/supervision/financial-units/kuwaiti-banks/conventional-banks. Accessed: April 16, 2021.

cbk.com (2021b) 'Islamic Banks'. Retrieved from: https://www.cbk.gov.kw/en/supervision/financial-units/kuwaiti-banks/islamic-banks. Accessed: April 16, 2021.

cbk.com (2021c) 'Specialized Banks'. Retrieved from: https://www.cbk.gov.kw/en/supervision/financial-units/kuwaiti-banks/specialized-banks. Accessed: April 16, 2021.

Chang, Y.-Z., Kao, C.-Y., Hsiao, C. J., Chan, R.-Y., Yu, C.-W., Cheng, Y.-W., Chang, T.-F., and Chao, C.-M. (2015) 'Understanding the Determinants of Implementing Telehealth Systems: A Combined Model of Theory of Planned Behaviour and the Technology Acceptance Model', *Journal of Applied Sciences*, 15(2), 277–282.

Chaubey, A., and Sahoo, C. K. (2021). 'Assimilation of business intelligence: The effect of external pressures and top leaders' commitment during pandemic crisis'. *International Journal of Information Management. 59* (2021) 102344.

Chen, H., Chiang, R., and Storey, V. (2012) 'Business Intelligence and Analytics: From Big Data to Big Impact', *MIS Quarterly*, 36(4), 1165–1188.

Chen, Y., and Lin, Z. (2021). 'Business Intelligence capabilities and firm performance: A study in China'. *International Journal of Information Management*, 5(2021), 102232.

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

Chomchalao, S. and Naenna, T. (2013) 'Influence of System Traits and Personal Traits on the Acceptance of e-Government Service', *Information Technology Journal*, 12(5), 880–893.

Choo, C., Bergeron, P., Detlor, B. and Heaton, L. (2008). 'Information Culture and Information Use: An Exploratory Study of Three Organisations', *Journal of the American Society for Information Science and Technology*, 59(5), 1–13.

Choi, C., Kim, C., and Kim, C. (2019). 'Towards Sustainable Environmental Policy and Management in the Fourth Industrial Revolution: Evidence from Big Data Analytics'. *Journal of Asian Finance, Economics and Business*, 6(3), 185-192.

Choy, L. T. (2014) 'The Strengths and Weaknesses of Research Methodology: Comparison and Complimentary between Qualitative and Quantitative Approaches', *IOSR Journal of Humanities and Social Science,* 19(4). 99–104.

Clark, V. L. P. and Ivankova, N. V. (2017). 'How do Personal Contexts Shape Mixed Methods? Considering Philosophical, Theoretical, and Experiential Foundations for Mixed Methods Research' In: *Mixed Methods Research: A Guide to the Field. SAGE research methods*, 2017, 191-216.

Coorevits, L., and Coenen, T. (2016) 'The rise and fall of wearable fitness trackers', *Academy of Management,* 1-23.

Côrte-Real, N., Ruivo, P. and Oliveira, T., (2014) 'The diffusion stages of business intelligence and analytics (BI&A): a systematic mapping study'. *Procedia Technology*, 16, 172–179.

Costa, C., Ferreira, E., Bento, F. and Aparicio, M. (2016) 'Enterprise resource planning adoption and satisfaction determinants', *Computers in Human Behaviour,* 63, 659–671.

Creswell, J. (2013) *Qualitative, Quantitative, and Mixed Methods Approaches*. London: SAGE.

Cramer-Petersen, C. L., Christensen, Bo, T., and Ahmed-Kristensen, S. (2018). 'Empirically analysing design reasoning patterns: Abductive-deductive reasoning patterns dominate design idea generation'. *Design Studies. 60*(2019), 39-70.

Curko, K., Bach, M. P., and Radonic, G. (2007) ‘Business intelligence and business process management in banking operations’, *Proceedings of the 29th ITI Conference on Information Technology Interfaces*, Cavtat, Croatia, 57–62.

Curry, A., Moore, C., (2003) ‘Assessing information culture – an exploratory model’, *International Journal of Information Management*, 23, 91–110.

Daradkeh, M. and Al-Dwairi, R.M. (2017) ‘Self-Service Business Intelligence Adoption in Business Enterprises: The Effects of Information Quality, System Quality, and Analysis Quality’. *International Journal of Enterprise Information Systems. 13* (3), 65-85.

Davenport, T. (2006) ‘Competing on Analytics’, *Harvard Business Review*, 84, 98–107.

Davenport, T. H., Harris, J. G., and Morison. R. (2010) *Analytics at Work: Smarter Decisions, Better Results*. Boston: Harvard Business School.

Davis, F. D. (1993) ‘User Acceptance of Information Technology: System Characteristics, User Perceptions and Behavioral Impacts’, *International Journal of Man-Machine Studies*, 38(3), 475–87.

Davis, F. D., Bagozzi, R. P., Warshaw. P. R. (1989) ‘User Acceptance of Computer Technology: A Comparison of Two Theoretical Models’, *Management Science*, 35(8), 982–1003.

Davis, F. (1989) ‘Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology’, *MIS Quarterly*, 13(3), 319–40.

Davis, K. (2014), ‘Different stakeholder groups and their perceptions of project success’, *International Journal of Project Management*, 32(2), 189-201.

Dawson, J. (2018) ‘An Introduction to Classical Test Theory and Quantitative Survey Data’, in *Analysing Quantitative Survey Data for Business and Management Students*, London: SAGE.

De Jager, T., and Brown, I. (2016). ‘A Descriptive Categorized Typology of Requisite Skills for Business Intelligence Professionals’. *SAICSIT '16*(2016), 26-28.

De Vaus, D. A. (2002). *Surveys in social research*. Fifth Ed. Psychology Press.

Dehning, B. and Richardson, V.J. (2002) ‘Returns on Investments in Information Technology: A Research Synthesis’, *Journal of Information Systems*, 16(1), 7–30.

DeLone, W. H. and McLean, E. R. (1992) ‘Information systems success: the quest for the dependent variable’, *Information Systems Research*, 3(1), 60–95.

Deng, X. and Chi, L. (2012). ‘Understanding post adoptive behaviors in information systems use: a longitudinal analysis of system use problems in the business intelligence context’, *Journal of Management Information Systems*, 29(3), 291–326.

Dudwick, N., Kuehnast, K., Jones, V. N., and Woolcock, M. (2006) *Analyzing Social Capital in Context: A Guide to Using Qualitative Methods and Data*, Washington: World Bank Institute.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., and Williams, M. D. (2017). ‘Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model’, *Information Systems Frontiers*, 1–16.

Eckhardt, A., Laumer, S., and Weitzel, T. (2009) 'Who influences whom? Analysing workplace referents' social influence on IT adoption and non-adoption', *Journal of Information Technology*, 24(1), 11–24.

Eekhout, I., de Vet, H. C. W., Twisk, J. W. R., Brand, J. P. L., de Boer, M. R., and Heymans, M. W. (2014) 'Missing data in a multi-item instrument were best handled by multiple imputation at the item score level', *Journal of Clinical Epidemiology*, 67(2014), 335–342.

El Ghalbzouri, H., and El Bouhdidi, J. (2022). 'Integrating Business Intelligence with Cloud Computing: State of the Art and Fundamental Concepts'. *Smart Innovation, Systems and Technologies, 237*(2022), 197-213.

El-Haddadeh, R., Osmani, M., Hindi, N., and Fadlalla, A. (2021). 'Value creation for realising the sustainable development goals: Fostering organisational adoption of big data analytics'. *Journal of Business Research, 131*(2021), 402-410.

Elbashir, M. Z., Collier, P. A. and Davern, M. J. (2008) 'Measuring the effects of business intelligence systems: the relationship between business process and organisational performance', *International Journal of Accounting Information Systems*, 9(3), 135–153.

Elbashir, M. Z., Sutton, S. G., Mahama, H., and Arnold, V. (2021). 'Unravelling the integrated information systems and management control paradox: enhancing dynamic capability through business intelligence'. *Accounting & Finance 61* (2021) 1775–1814.

Elgendy, N., and Elragal, A. (2014). 'Big data analytics: a literature review paper', in: Indus-trial Conference on Data Mining, *Springer*, 2014, 214-227.

English, V. and Hoffmann, M. (2018) 'Business Intelligence as a Source of Competitive Advantage in SMEs: A Systematic Review'. *DBS Business Review. 2*(2018), 10–32.

Epstein, D. A., Caraway, M., Johnston, C., Ping, A., Fogarty, J., and Munson, S. A. (2016) 'Beyond abandonment to next steps: understanding and designing for life after personal informatics tool use', in *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems,* ACM, May, 1109–1113.

Evans, J. R. and Mathur, A. (2005) 'The value of Online Surveys', *Internet Research*, 15(2), 195–219.

Foshay, N., Taylor, A., and Mukherjee, A. (2014) 'Winning the hearts and minds of business intelligence users: the role of metadata', *Information Systems Management*, 31(2), 167–180.

Furneaux, B. and Wade, M. (2011) 'An Exploration of Organisational Level Information Systems Discontinuance Intentions', *MIS Quarterly*, 35(3), 573–598.

Gaardboe, R., Nyvang, T., and Sandalgaard, N. (2017) 'Business intelligence success applied to healthcare information systems', *Procedia Computer Science,* 121(2017), 483–490.

Galal, H. S., Mahdy, Y. B. and Atiea, M. A. (2016) 'Behaviour-based features model for malware detection', *Journal of Computer Virology and Hacking Techniques,* 12(2), 59–67.

Gartner (2017) 'Gartner says worldwide business intelligence and analytics market to reach $18.3 billion in 2017'. Available at: https://www. gartner.com/newsroom/id/3612617. Accessed: September 6, 2019.

Gao, J., Wang, H., and Shen, H. (2020). 'Task failure prediction in cloud data centers using deep learning'. *IEEE Transactions on Services Computing*.

Gao, Z., Dai, X., Wang, X., Zhao, L., and Liu, J. (2020). 'Spectrum Sensing Method in Multi-primary users Environment. Application of Intelligent Systems in Multi-modal Information Analytics' Proceedings of the 2020. *International Conference on Multi-model Information Analytics* (MMIA2020), 1(2020), 3-8.

Garmaroodi, M. S. S., Farivar, F., Haghighi, M. S., Shoorehdeli, M. A., and Jolfaei, A. (2020). 'Detection of anomalies in industrial IOT systems by data mining: Study of CHRIST osmotron water purification system'. *IEEE Internet of Things Journal, 8* (2020), 10280–10287.

Garson, D.G. (2016) *Partial Least Squares: Regression & Structural Equation Models*. Statistical Publishing Associates. Asheboro. USA.

Ghauri, P. N. and Grønhaug, K. (2005) *Research Methods in Business Studies: A practical guide*, London: Pearson Education.

Ghalbzouri, H. and El Bouhdidi, J. (2022) 'Integrating Business Intelligence with Cloud Computing: State of the Art and Fundamental Concepts. Networking, Intelligent Systems and Security', *Proceedings of NISS 2021, 237*, 197-213.

Gill, J. and Johnson, P. (2010) *Research Methods for Managers*, London: Sage.

Gonzales, R., Wareham, J., and Serida, J. (2015) 'Measuring the impact of data warehouse and business intelligence on enterprise performance in Peru: a developing country', *Journal of Global Information Technology Management*, 18(3), 162–187.

Greener, S., 2008. *Business research methods*. BookBoon.

Greener, S. and Martelli, J., 2018. *An introduction to business research methods*. BookBoon.

Grublješič, T., Coelho, P. S. and Jaklič, J. (2014) ‘The importance and impact of determinants influencing business intelligence systems embeddedness’, *Issues in Information Systems*, 15(1), 106-117.

Grublješič, T. and Jaklič, J. (2015) ‘Conceptualisation of the business intelligence extended use model’, *Journal of Computer Information Systems*, 55(3), 72–82.

Grublješič, T., Coelho, P. S., and Jaklič, J. (2014) ‘The Importance and Impact of Determinants Influencing Business Intelligence Systems Embeddedness’, *Issues in Information Systems,* 15(1), 106–117.

Grublješič, T., Coelho, P. S., and Jaklič, J. (2017) ‘The Shift to Socio-Organisational Drivers of Business Intelligence and Analytics Acceptance’, *Journal of Organisational and End User Computing*, 31, 37–64.

GSMA (2017) *The Mobile Economy – Middle East and North Africa 2017*.

GSMA (2019) *The Mobile Economy – Middle East and North Africa 2019*.

Gulati, R., Goswami, A. and Kumar, S., (2018) ‘What drives credit risk in the Indian Banking industry? An empirical investigation’, *Economic Systems*, 43(1), 42–62.

Haigang, L. (2005) ‘Application of Business Intelligence Techniques in China Telecom’, *Proceedings of the Fifth International Conference on Electronic Business, Hong Kong, December 5–9*, 101–104.

Hair, J. F., Black, W. C., Babin, B. J. and Anderson, R. E. (2014) *Multivariate Data Analysis*, Seventh Ed. Essex: Pearson New International.

Hair, J. F., Hult, G. T. M., Ringle, C. M., and Sarstedt, M. (2017) *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Thousand Oaks, CA: SAGE.

Hameed, M. A., Counsell, S., and Swift, S. (2012) 'A meta-analysis of relationships between organisational characteristics and IT innovation adoption in organisations', *Information and Management*, 49(5), 218–232.

Harrison, R., Parker, A., Brosas, G., Chiong, R., and Tian, X. (2015) 'The role of technology in the management and exploitation of internal business intelligence', *Journal of Systems and Information Technology*, 17(3), 247–262.

Harwell, M.R. 2011. Research Design in Qualitative/Quantitative/Mixed Methods. In: *The SAGE Handbook for Research in Education: Pursuing Ideas as the Keystone of Exemplary Inquiry*, 2nd ed. Thousand Oaks, CA: SAGE Publications, Inc. pp. 147-164.

Hasan, M. M., Popp, J., and Oláh, J. (2020). 'Current landscape and influence of big data on finance'. *Journal of Big Data, 7*(2020), 21.

Hashem, I.A.T., Yaqoob, I., Anuar, N.B., Mokhtar, S., Gani, A., and Khan, U. S. (2015). 'The rise of "big data" on cloud computing: review and open research issues'. *Information Systems, 47* (2015), 98-115.

Hou, C. (2012). 'Examining the effect of user satisfaction on system usage and individual performance with business intelligence systems: An empirical study of Taiwan's electronics industry', *International Journal of Information Management*, 32(6), 560–573.

Hou, C.-K. (2013) ‘Investigating factors influencing the adoption of business intelligence systems: an empirical examination of two competing models’, *International Journal of Technology, Policy and Management*, 13(4), 328–353.

Hou C. (2014) ‘Exploring the user acceptance of business intelligence systems in Taiwan’s electronics industry: applying the UTAUT model’, *International Journal of Internet and Enterprise Management*, 8(3), 195–226.

Hou, W., and Gao, S. (2018) ‘An Investigation of the Managerial Use of Mobile Business Intelligence. An Investigation of the Managerial Use of Mobile Business Intelligence’, *Pacific Asia Journal of the Association for Information Systems*, 10(3), 87–108.

Housbane, S., Khoubila, A., Ajbal, K., Serhier, Z., Agoub, M., Battas, O., and Othmani, M. B. (2020). ‘Monitoring Mental Healthcare Services Using Business Analytics’. *Health Information Systems*, *26*(2), 146-152.

Huang, Y. K. and Kechad, T. (2013) ‘An effective hybrid learning system for telecommunication churn prediction’, *Expert Systems with Applications*, 40, 5635–5647.

Huang, Z-X., Savita, K. S. and Zhong-jie, J. (2022). ‘The Business Intelligence impact on the financial performance of start-ups’. *Information Processing and Management* 59(2022) 102761.

Hsu, C. H., Manogaran, G., Srivastava, G., and Chilamkurti, N. (2021). ‘6G-enabled network in box (NIB) for industrial applications and services’. *IEEE Transactions on Industrial Informatics*, 17, 7141–7144.

Huang, Z., Chen, H., Hsu, C.-J., Chen, W.-H., and Wu, S. (2004) 'Credit rating analysis with support vector machines and neural networks: A market comparative study', *Decision Support Systems*, 37(2004), 543–558.

Huang, Z-x., Savita, K.S., and Zhong-jie, J. (2022) 'The Business Intelligence impact on the financial performance of start-ups'. *Information Processing and Management. 59*(102761), 1-13.

Hwang, Y., Kettinger, W. J., and Yi, M. Y., (2013) 'A study on the motivational aspects of information management practice', *International Journal of Information Management*, 33, 177–184.

Ihuah, P. W. and Eaton, D. (2013) 'The Pragmatic Research Approach: A Framework for Sustainable Management of Public Housing Estates in Nigeria', *Journal of US-China Public Administration*, 10(10), 933–944.

International Monetary Fund (2020) *Kuwait: 2020 Article IV Consultation – Press Release, Staff Report, and Staff Supplement*. IMF Country Report 20/89. March 2020.

Ishaya, T. and Folarin, M. A. (2012). 'Service oriented approach to Business Intelligence in Telecoms industry', *Telematics and Informatics*, 29, 273–285.

Jaklic, J., Coelho, P. S., and Popovic, A. (2009) 'Do Business Intelligence Systems Actually Improve Information Quality?', *Mathematical Methods and Applied Computing*, 1, 144–449.

Jaklič, J., Grublješič, T., and Popovič, A. (2018) 'The role of compatibility in predicting business intelligence and analytics use intentions', *International Journal of Information Management*, 43, 305–318.

Jayakrishnan, M., Mohamad, A. K., and Yusof, M. M. (2018). 'Assimilation of Business Intelligence (BI) and Big Data Analytics (BDA) Towards Establishing Organisational Strategic Performance Management Diagnostics Framework: A Case Study', *Journal of Digital Information Management*, 16(1), 22–32.

Jordan, P. J., and Troth, A. C. (2020). 'Common method bias in applied settings: The dilemma of researching in organisations'. *Australian Journal of Management*, 45(1) 3-14.

Jorgensen, M. B., Svarre, T., and Christensen, T. (2021). 'The Role of End Users in Efficient Business Intelligence Solutions: A Preliminary Study'. *ICCMB 2021*, (1-4), Singapore,

Kamaghe, J., Luhanga, E. and Kisangiri, M. (2020) 'The Challenges of Adopting M-Learning Assistive Technologies for Visually Impaired Learners in Higher Learning Institution in Tanzania'. *International Journal of Emerging Technologies in Learning*. 15(1), 1-12.

Kang. Y. S. and Lee, H., (2010) 'Understanding the role of an IT artifact in online service continuance: An extended perspective of user satisfaction', *Computers in Human Behaviour*, 26, 353–364.

Kari, T., Koivunen, S., Frank, L., Makkonen, M., and Moilanen, P. (2016) 'Critical experiences during the implementation of a self-tracking technology', in *PACIS 2016: Proceedings of the 20th Pacific Asia Conference on Information Systems*. Association for Information Systems.

Kase, K., Slocum, A., Zhang, Y. Y. (2011) *Asian Versus Western Management Thinking: Its Culture-Bound Nature*, London: Palgrave Macmillan.

Kaur, B. and Singh, V. (2020) 'Business Intelligence: Need and Usage in Indian Corporate Sector', *Journal of Critical Reviews*, 7(11), 2486–2498.

Kester, Q.-A. and Preko, M. (2015) ‘Business Intelligence Adoption in Developing Economies: A Case Study of Ghana’, *International Journal of Computer Application*, 127, 5–11.

Khechine, H., Lakhal, S. and Ndjambou, P. (2016) ‘A meta-analysis of the UTAUT model: Eleven years later’, *Canadian Journal of Administrative Sciences*, 33(2), 138–152.

Kiwanuka, A. (2015) ‘Acceptance process: the missing link between UTAUT and diffusion innovation theory’, *Journal of Information Systems*, 3(2), 40–44.

Kohli, R., and Devaraj, S. (2003) ‘Measuring information technology payoff: A meta-analysis of structural variables in firm-level empirical research’, *Information Systems Research*, 14, 127–145.

Kohnke, O., Wolf, T. R., and Mueller, K. (2011) ‘Managing user acceptance: An empirical investigation in the context of business intelligence standard software’, *International Journal of Information Systems and Change Management*, 5(4), 269–288.

Kositanurit, B., Osei-Bryson, K.-M., and Ngwenyama, O. (2011) ‘Re-examining information systems user performance: using data mining to identify properties of IS that lead to highest levels of user performance’, *Expert Systems with Applications*, 38(6), 7041–7050.

Krishnamoorthi, S., and Mathew, S.K. (2018). ‘Business analytics and business value: A comparative case study’. *Information and Management 55* (2018), 643-666.

Kumar, B. R. (2012) *Mega Mergers and Acquisitions: Case Studies from Key Industries*, London: Palgrave Macmillan.

Kumar, G., Saha, R., Buchanan, W. J., Geetha, G., Thomas, R., Rai, M. K., and Alazab, M. (2020). 'Decentralized accessibility of e-commerce products through blockchain technology'. *Sustainable Cities and Society*, 62(2020), 102361.

Kwahk, K. and Lee, J. (2008) 'The role of readiness for change in ERP implementation: Theoretical bases and empirical validation', *Information and Managemen*t, 45(7), 474–481.

Lautenbach, P., Johnston, K., and 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.

Leidner, D. E., and Kayworth, T. (2006) 'A Review of Culture in Information Systems Research: Toward a Theory of Information Technology Culture Conflict', *MIS Quarterly*, 30(2), 357–399.

Lederer, M., and Schmid, P. (2021). Data Science for Business Analytics and Business Intelligence. *Encyclopedia of Organisational Knowledge, Administration, and Technology* (495–508). IGI Global.

Li, X., Hsieh, J. J. P-A., and 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.

Liang, T. P., and Liu, Y. H. (2018). 'Research landscape of business intelligence and big data analytics: A bibliometrics study'. *Expert Systems with Applications, 111*(128), 2-10.

Liu, L., Miguel Cruz, A., Rios Rincon, A., Buttar, V., Ranson, Q., and Goertzen, D. (2015). 'What factors determine therapists' acceptance of new technologies for rehabilitation-a study using the Unified Theory of Acceptance and Use of Technology (UTAUT)'. *Disability and Rehabilitation,* 37(5), 447-455.

Loon, M. (2019). 'Knowledge management practice system: theorising from an international meta standard'. *Journal of Business Research*, 94(2019), 432-441.

Lu, J., Yao, J. and Yu, C. (2005) 'Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology', *Journal of Strategic Information Systems*, 14(3), 245–268.

Maher, C., Ryan, J., Ambrosi, C., and Edney, S. (2017) 'Users' experiences of wearable activity trackers: a cross-sectional study', *BMC Public Health*, 17(1), 880.

Malhotra, N. K., Hall, J., Shaw, M., and Oppenheim, P. (2004) *Essentials of Marketing Research: An applied orientation*, Melbourne: Pearson Education Australia.

Marchand, D. A., Kettinger, W. J. and Rollins, J. D. (2001) *Information orientation: The link to business performance.* New York: Oxford University Press.

McCusker, K. and Gunaydin, S., 2015. Research using qualitative, quantitative or mixed methods and choice based on the research. *Perfusion*, 30(7), pp.537-542.

Mertens, D. M. (2014), 'Research and evaluation in education and psychology', *Integrating diversity with quantitative, qualitative, and mixed methods*, London: SAGE.

Michalczyk, S., Nadj, M., Azarfar, D., Maedche, A. and Gröger, C. (2020) 'A state-of-the-art overview and future research avenues of self-services business intelligence and analytics', *Proceedings of the 28th European Conference on Information Systems*, virtual conference, 15–17 June 2020.

Moore, G. C., and Benbasat, I. (1991) ‘Development of an instrument to measure the perceptions of adopting an information technology innovation’, *Information Systems Research*, 2(3), 192–222.

Moro, S., Cortez, P., and Rita, P. (2015) ‘Business Intelligence in Banking: A literature Analysis from 2002 to 2013 Using Text Mining and Latent Dirichlet Allocation’, *Expert Systems with Applications*, 42, 1314–1324.

Morville, A-L., Erlandsson, L-K., Danneskiold-Samsøe, B., Amris, K., and Eklund, M. (2015). ‘Satisfaction with daily occupations amongst asylum seekers in Denmark’, *Scandinavian Journal of Occupational Therapy, 22*(3), 207-215

Morris, M. G., Venkatesh, V. and Ackerman, P. L. (2005). ‘Gender and Age Differences in Employee Decisions About New Technology: An Extension to the Theory of Planned Behavior’. *IEEE Transactions on Engineering Management*, 52(1), 69-84.

Mudzana, T and 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.

Nascimento, B., Oliveira, T., and Tam, C. (2018) ‘Wearable technology: what explains continuance intention in smartwatches?’, *Journal of Retailing and Consumer Services,* 43, 157–169.

Nelson, R. R., Todd, P.A., and Wixom, B.H. (2005) ‘Antecedents of information and system quality: an empirical examination within the context of data warehousing’, *Journal of Management Information Systems*, 21(4), 199–235.

Neuman, W. L. (2007) *Basics of Social Research: Qualitative and Quantitative Approaches*, Second Ed. London: Pearson.

Ngai, E., Hu, Y., Wong, Y., Chen, Y., and Sun, X. (2011) 'The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature', *Decision Support Systems*, 50, 559–569.

Niño, H. A. C., Niño, J. P. C., and Ortega, R. M. (2020) 'Business intelligence governance framework in a university: Universidad de la cost a case study', *International Journal of Information Management*, 50, 405–412.

Nithya, N., and Kiruthika, R. (2021). 'Impact of Business Intelligence Adoption on performance of banks: a conceptual framework'. *Journal of Ambient Intelligence and Humanized Computing*, *12*(2021), 3139-3150.

Niu, Y., Ying, L., Yang, J. Bao, M. and Sivaparthipan, C.B. (2021) 'Organisational business intelligence and decision making using big data analytics'. *Information Processing and Management. 58*(102725), 1-13.

Nofal, M. I. M., and Yusof, Z. M. (2016) 'Conceptual model of enterprise resource planning and business intelligence systems usage', *International Journal of Business Information Systems*, 21(2), 178–194.

Nuseir, M.T., Aljumah, A. and Alshurideh, M.T. (2021) 'How the business intelligence in the new startup performance in UAE during COVID-19: The mediating role of innovativeness'. *In The effect of coronavirus disease (covid-19) on business intelligence* (pp. 63-79). Springer, Cham.

Oliveira, T. and Martins, M. F. (2011) ‘Literature review of information technology adoption models at firm level’, *Electronic Journal of Information Systems Evaluation*, 14(1), 110–121.

Olszak, C. (2016) ‘Toward better understanding and use of BI in organisations’. *Information Systems Management*, 33(2), 105–123.

Oncioiu, I., Bunget, O.C., Türkes, M.C., Capusneanu, S., Topor, D.I., Tamas, A.S., Rakos, I.-S., and Hint, M.S. (2019). ‘The Impact of Big Data Analytics on Company Performance in Supply Chain Management’. *Sustainability, 11*(2019), 4864.

ooredoo.com.kw (2020) ‘Ooredoo Kuwait Reports Revenue of KWD 294 million for the First Half of 2020’, press release. Retrieved from: https://www.ooredoo.com.kw/assets/portal/Frontend/Reports/NMTC-Earnings-Release-Q2-2020-English-v4_compressed.pdf. Accessed: Feb 5, 2021.

Owusu, A. (2017) ‘Business intelligence systems and bank performance in Ghana: The balanced scorecard approach: Operations, Information and Technology’, *Cogent Business and Management*, 4, 1–22.

Oyeniyi, O. and Abiodun, A. J. (2010) ‘Switching Cost and Customers Loyalty in the Mobile Phone Market: the Nigerian Experience’, *Business Intelligence Journal*, 3(1), 111–121.

Papadopoulos, T., and Kanellis, P., (2010). ‘A path to the successful implementation of Business Intelligence: An example from the Hellenic Banking sector’. *OR Insight, 23*(1), 15-26.

Paradza, D. and Daramola, O. (2021). ‘Business Intelligence and Business Value in Organisations: A Systematic Literature Review’. *Sustainability, 13*(2021), 11382.

Park, D., Bahrudin, F. I. and Han, J. (2020) ‘Circular Reasoning for the Evolution of Research Through a Strategic Construction of Research Methodologies’, *International Journal of Quantitative and Qualitative Research Methods*, 8(3), 1–23.

Patton, M. Q. (2002) *Qualitative Research and Evaluation Methods*. Third Ed. Thousand Oaks, CA: SAGE.

Passlick, J., Guhr, N., Lebek, B., and Breitner, M. H. (2020). ‘Encouraging the use of self-service business intelligence – an examination of employee-related influencing factors’. *Journal of Decision Systems,* 29(1), 1-26.

Paré, G., Trudel, M.C., Jaana, M. and Kitsiou, S., (2015). ‘Synthesizing information systems knowledge: A typology of literature reviews’. *Information and Management,* 52(2), pp.183-199.

Petter, S. and McLean, E. R, (2009). ‘A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level’. *Information and Management,* 46(3), 159-166.

Petter, S., DeLone, W. and McLean, E. (2013) ‘Information Systems Success: The Quest for the Independent Variables’, *Journal of Management Information Systems*, 29(4), 7–62.

Pham, D. V., Nguyen, G. L., Nguyen, T. N., Pham, C. V., and Nguyen, A. V. (2020). ‘Multi-topic misinformation blocking with budget constraint on online social networks’. *IEEE Access,* 8(2020), 78879–78889.

Phillips-Wren, G., Daly, M. and Burstein, F. (2021). ‘Reconciling business intelligence, analytics and decision support systems: More data, deeper insight’. *Decision Support Systems. 146*(113560), 1-13.

Pillay, K. and van der Merwe, A. (2021) ‘Big Data Driven Decision Making Guidelines for South African Banking Institutions’. *2021 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*, 1-6.

Pimmer, C., Brühlmann, F., Odetola, T. D., Oluwasola, D. O., Dipeolu, O., and Ajuwon, A. J. (2019). ‘Facilitating professional mobile learning communities with instant messaging’. *Computers and Education*, 128, 102-112.

Poonnawat, W., Pacharawongsakda, E., and Henchareonlert, N. (2019). ‘Jobs Analysis for Business Intelligence Skills Requirements in the ASEAN Region: A Text Mining Study’. *AISC, 807*(2019), 187-195.

Popovič, A. (2017) ‘If we implement it, will they come? User resistance in post-acceptance usage behaviour within a business intelligence systems context’, *Economic Research-Ekonomska Istraživanja*, 30(1) 911–921.

Popovič, A., Hackney, R., Coelho, P.S., and Jaklič, J. (2014) ‘How information-sharing values influence the use of information systems: an investigation in the business intelligence systems context’, *Journal of Strategic Information Systems*, 23(4), 270–283.

Popovič, A., Puklavec, B., and Oliveira, T. (2019) ‘Justifying business intelligence systems adoption in SMEs: Impact of systems use on firm performance’, *Industrial Management and Data Systems*, 119(1), 210–228.

Power, D. J., Heavin, C., McDermott, J., and Daly, M. (2018). ‘Defining business analytics: an empirical approach’. *Journal of Business Analytics, 1*(1), 40-53.

Pucciarelli, F. and Kaplan A, (2016). 'Competition and strategy in higher education: Managing complexity and uncertainty'. *Business Horizons,* 59(3), 311-320.

Puklavec, B., Oliveira, T. and Popovič, A. (2014) 'Unpacking business intelligence systems adoption determinants: an exploratory study of small and medium enterprises', *Economic & Business Review*, 16(2), 185–213.

Puklavec, B., Oliveira, T. and Popovič, A. (2017) 'Understanding the determinants of business intelligence system adoption stages: an empirical study of SMEs', *Industrial Management and Data Systems*, 118(1), 236–261.

Pulakkazhy, S. and Balan, R. (2013) 'Data Mining In Banking And Its Applications-A Review', *Journal of Computer Science*, 9(10), 1252–1259.

Ragab, M., and Arisha, A. (2018) 'Research Methodology in Business: A Starter's Guide', *Management and Organisational Studies*, 5(1), 1–24.

Ramana, A. V., Rao, A. S., and Reddy, E. K. (2019). 'Applications of Business Intelligence and Decision Making for the Customer Behaviour Analysis in Telecom Industry'. *International Journal of Recent Technology and Engineering (IJRTE),* 7(6S2), 688-693.

Ranjan, J. (2005) 'Business Intelligence: Concepts, Components, Techniques and Benefits', *Journal of Theoretical and Applied Information Technology*, 9, 60–70.

Rashidirad, M., Salimian, H., Soltani, E., and Fazeli, Z. (2017). 'Competitive strategy, dynamic capability, and value creation: Some empirical evidence from UK telecommunications firms'. *Strategic Change, 26*(4), 333–342.

Ravasan, A. Z. and Savoji, S. R. (2014) 'An investigation of BI implementation critical success factors in Iranian context', *International Journal of Business Intelligence Research*, 5(3), 41–57.

Renaud, K., and Van Biljon, J. (2008) 'Predicting technology acceptance and adoption by the elderly: A qualitative study', in *Proceedings of the Research Conference of the South African Institute of Computer Scientists and Information Technologists on IT Research in Developing Countries* New York, NY: ACM, 210–219.

Richards, G., Yeoh, W., Chong, A.Y.L., and Popovič, A. (2017) 'Business intelligence effectiveness and corporate performance management: an empirical analysis', *Journal of Computer Information Systems*, 59(2), 1–9.

Romanow, D., Napier, N. P., and Cline, M. K. (2020). 'Using Active Learning, Group Formation, and Discussion to Increase Student Learning: A Business Intelligence Skills Analysis'. *Journal of Information Systems Education, 31*(3), 218-231.

Rouhani, S., Ashrafi, A., Zare, A. and Afshari, S. (2016) 'The impact model of business intelligence on decision support and organisational benefits', *Journal of Enterprise Information Management*, 29(1), 19–50.

Rouhani, S., Ashrafi, A., Zare, A., and Afshari, S. (2018) 'Business Intelligence Systems Adoption Model', *The Journal of Organisational and End User Computing*, 30, 43–70.

Sabherwal, R., Jeyaraj, A. and Chowa, C. (2006). 'Information System Success: Individual and Organisational Determinants', *Management Science*, 52(12), 1849–1864.

Sahay, B. S, and Ranjan, J. (2008) 'Real time business intelligence in supply chain analytics', *Information Management and Computer Security*, 16(1), 28–48.

Salisu, S., Mohd Sappri, M. B., and Mohd Omar, F. B., (2021). 'The adoption of business intelligence systems in small and medium enterprises in the healthcare sector: A systematic literature review'. *Cogent Business & Management, 8*(1), 1935663.

Sallam, R. L., Richardson, J., Hagerty, J., and Hostmann, B. (2011) 'Magic Quadrant for Business Intelligence Platforms'. *Gartner RAS Core Research*, 1–50.

Samaradiwakara, G. and Gunawardena, C. (2014) 'Comparison of Existing Technology Acceptance Theories and Models to Suggest a Well Improved Theory/Model', *International Technical Sciences Journal,* 1(1), 21–36.

Saunders, M., Lewis, P. and Thornhill, A. (2009). *Research Methods for Business Students*. Pearson, New York.

Saunders, M., Lewis, P., and Thornhill, A. (2016) *Research Methods for Business Students*. Fifth Ed., Essex: Pearson Education.

Seddon, P.B., Constantinidis, D., Tamm, T., and Dod, H. (2016). 'How does business analytics contribute to business value?' *Information Systems Journal (ISJ), 27*(2016), 237-269.

Sharda, R., Delen, D., Turban, E., Aronson, J. E., Liang, T., and King, D. (2014). *Business intelligence: A managerial perspective on analytics (3rd ed.)*. New York: Prentice Hall.

Sharma, R. K. and Gandhi, P. (2019) 'Study of Reliability of Object-Oriented Structure Consuming CK Metrics', in *6th International Conference on Computing for Sustainable Global Development (INDIACom) 2019*, 828–831.

Shen, K.Y., and Tzeng, G.H. (2016). 'Contextual Improvement Planning by Fuzzy-Rough Machine Learning: Novel Bipolar Approach for Business Analytics'. *International Journal of Fuzzy Systems*, *18*(6), 940-955.

Shirish, A and Batuekueno, L. (2021). 'Technology renewal, user resistance, user adoption: status quo bias theory revisited'. *Journal of Organisational Change Management 34*(5), 874-893.

Shollo, A. and Galliers, R.D. (2015) 'Towards an understanding of the role of business intelligence systems in organisational knowing', *Information Systems Journal*, 26(4), 339–367.

Shu, W., and Strassmann, P. A. (2005) 'Does information technology provide banks with profit?', *Information and Management*, 42, 781–787.

Singh, J., Flaherty, K., Sohi, R.C., Deeter-Schmelz, C., Habel, J., Le Meunier-FitzHugh, K., Malshe, A., Mullins, R. and Onyemah, V. (2019). 'Sales profession and professionals in the age of digitization and artificial intelligence technologies: concepts, priorities, and questions', *Journal of Personal Selling and Sales Management, 39*(1), 1-21.

Skyrius, R., Nemitko, S and Talocka, G. (2018) 'The emerging role of business intelligence culture', *Information Research*, 23(4), 1–20.

Song, J., Kim, J., Jones, D. R., Baker, J., and Chin, W. W. (2014) 'Application discoverability and user satisfaction in mobile application stores: an environmental psychology perspective', *Decision Support Systems*, 59, 37–51.

Spanagel, F. F. (2022). 'Legal Issues of Big Data Application in the Russian Federation'. *Digital Technologies in the New Socio-Economic Reality, 304*(2022), 115-121.

Statista.com (2020) ‘Number of employed people in Kuwait from 2012 to 2015, by gender’. Available at: https://www-statista-com.liverpool.idm.oclc.org/statistics/647326/kuwait-number-of-employed-people-by-gender/. Accessed: July 9, 2020.

stc.com.kw (2021) ‘Key Financial Indicators’. Available at: https://www.stc.com.kw/DigitalStatic/AnnualReport2019/en-annual-report-2019.html. Accessed: February 5, 2021.

Strohmeier, L. (2021). ‘Central Business Intelligence: A lean development process for SMEs’. *Management for Professional*, (2021), 685-698.

Sun, X., Sun, W., Wang, J., Yixin, Z., and Yining, G. (2016). ‘Using a Grey–Markov model optimized by Cuckoo search algorithm to forecast the annual foreign tourist arrivals to China’. *Tourism Management, 52*(2016), 369-379.

Sun, Z., Sun, L., and Strang, K. (2018). ‘Big data analytics services for enhancing business intelligence’. *Journal of Computer Information Systems, 58*(2), 162-169.

Tamer, C., Kiley M., Ashrafi N., and Kuilbar J., (2013) ‘Risk and benefits of Business Intelligence in the Cloud’, *Northeast Decision Sciences Institute Annual Meeting Proceedings*. 86-95.

Tarhini, A., El-Masri, M., Ali, M., and Serrano, A. (2016) ‘Extending the UTAUT model to understand the customers’ acceptance and use of internet banking in Lebanon: A structural equation modelling approach’, *Information Technology and People*, 29, 830–849.

Thompson, R. L., Higgins, C. A., and Howell, J. M. (1991) ‘Personal computing: Toward a conceptual model of utilization’, *MIS Quarterly*, 15(1), 125–143.

Trieu, V.-H. (2017) ‘Getting value from business intelligence systems: a review and research agenda’, *Decision Support Systems*, 93, 111–124.

Tunowski, R. (2020). ‘Sustainability of Commercial Banks Supported by Business Intelligence System’. *Sustainability, 12*(2020), 4754.

Turban, E., Sharda, R., Dursun, D. and King, D., (2011) *Business Intelligence: A Managerial Approach*, New York: Prentice Hall.

Tutunea, M. F. and Rus, R. V. (2012) ‘Business Intelligence Solutions for SMEs’, *Procedia Economics and Finance*, 3, 865–870.

UL-Ain, N., Vaia, G., Delone, W. H., Waheed, M., and Giovanni, V. (2019). ‘Two decades of research on business intelligence system adoption, utilization and success—A systematic literature review’. *Decision Support Systems 125*(2019), 113113.

van den Dam, R. (2013). ‘Big data a sure thing for telecommunications: Telecom's future in big data’, in *2013 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery*, 148–154.

Van Raaij, E. M., and Schepers, J. J. (2008) ‘The acceptance and use of a virtual learning environment in China’, *Computers and Education*, 50(3), 838–852.

Varma, A. (2018) ‘Big Data Usage Intention of Management Accountants: Blending the Utility Theory with the Theory of Planned Behaviour in an Emerging Market Context’, *Theoretical Economics Letters*, 8, 2803–2817.

Veeramisti, N., Paz, A., and Baker, J. (2020) ‘A framework for corridor-level traffic safety network screening and its implementation using Business Intelligence’, *Safety Science* (2020), 100–110.

Venkatesh, V. (2000) ‘Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model’, *Information Systems Research*, 11(2000), 342–365.

Venkatesh, V. and Davis, F. (2000). ‘A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies’, *Management Science, 46*(2), 186–204.

Venkatesh, V., Morris, M., Davis, G. and Davis, F. (2003). ‘User Acceptance of Information Technology: Toward a Unified View’, *MIS Quarterly*, 27(3), 425–478.

Venkatesh, V., Thong, J. and Xu, X. (2012). ‘Consumer Acceptance and Use of information Technology: Extending the Unified Theory of Acceptance and Use of technology’, *MIS Quarterly*, 36(1), 157–178.

Verma, S. & Bhattacharyya, S. S. (2017). ‘Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms’. *Journal of Enterprise Information Management, 30*(3), 354-382.

Visinescu, L. L., Jones, M. C., and Sidorova, A. (2017) ‘Improving decision quality: the role of business intelligence’, *Journal of Computer Information Systems*, 57(1), 58–66.

Volery, T. and Lord, D. (2000) ‘Critical success factors in online education’, *International Journal of Educational Management*, 14(5), 216–223.

Wang, H.-C. (2014) ‘Distinguishing the adoption of business intelligence systems from their implementation: the role of managers’ personality profiles’, *Behaviour and Information Technology*, 33(10), 1082–1092.

Wang, Y., Kung, L. and Byrd, T. A. (2018) ‘Big data analytics: understanding its capabilities and potential benefits for healthcare organisations’, *Technological Forecasting and Social Change*, 126, 3–13.

Wang, S., Yeoh, W., Richards, G., Wong, S. and Chang, Y., 2019. ‘Harnessing business analytics value through organizational absorptive capacity’. *Information & Management*, 56(7), p.103152.

Warshaw, P. R., and Davis, F. D. (1985) ‘Disentangling behavioral intention and behavioral expectation’, *Journal of Experimental Social Psychology*, 21, 213–228.

Wanda, P., and Stian, S. (2015). ‘The secret of my success: An exploratory study of Business Intelligence management in the Norwegian industry’. *Procedia Computer Science, 6* (2015), 240–247.

Watson H. J. (2014) ‘Tutorial: big data analytics: Concepts, technologies, and applications’, *Communications of the Association for Information Systems*, 34(1), 1247–1268.

Wei, W., Li, J., Cao, L., Ou, Y. and Chen, J. (2012) ‘Effective detection of sophisticated online banking fraud on extremely imbalanced data’, *World Wide Web*, 16(4), 449–475.

Wei, L. and Xie, H. (2021) ‘Construction of Churn Customer Analysis System for Telecom Companies Based on Big Data. Application of Intelligent Systems in Multi-modal Information Analytics’. *Proceedings of the 2020 International Conference on Multi-model Information Analytics (MMIA2020), 1* (1233), 695-701.

Williams, M. D., Rana, N. P., and Dwivedi, Y. K. (2015) ‘The unified theory of acceptance and use of technology (UTAUT): a literature review’, *Journal of Enterprise Information Management*, 28(3), 443–488.

Wixom, H. B. and Todd, P.A. (2005) ‘A Theoretical Integration of User Satisfaction and Technology Acceptance’, *Information Systems Research*, 16(1), 85–102.

Wixom, B. and Watson, H., 2001. ‘An Empirical Investigation of the Factors Affecting Data Warehousing Success’, *MIS Quarterly*, 25(1), p.17.

Wixom, B. and Watson, H. (2010) ‘The BI-based organisation’, *International Journal of Business Intelligence Research*, 1(1), 13–28.

World Bank (2020) ‘Kuwait’s Economic Update – April 2020’. Available at: https://www.worldbank.org/en/country/gcc/publication/kuwait-economic-update-april-2020. Accessed: 12 June 2020.

Wu, W. H., Wu, Y. C. J., Chen, C. Y., Kao, H. Y., Lin, C. H. and Huang, S. H. (2012) ‘Review of trends from mobile learning studies: a meta-analysis’, *Computers and Education*, 59(2), 817–827.

Yap, B. W., Ong, S. H. and Husain, N. H. (2011). ‘Using data mining to improve assessment of credit worthiness via credit scoring models’, *Expert Systems with Applications*, 38(10), 13274–13283.

Yeoh, W. and Popovič, A. (2015) ‘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.

Yilmaz, K. (2013) 'Comparison of Quantitative and Qualitative Research Traditions: Epistemological, Theoretical, and Methodological Differences', *European Journal of Education*, 48(2), 311–325.

Yin, R. K. (2009). *Case study research: design and methods (4th ed.)*. Los Angeles, Calif: Sage Publications.

Yin, J. and Fernandez, V. (2020). 'A Systematic Review on Business Analytics'. *Journal of Industrial Engineering and Management JIEM, 13*(2), 283-295.

Yiu, L. D., Yeung, A. C., and Cheng, T. E. (2021). 'The impact of Business Intelligence systems on profitability and risks of firms'. *International Journal of Production Research, 59*(1), 3951–3974.

Yoon, T. E., Ghosh, B., and Jeong, B.-K. (2014) 'User acceptance of business intelligence (BI) application: Technology, individual difference, social influence, and situational constraints', in *47th Hawaii International Conference on Systems Sciences*, 3758–3766.

Yoon, C. Y. (2008) 'A structural model of end-user computing competency and user performance', *Knowledge-Based Systems*, 21(5), 415–420.

Youssef, M. A. E., and Mahama, H. (2021). 'Does business intelligence mediate the relationship between ERP and management accounting practices?' *Journal of Accounting & Organisational Change*, 17(5), 686-703.

Yuen, Y. Y., Yeow, P. H. P., Lim, N., and Saylani, N. (2010) 'Internet banking adoption: Comparing developed and developing countries', *Journal of Computer Information Systems*, 51(1), 52–61.

Yusof, E. M. M., Othman, M. S., Yusof, A. R. M, and Baharum, Z. (2020) ‘A model of determinants for continuous usage of business intelligence in Malaysian manufacturing organisations using theoretical’, *Indonesian Journal of Electrical Engineering and Computer Science,* 18(3), 1439–1445.

Zadeh, M., Karkon, A., and Golnari, H. (2015) ‘The Effect of Information Technology on the Quality of Accounting Information’, *Shiraz Journal of System Management,* 3(3), 61–76.

zain.com (2020) ‘Zain Group 2019 Revenues soar 26% to KD 1.66 billion (USD 5.5 billion), Net Profit up 10% to KD 217 million (USD 715 million)’. Available at: https://zain.com/en/press/ZainFY2019/. Accessed: 5 February 2021.

Zhao, Z., Navarrete, C., and Iriberri, A. (2012) ‘Open-Source Alternatives for Business Intelligence: Critical Success Factors for Adoption’, *AMCIS 2012 Proceedings,* 29.

Zhao, J. L., Fan, S., and Hu, D. (2014) ‘Business challenges and research directions of management analytics in the big data era’, *Journal of Management Research and Analysis* 1, 169–174.

Zhu, Z., Zhao, J., Tang, X., and Zhang, Y. (2015) ‘Leveraging e-business process for business value: A layered structure perspective’, *Information and Management,* 52(6), 679–691.

Zong, K., Yuan, Y., Montenegro-Marin, C. E., and Kadry, S. N. (2021). ‘Or-based intelligent decision support system for E-commerce’. *Journal of Theoretical and Applied Electronic Commerce Research, 16*(4), 1150–1164.

Zraqat, O. M. (2020) ‘The Moderating Role of Business Intelligence in the Impact of Big Data on Financial Reports Quality in Jordanian Telecom Companies’, *Modern Applied Science,* 14(2), 71–85.

Žukauskas, P., Vveinhardt, J. and Andriukaitienė, R., 2018. *Management Culture and corporate social responsibility*. BoD–Books on Demand.

Appendix 1: Questionnaire

ANTECEDENTS OF BUSINESS INTELLIGENCE SYSTEM USE SURVEY

Contact Information
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Part 1: Demographic Information

DI1	**I Work as an:**	☐Employee ☐Vendor ☐Contractor
DI2	**Gender:**	☐Male ☐Female
DI3	**Age Group:**	☐20 – 29 years old ☐30 – 39 years old ☐40 – 49 years old ☐50 and above
DI4	**Business Unit:**	☐Information Technology ☐Marketing ☐Finance ☐Network ☐Sales ☐Customer Care ☐Human Resources Other:………………
DI5	**Job Role:**	☐Team Member ☐Supervisor/Team Lead ☐Manager ☐Director
DI6	**Years of Experience:**	☐ Less than 1 ☐1 – 5 ☐6 – 10 ☐11 – 15 ☐16 – 20 ☐Above 20

Please tick the below based on the following rating scale: **1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree**. Please note that **BI abbreviates Business Intelligence**. These are the systems used in analysing enterprise data to assist in decision making.

Part 2: BIEUM Constructs

System Quality		**1**	**2**	**3**	**4**	**5**
SQ1	The BI system operates reliably.	☐	☐	☐	☐	☐
SQ2	The BI system can be adapted to meet a variety of needs.	☐	☐	☐	☐	☐
SQ3	The BI system effectively integrates data from different areas of the company.	☐	☐	☐	☐	☐

SQ4	The BI system allows information to be readily accessible to me.	☐	☐	☐	☐	☐
SQ5	It does not take long for the BI system to respond to my requests.	☐	☐	☐	☐	☐
SQ6	In terms of system quality, I would rate the BI system highly.	☐	☐	☐	☐	☐

Information Quality		**1**	**2**	**3**	**4**	**5**
IQ1	The BI system provides me with a complete set of information.	☐	☐	☐	☐	☐
IQ2	The BI system produces correct information.	☐	☐	☐	☐	☐
IQ3	The information provided by the BI system is well formatted.	☐	☐	☐	☐	☐
IQ4	The BI system provides me with the most recent information.	☐	☐	☐	☐	☐
IQ5	Overall, I would give the information provided by the BI system a high rating in terms of quality.	☐	☐	☐	☐	☐

Self-Efficacy		**1**	**2**	**3**	**4**	**5**
SE1	I could do my job using the BI system if there is no one around me to tell me what to do as I go.	☐	☐	☐	☐	☐
SE2	I could do my job using the BI system if I could call someone for help if I get stuck.	☐	☐	☐	☐	☐
SE3	I could do my job using the BI system if I had a lot of time to complete the job for which the system was provided.	☐	☐	☐	☐	☐
SE4	I could do my job using the BI system if I had just the built-in help facility for assistance.	☐	☐	☐	☐	☐

Personal Innovativeness in IT		**1**	**2**	**3**	**4**	**5**
PIIT1	When I hear about a new Information Technology, I look for ways to experiment with it.	☐	☐	☐	☐	☐
PIIT2	Among my peers, I am usually the first to explore new information technologies.	☐	☐	☐	☐	☐
PIIT3	I like to experiment with new information technologies.	☐	☐	☐	☐	☐
PIIT4	In general, I am not hesitant to try out new information technologies.	☐	☐	☐	☐	☐

Readiness to Change		1	2	3	4	5
RTC1	I look forward to changes at work.	☐	☐	☐	☐	☐
RTC2	I find most change to be pleasing.	☐	☐	☐	☐	☐
RTC3	Other people think that I support change.	☐	☐	☐	☐	☐
RTC4	I am inclined to try new ideas.	☐	☐	☐	☐	☐

Top Management Support		1	2	3	4	5
TMS1	Top management demonstrates continuous enthusiasm and interest in the BI system.	☐	☐	☐	☐	☐
TMS2	I think highly of the overall level of management support towards the BI system.	☐	☐	☐	☐	☐
TMS3	Personal involvement of upper-level managers in matters related to the BI system exist.	☐	☐	☐	☐	☐

Information Culture		1	2	3	4	5
IC1	I often exchange information with the people with whom I work regularly.	☐	☐	☐	☐	☐
IC2	I actively seek out relevant information on changes and trends going on outside my organisation.	☐	☐	☐	☐	☐
IC3	Managers and supervisors of my work unit encourage openness.	☐	☐	☐	☐	☐
IC4	Among the people I work with regularly, it is common to distribute information to justify decisions already made.	☐	☐	☐	☐	☐
IC5	I trust formal information sources (i.e. reports) more than I trust informal sources (i.e. colleagues).	☐	☐	☐	☐	☐
IC6	I receive information about the performance of my organisation.	☐	☐	☐	☐	☐

Part 3: UTUAT Constructs

Performance Expectancy		1	2	3	4	5
PE1	I find the BI system useful in my job.	☐	☐	☐	☐	☐
PE2	Using the BI system enables me to accomplish my tasks more quickly.	☐	☐	☐	☐	☐
PE3	Using the BI system increases my productivity.	☐	☐	☐	☐	☐

PE4	If I use the BI system, I will increase my chances of getting a raise.	☐	☐	☐	☐	☐

Effort Expectancy		**1**	**2**	**3**	**4**	**5**
EE1	My interaction with the BI system is clear and understandable.	☐	☐	☐	☐	☐
EE2	It is easy for me to become skillful at using the BI system.	☐	☐	☐	☐	☐
EE3	I find the BI system easy to use	☐	☐	☐	☐	☐
EE4	Learning to operate with the BI system is easy for me.	☐	☐	☐	☐	☐

Social Influence		**1**	**2**	**3**	**4**	**5**
SI1	People who influence my behaviour think that I should use the BI system.	☐	☐	☐	☐	☐
SI2	People who are important to me think that I should use the BI system.	☐	☐	☐	☐	☐
SI3	Senior management has encouraged the use of the BI system.	☐	☐	☐	☐	☐
SI4	In general, the organisation has supported the use of the BI system.	☐	☐	☐	☐	☐

Voluntariness of Use		**1**	**2**	**3**	**4**	**5**
VU1	My use of the BI system is optional.	☐	☐	☐	☐	☐
VU2	My supervisor does not require me to use the BI system.	☐	☐	☐	☐	☐
VU3	Although it might be helpful, using the BI system is certainly not compulsory in my job.	☐	☐	☐	☐	☐

Business Intelligence System Use		**1**	**2**	**3**	**4**	**5**
BISU1	I depend on the BI system to achieve my work tasks.	☐	☐	☐	☐	☐
BISU2	I have used the BI system a lot in the past 4 weeks.	☐	☐	☐	☐	☐
BISU3	I have been using the BI system regularly in the past 4 weeks.	☐	☐	☐	☐	☐
BISU4	I create my own analyses using the BI system.	☐	☐	☐	☐	☐