BUSINESS INTELLIGENCE AND ANALYTICS, MAPs INFERENCE CAPABILITY, MANAGEMENT ACCOUNTANT'S ANALYTICAL SKILLSET: A STUDY ON UAE COMPANIES

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KECERDASAN DAN ANALITIK PERNIAGAAN, KEUPAYAAN INFERENS MAP, SERTA KEMAHIRAN ANALITIK AKAUNTAN PENGURUSAN: SATU KAJIAN TERHADAP SYARIKAT DI EMIRIAH ARAB BERSATU

HESHAM MOHAMED HAMED SALAMA

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DECLARATION

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ABSTRAK

Kecerdasan dan Analitik Perniagaan (Business Intelligence and Analytics, BI&A) telah memainkan peranan penting dalam meningkatkan proses membuat keputusan organisasi, di samping melengkapkan peranan tradisional amalan perakaunan pengurusan (Management Accounting Practices, MAPs) dan mendorong Akauntan Pengurusan (Management Accountants, MAs) untuk memperkukuh kemahiran analitikal mereka serta bersedia mengambil alih peranan baharu. Walau bagaimanapun, literatur masih kurang meneroka sinergi ini. Kajian ini meneliti bagaimana penerapan BI&A mempengaruhi keupayaan inferens MAPs serta set kemahiran analitikal MAs. Ia juga mengkaji sejauh mana keupayaan-keupayaan ini dan set kemahiran analitikal baharu MAs berperanan sebagai pengantara dalam hubungan antara penggunaan BI&A dan prestasi organisasi. Berdasarkan 192 respons tinjauan daripada MAs dan profesional kewangan di organisasi bersaiz sederhana dan besar di Emiriah Arab Bersatu (UAE), kajian ini menggunakan kaedah Partial Least Squares dalam Pemodelan Persamaan Struktur (PLS-SEM) untuk menganalisis data. Bertentangan dengan jangkaan, keputusan menunjukkan bahawa penerapan BI&A mempunyai hubungan negatif yang signifikan terhadap prestasi organisasi. Namun demikian, keupayaan inferens MAPs dan set kemahiran berorientasikan analitik data dalam kalangan MAs menunjukkan pengaruh positif yang signifikan terhadap prestasi organisasi. Selain itu, penggunaan BI&A didapati meningkatkan keupayaan inferens MAPs secara signifikan. Dapatan kajian ini menunjukkan bahawa keupayaan inferens MAPs bertindak sebagai pengantara separa dalam hubungan antara BI&A dan prestasi organisasi, manakala set kemahiran analitikal MAs bertindak sebagai pengantara penuh dalam hubungan tersebut. Penemuan ini menyokong integrasi strategik BI&A ke dalam perakaunan pengurusan, yang berpotensi meningkatkan kecekapan organisasi secara signifikan. Kajian ini menyumbang kepada literatur dengan menggambarkan hubungan empirikal antara BI&A dan MAPs, sekali gus menawarkan asas kepada kajian masa depan dalam domain yang bertindih ini. Selain itu, kajian ini memberikan sumbangan teori dan metodologi yang signifikan dengan meneliti peranan keupayaan inferens MAPs sebagai keupayaan strategik di bawah rangka kerja Pandangan Berasaskan Sumber (Resource-Based View, RBV) dalam penyelidikan perakaunan pengurusan, mengoperasikan dan mengukur keupayaan inferens MAPs serta mengesahkan secara empirikal kesannya terhadap prestasi firma. Kajian ini turut mengetengahkan peranan pengantaraan keupayaan inferens MAPs dan set kemahiran analitikal MAs dalam hubungan antara BI&A dan prestasi organisasi, serta memberi pemahaman yang lebih mendalam mengenai mekanisme penjanaan nilai. Rangka kerja kajian ini menawarkan perspektif baharu mengenai integrasi perakaunan pengurusan dengan kemahiran insan, sekali gus membuktikan kepentingan kedua-duanya dalam memajukan BI&A.

ABSTRACT

Business intelligence and analytics (BI&A) has become pivotal in enhancing organisational decision-making processes, complementing the traditional role of management accounting practices (MAPs) and urging Management accountants (MAs) to sharpen their nalytical skills and be ready for new roles. However, the literature has underexplored this synergy. This study investigates how BI&A adoption influences MAPs inference capability as well as the MAs' Analytical Skillset. It also examines the extent to which these capabilities and the new analytical skillset of MAs mediate the relationship between BI&A utilisation and organisational performance. Based on 192 usable survey responses from MAs and financial professionals in medium and large organisations in the UAE, this study uses the Partial Least Squares to Structural Equation Modelling (PLS-SEM) to analyse the data. Contrary to the expectations, the results demonstrate that BI&A adoption has a significant negative relationship with organisational performance. MAPs inference capability as well as MAs' data analytics-oriented skillset, however, have a significant and positive influence on organisational performance, while BI&A adoption significantly augments the inferential ability of MAPs. The findings indicate that MAPs inference capability partially mediates the association between BI&A and organisational performance, while MAs' Analytical Skillset fully mediate this relationship. These findings advocate the strategic integration of BI&A into management accounting, suggesting that such an alignment could significantly improve organisational efficiency. This study contributes to the literature by portraying the empirical relationship between BI&A and MAPs, thus offering a foundation for future studies in this intersecting domain. Furthermore, this study makes significant theoretical and methodological contributions by examining the role of MAPs inference capability as a strategic capability under the Resource-Based View (RBV) framework. It expands the application of RBV in management accounting research by operationalising and measuring MAPs' inference capability and empirically validating its impact on firm performance. The study also theorises the mediating role of MAPs inference capability and MAs' Analytical Skillset between BI&A and organisational performance, providing an understanding of value-creation mechanisms. The framework of this study offers current perspectives on the integration of management accounting mechanisms and the role of human skills, thus providing evidence of the relevance of both in the advancement of BI&A.

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LIST OF ABBREVIATIONS

ADX	Abu Dhabi Exchange Market
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ANN	Artificial Neural Networks
B2B	Business-to-Business
BA	Business Analytics
BDAC	Big Data Analytics Capability
BI&A	Business Intelligence and Analytics
BPA	Business Performance Analytics
BPM	Business Process Management
BSC	Balanced Scorecard
BV	Business Value
CR	Composite Reliability
CRM	Customer Relationship Management
CVP	Cost-Volume-Profit
DA	Data Analytics
DCT	The Dynamic Capabilities Theory
DFM	Dubai Financial Market
DSS	Decision Support Systems
DW	Data Warehouses
EIS	Executive Information Systems
EPI	Environmental Performance Index
ERP	Enterprise Resource Planning
ETL	Extraction Transformation and Loading
GCC	Gulf Cooperation Council
GCI	Global Competitiveness Index
GDP	Gross Domestic Product

GII	Global Innovation Index
HDI	Human Development Index
HTMT	Heterotrait-Monotrait Ratio
ICT	Information and Communication Technology
IIS	Integrated Information Systems
IoT	Internet of Things
KBV	Knowledge-Based View
KEI	Knowledge-Economy Index
KPIs	Key Performance Indicators
MA	Management Accounting
MACS	Management Accounting and Control Systems
MAPs	Management Accounting Practices
MAs	Management Accountants
MCS	Management Control Systems
MIS	Management Information Systems
OLAP	Online Analytical Processing
PMS	Performance Measurement System
RBV	Resource-Based View Theory
RDBMS	Relational Database Management Systems
ROA	Return on Assets
ROI	Return on Investments
RPA	Robotic Process Automation
SVM	Support Vector Machines
UAE	United Arab Emirates
VRIN	Valuable, Rare, Imitable, and Non-substitutable
XBRL	Extensible Business Reporting Language

CHAPTER I

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

The last two decades have witnessed a notable revolution in technology that has infused the corporate environment. Accounting tasks have been significantly affected by these substantial advances in information technology. Accounting information systems (AIS) have evolved over time and are crucial to the success of several organisations and services. The primary function of AIS extends beyond the provision and management of financial data; they have been promoted in order to help businesses accomplish their strategic objectives (Spraakman et al. 2020). It became critical in boosting a business's profitability, operational effectiveness, and efficiency; they perform accounting duties and processes, as well as strategies for generating, storing, updating, and retrieving internal and external reporting data (Sunarta & Astuti 2023). Additionally, it functions as a tool for preparing financial statements and providing analytical insights to enhance operational performance. For example, Enterprise Resource Planning (ERP) provides extensive data storage and computational power for analysing internal and some external data (Appelbaum et al. 2017; Saira et al. 2010). Data-driven enterprises are rethinking business choices, which were formerly the domain of intuition and subjective experience and replacing them with data-driven ones. An organisation's ability to make sound business decisions relies on a variety of factors, including its own internal and external dynamics as well as the behaviour of its customers and suppliers (George et al. 2020).

Accounting and AIS researchers have linked other technologies to AIS, such as Business intelligence and analytics (BI&A) which have been used to conduct accounting and finance-related tasks. There is an integration between the two, and where there is a limited understanding of this development in the accounting academia (Chu & Yong 2021; Elbashir et al. 2021; Geddes 2020; Rikhardsson & Yigitbasioglu 2018). Organisations can exponentially achieve more data-driven decisions by incorporating business intelligence (BI) with business analytics (BA) and other parameters such as data visualisation, data tools, and infrastructure. Accordingly, the decision-making progress will be supported by processing and analysing the captured data in the AIS, identifying critical trends, weaknesses, and strengths, and producing actionable knowledge (Chau & Xu 2012). BI&A has been used in management accounting for the purpose of better data analysis and decision support to create value for their companies (Chen & Lin 2021; IBM 2021).

Management accounting encompasses a wide range of tasks and practices, collectively known as MAPs. These include cost accounting and value generation, internal control, resource management aligned with strategic objectives, risk management and response strategies, performance evaluations, budgeting, forecasting, and pricing strategies. Management accounting is defined as the practice of compiling and analysing financial and non-financial data for strategic planning and day-to-day operations control (Nishimura 2005). It generates detailed financial forecasts and analytical reports for company executives' use (Chapman et al. 2006). MAPs emphasise the integration of AIS and management information systems, providing decision-makers with not only factual information but also sophisticated models and tools for action. Furthermore, it plays a crucial role in decision-making and strategy formulation, working closely with executive managers to provide vital information for planning, control, and decision-making purposes (Kalifa et al. 2020).

MAPs are fundamental to organisational decision-making across all business types, regardless of their profit orientation or operational scale. The implementation of MAPs, including activity-based costing, strategic management accounting, and balanced scorecard, enables organisations to enhance both cost control and value creation through optimised resource allocation (Kalifa et al. 2020). As organisations generate increasingly voluminous financial and operational data, the traditional approaches to data processing and analysis have become insufficient (Chen et al. 2012). This evolution has necessitated the adoption of more sophisticated technological solutions that can effectively process large datasets and facilitate timely decision-making (Davenport & Harris 2017). BI&A has emerged as a critical solution to address these challenges, particularly in supporting management accounting functions (Chaudhuri et al. 2011). Given management accounting's central role in organisational control and decision-making, the integration of BI&A solutions offers substantial potential for enhancing decision support capabilities (Elbashir et al. 2013).

BI&A is one of the seven trends that are occurring in management accounting (Cokins 2013):

(1) Development from product to channel and customer profitability analysis.
(2) Enterprise Performance Management (EPM) development and expansion that enlarge the role of management accounting.
(3) The shift to predictive accounting.
(4) Business analytics.
(5) Improving management accounting methods.
(6) Managing information technology and shared services as a business.
(7) The need for better skills and competency in behavioural cost management.

There is a clear link between BI&A and MAPs, which is a decision support activity, while BI&A uses sophisticated technologies that digitise the decision support operations (Rikhardsson & Yigitbasioglu 2018). The connection between management accounting and BI&A has been studied in many aspects, such as; the area of management control systems (Elbashir et al. 2021; Gomez-Conde et al. 2019; Marx et al. 2012); the impact on organisational performance (Adu-Gyamfi & Chipwere 2020; Appelbaum et al. 2017; Elbashir et al. 2011); the usage of BI&A to improve organisational performance through the perceived improvement in processes, and value creation (Ahmed et al. 2019; Bronzo et al. 2013; Elbashir et al. 2013); identification of tensions that face the application of BI in the managerial accounting environment and main tactics to overcome it (Kowalczyk & Buxmann 2015); and sustainability accounting (Petrini & Pozzebon 2009).

The effective execution of MAPs in today's complex business environment demands that management accountants (MAs) cultivate an increasingly sophisticated repertoire of analytical capabilities (Oesterreich & Teuteberg 2019). This evolution in required competencies reflects the growing complexity of decision-making contexts and the increasing integration of advanced technological solutions in accounting processes (Spraakman et al. 2020; Wolf et al. 2020). The evolution of MAs' analytical skillset has become increasingly crucial in the modern technological landscape. Recent studies indicate a significant shift from traditional accounting competencies towards advanced analytical capabilities (Franke & Hiebl 2023; Steens et al. 2024). MAs are now expected to possess sophisticated data analytics skills, including predictive modeling, machine learning application, and advanced visualisation techniques (Arkhipova et al. 2024). Bhatta and Hiebl (2022) emphasise that contemporary management accountants must develop proficiency in coding, data manipulation, and statistical analysis while maintaining their core accounting expertise. This transformation reflects the growing integration of traditional accounting functions with modern analytical tools, requiring professionals to bridge the gap between financial expertise and technological competence (Venkatesh et al. 2023).

BI&A provides outstanding support to the management accounting activities and functions in terms of cost reduction and efficiency, timely information such as cost and revenue forecasting, production change impact, product profitability analysis, and value-producing opportunities (Lee & Park 2005; Möller et al. 2020; Pickard & Cokins 2015). It is also used to efficiently to predict business segments by assessing customer segment profitability (Bronzo et al. 2013; Mikalef et al. 2018). The implementation adoption of BI&A is evident in the area of performance management through the provision of performance information to streamline actions (Vukšić et al. 2013). Several businesses have already implemented data analytics and automated forecasting technologies that incorporate time series approaches, machine/deep learning, and/or simulation. Among the key issues are finding and properly deploying relevant strategies and drivers, as well as determining the optimal combination of skills and machines in the application process. Particularly in light of structural failures (such as the coronavirus/Covid-19 problem), it appears to be becoming clear that a mix of human judgment and commercial acumen, as well as substantial use of data and technology, is critical. Complete automation is likely to be effective only in well-defined and well-understood niches (Möller et al. 2020).

1.2 BACKGROUND OF UAE ECONOMY

The United Arab Emirates (UAE) is one member of the Gulf Cooperation Council (GCC), which is in the Arabian Gulf Peninsula and is the projected location for the current study. It follows the federal system consisting of seven emirates (Abu Dhabi, Dubai, Sharjah, Ras Al Khaimah, Ajman, Umm Al Quwain, and Fujairah). The constitutional federation of the UAE assures mutual respect by each emirate for the independence and sovereignty of the other emirates in matters related to their internal affairs within the framework of the Constitution. Two financial markets exist in Abu Dhabi (Abu Dhabi Exchange Market - ADX) and Dubai (Dubai Financial Market - DFM), where big corporations list their stock and capitals. The UAE is one of the encouraging spheres of investment; The UAE’s economy is the fifth largest in the Middle East, with a gross domestic product (GDP) of $421 billion in 2020. The UAE has launched a diversification strategy to diversify sources of income, especially a sectoral diversification towards a knowledge-based economy as presented in table 2.1 trade and manufacturing present almost one-third of the GDP in 2023. It is one of the most successful diversified countries in the GCC; for example, the UAE's tourism industry has grown to be very promising, with revenues of USD 43.3 billion, accounting for 12% of total GDP (Siddiqui & Afzal 2022).

Table 1.1 The economic sectors and their contribution to the 2023 UAE GDP

Economic Sector	**Contribution to GDP (%)**
Trade	16.1
Manufacturing	14.6
Financial and Insurance	13.4
Construction and Building	11.8
Real Estate	7.1
Other sectors	37

Source: UAE Ministry of Economy and Commerce

The UAE's economy is evolving into a knowledge-based economy, relying heavily on technology and skilled labour. Huge investments are being made in areas such as telecommunication and information technology, renewable energies, service industries, transportation and aviation, tourism, and re-export commerce petrochemicals. The economy in UAE is going towards a knowledge-based economy where it is based on technology and skilled labour where huge investments are pouring on telecommunication and information technology, renewable energies, service industries, transportation and aviation, tourism, and re-export commerce petrochemicals. The UAE has almost completed the largest solar power plant in the world in Abu Dhabi in a plan to embed renewable energy and diversify the energy sector in the economy. This concentrated solar power plant will contribute massively to the energy market in the UAE by serving 160,000 households across the UAE and eradicating more than 2.4 million metric tonnes of CO_2 emissions annually. In 2023 tourism and travel sectors significantly bolstered the nation's economic growth and diversification efforts. The sector's contribution to the GDP reached AED 220 billion, accounting for 11% of the total GDP. This impressive performance was marked by over 28 million guests in hotel establishments, generating AED 43.5 billion in revenues. The UAE's tourism sector also supported approximately 809,300 jobs, representing 12.3% of total employment (Ministry of Economy 2023). The following table 2.2 uses the world ranking in some criteria to compare the UAE's performance with the rest of the world. The used indexes are:

- Human Development Index (HDI)
- Knowledge-Economy Index (KEI)
- Global Innovation Index (GII)
- Global Competitiveness Index (GCI)
- Environmental Performance Index (EPI).

Table 1.2 UAE's performance with the rest of the world

Countries	HDI 2021[1]	KEI 2019[2]	GII [3]2021	GCI 2019[4]	EPI 2020[5]
World top	0.957	9.58	65.5	84.8	82.5
World bottom	0.394	0.91	15	35.1	22.6
World average	0.737	5.15	34.3	--	46.44
Arab average	0.70	4.70	28.3	--	45.2
UAE	0.890	6.66	43	75	55.6

The table 2.2 shows The UAE's indices (2020-2021) surpass global and Arab averages in HDI (0.890), KEI (6.66), and CCI (75), yet trail top global scores. Its GII (48) and EPI (55.6) exceed regional averages but lag behind leading nations, reflecting advancements in development and economy with room for improvement in gender equality and environmental sustainability. Listed companies in the UAE are the backbone of the economy and also a great driver of the digital economy in the country. Listed companies have the capability to invest in highly sophisticated technology to run their business and operations, whether local or international operations. Big corporations in the UAE benefit from the advanced ICT infrastructure that fosters the digital economy besides policies, laws, regulations, etc. Listed companies that are recorded in ADX and DFM are located in various sectors, which are banking, telecommunication, transportation, real estate and construction, industrial and energy, insurance, services, consumer goods and investments, and financial services. The main business activities of those corporations penetrate all other economic activities in the country; accordingly, the involvement of ICT in all its operations, as a requirement of the digital

[1] United Nations Development Programme https://hdr.undp.org/en/content/download-data
[2] World Bank http://web.worldbank.org/archive/website01030/WEB/IMAGES/KAM_V4.PDF
[3] World Intellectual Property Organisation https://www.wipo.int/global_innovation_index/en/2021/
[4] World Economic Forum https://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf
[5] Environmental index https://epi.yale.edu/epi-results/2020/component/epi

economy, will assist the country in achieving its strategy of industry 4.0 that was launched in 2017.

The UAE, as one of the world's leading countries in terms of ICT use, government efficiency, and cell coverage per capita, offers a promising environment compared to other GCC countries. The UAE has attained this accomplishment by diligently pursuing its Industry Revolution 4.0 plan and its focus on the digital economy. This accomplishment has been attained by diligently pursuing the UAE's Industry Revolution 4.0 plan and its focus on the digital economy. Understanding the many aspects of incorporating ICT solutions in the decision-making process described by BI&A and MAPs is extremely important. There is a noteworthy dearth of research on both BI&A and MAPs in the context of the UAE, which prompts the current study to investigate both domains in the UAE.

1.3 UAE DIGITAL ECONOMY

The world is currently experiencing undergoing the era of industry revolution 4.0 and the digital economy, where more sophisticated technological-based systems are employed and integrated into the manufacturing and service industries with cyber-physical systems (Bordeleau et al. 2020). The digital economy is the economic activity that experiences considerable and huge daily and instant online transactions among people, businesses, machines, data, and processes resulting from the Internet, mobile technology, cloud computing, data analytics, big data, intelligence solutions, augmented reality, cybersecurity, blockchain and the Internet of Things (IoT) (Božič & Dimovski 2019). In other words, the digital economy is based on emerging technologies, which are currently employed to introduce new products and services, enhance business processes and boost competitive advantages (Schwab 2016).

Tavana et al. (2020) stated that digital economy-related technology is a significant enabler of competitive competition. For example, integrated systems such as ERP systems integrate a variety of technologies, including the IoT, business intelligence and data analytics. The Internet of Things uses a proprietary Internet protocol to identify, regulate, and transport data to both persons and databases. The data is gathered via IoT, stored in the cloud, and then retrieved and controlled using integrated systems. These objectives are achievable along with creating value for the organisation through leveraging BI&A functionalities at both strategic and operational levels (Fink et al. 2017).

In their study, Alfaki and Ahmed (2013)looked at how well the UAE performed regionally in terms of technical preparedness and competitiveness, as well as the influence of ICTs and education on enhancing the UAE's technological preparedness. They employed a situational analysis and a comparative method to define the UAE's position in terms of global competitiveness, identifying flaws, strengths and prospects. Evidently, the UAE has achieved significant strides in the global competitiveness index, particularly in the macroeconomic climate and infrastructure quality, particularly in ICT (World Economic Forum 2020). It has achieved the second place in terms of the ICT adoption around the globe and fourth place in the digital legal framework.

The World Economic Forum (2021) stated that the UAE continues to top the Arab world in terms of networked readiness in 25th place. The government is leading the way to expand digital connections, offering a coherent strategy for the sector and finding success at marketing it. Mobile broadband subscriptions and Internet access in homes have increased, but other critical ICT services are still not generally available: in 2014, fixed broadband subscribers remained at 11.6 per 100 people. In recent years, businesses have improved their use of and economic effect of ICTs, although there is still a gap with the majority of advanced economies in this sector. Patent activity, both general and ICT-related, is quite low (Baller et al. 2016). This complements the UAE's long-standing competitive advantages, with the first position in a stable macroeconomic environment, the fourth position in a strong product market and the 12th in infrastructure. Transport infrastructure increases by four points this year, possibly due to investments connected to the impending Expo-2020, giving the country one of the most advanced transportation networks in the world. This signifies the significance of investing in the ICT technologies and embedding them in daily operations in all sectors. UAE's digital economy is connected to the scope of the current study for the following reasons; since the country is progressing and achieving advancements in ICT and its related fields, this must be used in the business environment to reap the benefits of these investments. Furthermore, the UAE government has been paving the path for organisations in the public and private sectors to embed ICT in their operations and achieve full digital transformation. BI&A has established its presence in the UAE economy, so the justification for another study on the impact of the technology and companies' performance is necessary.

Thus, the country has developed its strategy of for the Fourth Industrial Revolution, which focuses on all sectors in the country in 2017, with a vision of "*to become a leading global hub* *and an open lab for the Fourth Industrial Revolution's applications*". The UAE digital economy strategy is based on six main pillars:

The human pillar

the strategy intends to promote healthcare capabilities by involving robotic medical services by exploiting and adopting clinical cobots and nanobots and providing intelligent healthcare interventions through implantable technologies. The same pillar also focuses on embedding augmented learning to improve the education outcomes of advanced sciences and technologies.

The security pillar

another focus area under the I4.0 strategy is food and water security by providing renewable energy and bioengineering solutions and applying Blockchain to enhance the country's financial ecosystem. UAE has developed Emirates Blockchain strategy 2021 to transform 50% of government transactions entirely operated by blockchain platforms, while Dubai now becomes entirely powered by Blockchain. Increasingly, the country has established the Blockchain council membered with international experts, government entities, UAE banks, etc., to expedite transactions within the different financial and non-financial sectors and boost efficiency and trustworthiness levels. Under this pillar, UAE looks to advance its defence manufacturing facilities to engage robotic solutions and cognitive technologies.

The experience pillar

UAE intends to build intelligent government services that are consumer-centred to achieve a high level of satisfaction and consumer happiness. Additionally, this strategy paves the path to developing intelligent cities that promote environmental sustainability and autonomous mobility in transportation.

The productivity pillar

The country intends to establish intelligent terminals and logistics ecosystems that achieve sustainability and simultaneously amplify productivity. It also intends to decentralise energy generation facilities by establishing intelligent grids (interconnected energy delivery networks) to achieve sustainable consumption. Finally, the I4.0 strategy includes being the world's centre of excellence in 3D printing and robotic construction.

The frontiers of the future pillar

The strategies to be at the frontiers of the future include being positioned as a global hub for ambitious space players and supporting space entrepreneurship to accelerate the accessibility to commercialisation of space. Additionally, national research and application efforts in national universities and specialised centres focused on brain, neuroscience, and human enhancement can be supported in collaboration with global leaders in the field in order to advance cognitive human enhancement. Through these strategies, the forefront of innovation can be achieved, and the future can be shaped.

The UAE has been reported to be a 100% smartphone usage nation; besides, the top leading country to use ICT, government efficiency and mobile coverage per capita; this would enhance the achievement of the digital economy by involving young people to contribute to a digital transformation (telecommunication regulatory authority 2019). The World Economic Forum has ranked the UAE as the leading Arab and regional e-commerce centre in 2017, which proliferates in the retail front on account of the traditional retail sales. Moving towards a fully digital economy in the UAE has contributed to GDP by 4.3% with anticipation of a dramatic increase in the forthcoming years, especially, now that 40% of the UAE population engages in government digital services more than once a week (Siddiqui & Afzal 2022). Yet the UAE government has declared the following objectives into its 2030 economic vision to boost the digital economy:

- Continuous improvements to e-Commerce,
- Enhancements to the IT infrastructure,
- Expanded spread of Internet services,
- The use of smartphones and the expansion of electronic payment systems,
- Significant government support for digital transformation

BI&A can contribute to the digital economy at the operational level by utilising the exponential data generated from operations and providing deep analysis to process improvement and value creation of the business entity. Since I4.0 is a business transformation that optimises decision-making, creating new value opportunities, the BI&A plays a significant role in achieving those objectives. For example, Business Performance Analytics (BPA) involves the systematic utilisation of data and analytical methods (mathematical, econometric and statistical) for performance management and performance measurement (Wamba et al. 2017). BI&A is an integral part of the digital economy and I4.0; accordingly, it is highly recommended for the UAE government to ensure this is applied to companies that operate in the UAE. Besides, it is highly crucial to study BI&A adoption in the UAE context.

The BI&A plays a crucial role in data generation, data processing, and deriving insights from big data, where the digital economy mainly depends on big data from connected entities, different digital transactions, and social media. In addition, BI&A has a real-time capability that enables the real-time output that I4.0 demands to facilitate dynamic and data-driven decision-making. Finally, since the digital economy and I4.0 depend on producing intelligent services and products, data-fuelled BI&A underpins development besides the development of IoT-enabled activities. It is essential to accurately define BI&A and analyse its structure in order to understand its connection with MAPs and organisational performance (Awan et al. 2021).

BI&A, as a clear example of cutting-edge technologies, benefits organisations' performance. Chen and Lin (2020) demonstrated that the advancement of artificial intelligence (AI) technology has pushed the boundaries of business practice, leading to the development and utilisation of BI. This has ameliorated the efficiency of information techniques for the purpose of optimising business decision-making and operations. In the context of MAPs, BI&A is used to support a variety of management accounting tasks, including cost forecasts, product profitability analyses, financial impact analyses of production modifications, and profitability analyses of client segments (Abdel-Maksoud et al. 2012) . Nevertheless, the extent of progress and advancement in MAPs and the role of MAPs in effectively using BI&A have not been addressed in the existing research on management accounting. It is highly significant to empirically understand the ability of BI&A to update the capabilities of MAPs as a result of employing BI&A. The application of BI&A-supported analytical tools enhances organisational performance across a variety of aspects, including financial, customer, process, and learning and growth. BI&A can be used to make a variety of normal and non-routine decisions, including product pricing and product mix selection (Rikhardsson & Yigitbasioglu 2018; Vukšić et al. 2013). In performance management, BI&A solutions are used to deliver performance information to knowledge workers, enabling them to make the best decisions and take the best actions. While BI&A has an impact on business process performance, management control, and organisational performance, it is critical that it be assimilated through shared knowledge and top management support (Bronzo et al. 2013; Rikhardsson & Yigitbasioglu 2018).

Even though the use of BI&A tools in the context of business process management might not be aligned in practice, it is important to match needs, capabilities, and tools. In addition, although BI&A is used in the context of MAPs there are limited studies that show the degree of inference in implementing MAPs through the BI&A. At the same time, there is a lack of research to show the significance of MAPs in reaping the benefits of BI&A. In other words, since the BI&A depends on financial and massive amounts of non-financial data such as social media posts, website visits, etc., the BI&A impact on MAPs needs to be tested and investigated, where the research shows a lack in this area.

1.4 PROBLEM STATEMENT

Research indicates that only 21% of firms achieve substantial benefits from their BI&A investments, primarily due to organisational barriers rather than technological limitations (Mikalef et al. 2020). This alarming failure rate persists despite organisations investing billions globally in sophisticated analytics platforms, data warehouses, and visualisation tools. The UAE exemplifies this paradox, where ambitious digital transformation initiatives targeting 19.4% GDP contribution by 2032 contrast sharply with organisational struggles to realise measurable returns from BI&A implementations (UAE Government Official Portal 2023). This implementation crisis suggests fundamental gaps in understanding how technological resources translate into organisational value, particularly through the intermediate capabilities that bridge technology adoption and performance outcomes.

The core problem lies in the theoretical disconnect between BI&A resource acquisition and performance improvement. Organisations readily invest in advanced analytics technologies yet fail to establish effective pathways for converting analytical capabilities into competitive advantage (Schnegg & Möller 2022). This failure stems from treating BI&A as a direct performance driver rather than understanding the organisational mechanisms that transform technological resources into business value. Current literature predominantly examines either BI&A implementation factors or performance outcomes in isolation, neglecting the critical mediating processes that link these elements (Peters et al. 2016; Torres et al. 2018).

The Resource-Based View suggests that competitive advantage emerges when organisations develop capabilities that effectively leverage valuable resources (Barney 1991). However, existing research fails to identify the specific organisational capabilities that mediate between BI&A resources and performance outcomes. This theoretical gap is particularly pronounced in management accounting, where professionals routinely process vast financial and operational data yet lack frameworks for understanding how BI&A enhances their analytical effectiveness. The absence of clear theoretical mechanisms explaining BI&A value creation impedes both academic understanding and practical implementation guidance, leaving organisations without direction for optimising their substantial technological investments.

Most critically, MAPs inference capability represents an unexplored mediating mechanism between BI&A resources and organisational performance. MAPs inference capability is defined as an organisation's systematic ability to derive meaningful, real-time insights and actionable conclusions from management accounting data through sophisticated analytical interpretation of financial and operational information. This capability differs fundamentally from general analytical competency by focusing specifically on transforming accounting data into strategic intelligence that supports decision-making processes (Schneider et al. 2015). Unlike traditional management accounting that emphasises historical reporting and basic variance analysis, inference capability encompasses sophisticated pattern recognition, causal relationship identification, and forward-looking analysis that enables organisations to anticipate market changes and identify operational inefficiencies before they impact performance.

Empirical evidence demonstrates that organisations with superior inferential capabilities achieve higher levels of strategic alignment and operational effectiveness (Paradza & Daramola 2021; Yoshikuni et al. 2023). However, the specific mechanisms through which BI&A enhances these inferential capabilities remain theoretically underdeveloped. Existing studies examine BI&A's broad impact on organisational performance without identifying the intermediate capabilities that explain how technological resources create value (Elbashir et al. 2021). This theoretical gap is compounded by the transformation of management accountants' roles, as BI&A systems create demands for enhanced analytical skillsets that bridge traditional accounting expertise with advanced data analytics capabilities (Arkhipova et al. 2024; Franke & Hiebl 2023).

Contemporary management accountants are expected to possess competencies in statistical analysis, predictive modelling, and data visualisation that extend beyond traditional accounting functions. However, existing research provides conflicting evidence regarding this professional transformation, with some studies suggesting rapid adoption of data scientist competencies (Brands & Holtzblatt 2015) whilst others indicate more gradual change (Spraakman et al. 2020). The theoretical importance of these evolving competencies as mediating mechanisms between BI&A and performance remains unexplored, creating uncertainty about how organisations should develop human capabilities to complement their technological investments.

Additionally, empirical evidence examining BI&A's impact on MAPs and management accounting professionals remains severely limited in emerging economy contexts, particularly within the UAE. This geographic gap is theoretically significant given the unique cultural, institutional, and organisational factors that may influence technology adoption and capability development (Ahmed et al. 2019; Youssef & Mahama 2021). The UAE's hierarchical organisational structures, multicultural workforce, and rapid digital transformation initiatives create distinctive implementation challenges not captured by research conducted in developed economies (Suliman 2013).

Recent evidence suggests UAE organisations face specific BI&A implementation challenges, including insufficient data quality, limited adoption of advanced analytics capabilities, and difficulties aligning technological investments with organisational capabilities. Furthermore, research indicates that traditional MAPs are more commonly used than innovative approaches in UAE organisations, suggesting potential resistance to advanced analytical methodologies that may affect BI&A implementation success (Halbouni & Nour 2014). These contextual factors indicate that UAE organisations may face unique barriers to developing inference capabilities, yet these remain unexplored in current literature.

The absence of emerging economy research is particularly problematic given that these contexts may exhibit different relationships between technological resources, organisational capabilities, and performance outcomes due to institutional and cultural factors absent in developed economies. Without context-specific evidence, existing theoretical frameworks may inadequately explain BI&A value creation mechanisms in emerging economy settings, limiting both theoretical understanding and practical guidance for organisations in these contexts.

Furthermore, existing research has predominantly examined either BI&A implementation factors or organisational performance outcomes in isolation, without comprehensive frameworks that simultaneously test relationships between technological resources, intermediate capabilities, and performance outcomes. This methodological limitation impedes understanding of the complex, multi-stage processes through which BI&A creates organisational value. Current studies typically employ single-mediator models that examine one intermediate variable, neglecting the potential for multiple, simultaneous mediating mechanisms (Ramakrishnan et al. 2020). Additionally, performance measurement has traditionally emphasised financial metrics whilst neglecting comprehensive frameworks that capture BI&A's multifaceted impacts across customer relationships, internal processes, and organisational learning capabilities (Bronzo et al. 2013).

The convergence of these theoretical, empirical, and methodological gaps creates an urgent need for comprehensive research examining how BI&A influences MAPs inference capability and management accountants' analytical skillsets, and how these capabilities subsequently impact organisational performance. This research is theoretically necessary to understand value creation mechanisms, empirically critical for validating relationships in emerging economy contexts, and methodologically essential for developing frameworks that guide practical implementation. The UAE context provides an ideal setting for this investigation, combining ambitious digital transformation initiatives with unique organisational factors that may reveal new insights about BI&A value creation processes in emerging economies.

1.5 RESEARCH QUESTIONS

In contemporary times, the significance of BI&A in accounting and its role in improving organisational performance is increasing. Research on Business Intelligence and Analytics in management accounting is limited, especially in the GCC. This paper examines the implementation adoption of BI&A in management accounting within the UAE setting and the impact of this adoption on organisational performance. The main research questions will be succinctly summarised as follows:

RQ1: What is the influence of BI&A on MAPs' inference capability, MAs' Analytical Skillset and organisational performance in UAE companies?

RQ2: What is the influence of MAPs inference capability and MAs' Analytical Skillset on organisational performance in UAE companies?

RQ3: What is the mediating effect of MAPs inference capability and MAs' Analytical Skillset on the relationship between BI&A and organisational performance?

1.6 RESEARCH OBJECTIVES

The research objectives can be summarised as follows:

RO1: To investigate the influence of BI&A on inference capability of MAPs and MAs' Analytical Skillset, and organisational performance in UAE companies.

RO2: To investigate the influence of MAPs inference capability and MAs' Analytical Skillset on organisational performance in UAE companies.

RO3: To investigate the mediating effect of MAPs inference capability and MAs' Analytical Skillset between BI&A and organisational performance in the UAE companies.

1.7 CONTRIBUTIONS OF THE STUDY

1.7.1 Theoretical contribution

The current research provides a framework to explain the impact of BI&A on MAPs in the Middle East and UAE contexts. This would add a theoretical contribution to the literature where MAPs capabilities have not been examined as a mediator between BI&A and performance. The study will also contribute to the literature by showing the extent to which BI&A affects the Analytical Skillset requirements of MAs from an IT perspective. AIS has always been used in the literature as a significant resource to drive the firm's competitive advantage and enhance the business value by employing corporate capabilities; this is the theoretical ground of the RBV. The current study extends existing research by proposing that BI&A resources enable firms to generate insights that most probably strengthen MAPs capabilities, which, in turn, positively support organisational capabilities. The current study emphasises the significance of addressing BI&A as one of the considerable resources for organisations; besides, the study adds MAPs inference capability and MAs' Analytical Skillset as significant capabilities that use those resources to drive the organisation's performance. MAPs inference capability has been considered capabilities as their application varies between firms; even the MAs' qualities vary between firms. Accordingly, one dimension or capability has been added to evaluate the utilisation of BI&A as contemporary resources by the MAPs. This dimension will add value to measuring the degree of influence of BI&A on the inference capability of the employed MAPs in the organisation. The newly examined dimension or capability will provide insights into the nature of the relationship between the BI&A and the MAPs and how this is reflected in the overall organisation performance.

1.7.2 Practical contribution

This research aims to elucidate the significant role of BI&A to drive the performance of organisations through the MAPs and the MAs' Analytical Skillset. Additionally, understand if there is obtained advantages from business intelligence and analytics adoption. Identification of the management accounting tasks and techniques deriving particular value from business intelligence and analytics adoption will provide decision-makers with vital insights to inform targeted, worthwhile investments in solutions supporting those precise functions. The findings from this study seek to validate and provide rationale for enterprise expenditures on analytical capabilities within management accounting activities. At the same time, the research would recommend and advise firms to establish and apply MAPs in order to reap the benefits of BI&A. In addition, this research would highlight which areas are not using or benefiting from the BI&A and hence find solutions to improve these practices by using the BI&A (e.g., financial control, planning and control, reduction of waste in business resources, and effective use of resources).

The research also assures organisations and decision-makers' confidence in the BI&A to enhance the degree of inference of management accounting tasks and techniques. Consequently, the study will measure the prominent updated analytical skillset of MAs due to the integration of BI&A in MAPs and compare them to IT-based roles such as data analysts. This would enable organisations to update their training and development strategies and objectives to suit the current trends in the market and the integration between BI&A and MA functions. Eventually, the research findings will contribute to achieving the country's strategy towards the digital economy by quantifying the impact of BI&A on MAPs in UAE companies and how this would improve the decision-making strategies of the organisations.

1.7.3 Methodological Contribution

The research is conducted in a different business environment from what is found in the literature to examine the primary research constructs of MAPs, BI&A, organisational performance, and MAs' Analytical Skillset. Additionally, the research covers multiple industries in the UAE, presented by listed companies and medium and large corporations in the UAE market. The current research follows the same research approach and methods as most of the literature; it is quantitative and explanatory.

This research makes three distinct methodological contributions to the existing literature. First, it introduces a novel approach to operationalising MAPs inference capability as a specific construct. While previous studies have examined MAPs broadly, this research is the first to develop and validate measurement scales specifically for assessing the real-time inference capability of management accounting practices in the context of BI&A adoption.

However, this research uses a measurement approach by specifying one dimension—the inference capability of MAPs. This will provide more insights on the ability of the BI&A to conduct more sophisticated tasks of MAPs with the ability to infer perceptions and acumens in different contexts and business cases. BI&A is measured as a single instrument since they are integrated and operated subsequentially. For example, BI includes the descriptive part of the data analytics, and data analytics functions require all the processed data from BI&A. It also enhances the construct validity of key measures by using refined multiple-item measures to measure the BI&A (such as OLAP, data mining, digital dashboarding, descriptive, diagnostic, predictive, and prescriptive analytics). Another methodological contribution lies in the comprehensive integration of measurement approaches. The study uniquely combines traditional management accounting metrics with modern analytics capabilities measurement, providing a more nuanced understanding of how BI&A enhances MAPs. This integration is reflected in both the measurement instruments and analytical approaches used. Additionally, this study emphasises the integration of BI and analytics, where BI converts raw operational data into meaningful financial dashboards and reports, whereas data analytics focuses on combining data in order to discover new patterns relevant to the business or other stakeholders, as well as future patterns. Accordingly, the study uses BI&A as one single variable. Moreover, the measurement used for organisational performance has four dimensions of the BSC models instead of focusing on a single measurement such as financial performance-related measures.

1.8 SCOPE OF STUDY

While the impact of BI&A on organisations is evident, the impact of BI&A on MAPs still requires further research.

This study investigates how organisations leverage BI&A through MAPs inference capability to enhance performance in the UAE context. Specifically, the scope encompasses examining the extent to which BI&A affects the inference capability of MAPs, which is presented under four main categories: financial control, planning and control, reduction of waste in business resources, and effective use of resources. The research focuses on both the direct relationships between these constructs and the mediating role of MAPs inference capability in translating BI&A investments into improved organisational performance.

While conducting the MAPs, the BI&A obliged the MAs to earn specific analytical skills; that overlap with the data analysts. Accordingly, the research investigates the current management accountants' analytical skillsets after conducting the BI&A. This provides insights into the transformation of the management accounting profession in response to technological advancement.

The research population comprises medium and large companies in the UAE that have implemented BI&A solutions, including but not limited to organisations listed on both the ADX and DFM. Small and micro enterprises are deliberately excluded from the scope as they typically lack significant BI&A investments. This boundary ensures the study focuses on organisations with sufficient technological infrastructure to meaningfully examine the relationships between BI&A adoption and management accounting practices.

Theoretically, the study is grounded in RBV theory, examining how organisations utilise BI&A as primary resources through management accounting capabilities. This theoretical framework guides the investigation of how firms transform technological investments into enhanced performance through organisational and human capabilities. Methodologically, the research employs quantitative methods, utilising survey instruments to collect data from MAs, CFOs, and financial professionals, with subsequent analysis using advanced statistical techniques to test hypothesised relationships.

This focused scope enables comprehensive examination of the relationships between BI&A adoption, management accounting practices, and organisational performance while maintaining clear boundaries that ensure research feasibility and meaningful results. The geographical focus on the UAE provides insights into these relationships within an emerging economy context, while the theoretical and methodological boundaries ensure rigorous academic investigation of the research questions.

1.9 RESEARCH SIGNIFICANCE

This study addresses the problem of limited empirical understanding regarding the concrete influence of BI&A on core MAPs and the evolving roles and skillsets of MAs. Examining this gap is critical, as organisations persistently endeavour to optimise operational and financial performance. The findings of this research will demonstrate to managers the value proposition of implementing robust analytics resources and leveraging the multifaceted data these systems deliver. While companies, especially small and medium enterprises, have historically depended on conventional management accounting processes and aggregated cost information, such techniques alone are insufficient for competing within modern intensely dynamic markets. As a result, effective corporate management necessitates increasingly advanced cost and management accounting systems (Uyar & Kuzey 2016). Findings will help UAE organisations align their BI&A investments with the country's digital economy strategy by providing empirical evidence of how these technologies enhance MAPs. This is particularly relevant as the UAE aims to double its digital economy contribution to GDP by 2031 (UAE Government Official Portal 2022).

The study's objective is to demonstrate enhanced internal management systems (through the MAPs) as a result of BI&A technology investment. Businesses' prosperity is contingent upon their capacity to exploit technology effectively—otherwise, substantial investments risk being squandered. Additionally, organisations must hire and coordinate qualified and educated accountants to ensure system effectiveness. This study will show how the abilities of accountants contribute significantly to the performance-enhancing impact of BI&A.

The management accounting function is not confined to the accounting department alone but extends into other operational areas, supplying vital information for decision-makers. Its role is increasingly pervasive and strongly linked to the strategic objectives of firms—for example, implementing management and operational control for corporate performance measurement, planning internal cost activities, and preparing financial statements (Brands & Holtzblatt 2015). Accordingly, MAs' roles can be categorised as follows (Cokins 2013):

1. Preparing financial statements
2. Measuring the company's performance
3. Providing decision-related information

More specific examples are required to demonstrate the tangible improvements BI&A enables for key accounting processes such as budgeting, forecasting, product costing, profitability analysis, financial auditing, and anomaly detection. The study also addresses gaps in the academic literature regarding the practical application and impact of BI&A specifically on accounting tasks and MA roles.

While considerable research exists on BI&A adoption at a general level, a focused examination of its usage in core MAPs and the implications for MAs' skillsets remains scarce. This study aims to fill this gap by empirically examining how BI&A concretely enhances these practices. BI&A solutions empower MAs to utilise vast amounts of data spanning nearly all organisational functions, which necessitates improvements to their analytical skillsets. The significance of this research lies in its implication that organisations must prepare their MAs with state-of-the-art skills and tools. Increasingly, BI&A impacts not only MA roles and skills, but also the underlying tasks and techniques of MAPs.

This research is also significant in raising awareness and urgency among organisations to provide the appropriate readiness, flexibility, and capability to adopt the latest BI&A technologies. It identifies specific MAPs notably affected by BI&A, such as Financial Control, Planning and Control, Waste Reduction, and Resource Efficiency. Moreover, top management must support MAs in leveraging a wide range of data, internal or external, financial or non-financial, structured or unstructured (Nielsen 2015). For instance, in preparing financial statements, MAs must go beyond relying solely on historical data, which is backward-looking, and instead incorporate forward-looking data from varied sources such as emails, audio files, internet clickstreams, social media, news media, sensor recordings, video content, and RFID tags (Zhang et al. 2015).

MAs are increasingly required to undertake predictive and prescriptive analyses, particularly in evaluating uncertainty and risk in decision-making (Nielsen 2015). For example, MAs may use prescriptive analytics to advise manufacturing firms on vendor selection, discontinuing underperforming segments, or making strategic sourcing decisions—all aimed at reducing cost, boosting revenue, and creating value (Taleizadeh et al. 2015). Management accounting is thus evolving from a descriptive focus to a more strategic and performance-oriented role, relying on predictive and prescriptive methods (Geddes 2020; Nielsen 2018). Studying the influence of advanced drivers such as BI&A is therefore essential to understand this shift.

MAPs are increasingly influenced by innovative non-financial metrics and approaches whose impacts are still being explored by researchers and practitioners (Ahmed et al. 2023; Geddes 2020; Halbouni & Nour 2014; Pasch 2019). MAs now work cross-functionally with departments such as marketing, supply chain, HR, and operations to resolve practical business problems that influence value creation (Birnberg 2009).

To summarise the significance and implications of this study: its practical value lies in reinforcing existing MAPs by illustrating the contribution of BI&A to areas like Financial Control, Planning and Control, Waste Reduction, and Resource Efficiency. The research clarifies why investing in BI&A is critical for MAPs and demonstrates how it aligns with the skill demands of both organisations and MAs. It also provides guidance to educational and professional institutions on tailoring programmes to the sophistication required for MA techniques. Furthermore, this research will document best practices in BI&A implementation by evaluating how closely the analytical skillsets of MAs align with those of data analysts.

1.10 DEFINITION OF VARIABLES

The main variables in the study are business intelligence and analytics, which present the independent variables. At the same time, MAPs capabilities, MAs' Analytical Skillset, and organisational performance are the dependent variables. The following sections are the main definitions for each variable:

1.10.1 Business Intelligence and Analytics (BI&A)

Business Intelligence and Analytics (BI&A) is a multifaceted construct that encompasses the methodologies, technologies, and processes used to collect, transform, and analyse data to support decision-making in organisations. It operates on a continuum from descriptive to predictive and prescriptive analytics. The integration of BI and BA as a single construct reflects their complementary nature and operational reality in contemporary organisations. While BI traditionally focuses on reporting and data visualisation, BA extends these capabilities through advanced analytical techniques. This integration is supported by extensive literature that treats them as interconnected components of a unified decision support system (Rikhardsson & Yigitbasioglu 2018; Elbashir et al. 2021). Recent empirical studies demonstrate that organisations implement these technologies as an integrated solution rather than separate systems, enabling a continuous flow from data gathering to advanced analytics (Bordeleau et al. 2020; Bronzo et al. 2013; Chen et al. 2012; Yansheng Chen & Lin 2021; Rikhardsson & Yigitbasioglu 2018).

1.10.2 MAPs inference capability

The MAPs inference capability refers to the real-time conclusions and insights that can be perceived from conducting the MAPs using BI&A (Moller et al. 2020; Schneider et al. 2015; Scapens and Jazayeri 2003). MAPs inference capability represents the integration of traditional MAPs with real-time analytical insights. This construct combines the systematic execution of management accounting tasks (such as budgeting, forecasting, cost management and performance measurement) with the ability to derive meaningful, timely conclusions from these practices (Uyar & Kuzey 2016). The inference capability specifically refers to how effectively organisations can extract actionable insights from their management accounting activities when supported by BI&A systems (Moller et al. 2020). This includes the ability to identify patterns, understand causal relationships, and generate forward-looking insights across four main categories: financial control, planning and control, reduction of waste in business resources, and effective use of resources (Schneider et al. 2015). The construct measures not just the presence of MAPs but their effectiveness in generating real-time, decision-relevant insights that support strategic and operational decision-making (Scapens & Jazayeri 2003).

1.10.3 MAs' Analytical Skillset

The analytical skillset of management accountants encompasses the technical and analytical skills required in the modern data-driven business environment. This construct measures the extent to which management accountants have integrated data analyst competencies into their professional practice, including the ability to create and interpret operational reports, provide data-driven recommendations, identify patterns in data, and develop technological solutions for business operations (De Mauro et al. 2018). The assessment includes proficiency in technical tools such as SQL, Tableau and Excel, alongside the capability to transform analytical findings into actionable business insights. This evolution reflects the transformation of the management accountant's role from traditional accounting functions to encompassing analytical business advisory and project management capabilities (Mukozho & Seymour 2020; CIMA 2016).

1.10.4 Organisational Performance

Organisational performance represents the achieved outcomes of a firm compared to planned objectives. The performance is evaluated using multiple dimensions of the balance scorecard model including traditional financial measures, customer and market perspectives, internal business processes, and learning and growth indicators. Each perspective comprises specific measures that collectively reflect the central dimension, such as profitability and sales increase over the last two years, cost reduction for a given duration, and accurate tracking of sales, marketing, and financial performance to measure the dimension of financial performance (Appelbaum et al. 2017; Bronzo et al. 2013).

1.11 ORGANISATION OF THE THESIS

After presenting the introduction chapter, the rest of the thesis is organised as follows: Chapter two presents a critical review of relevant literature on the AIS and BI&A and their implementation in different management accounting practices. Then chapter three highlights the conceptual theoretical framework, which is developed to display the research constructs and formulated the research hypotheses. Chapter four elaborates the research methods, data collection methods, developed instruments, and proposed data analysis techniques. Chapter five includes the analysis and reports the main findings for the research and answering the research questions; this is followed by the discussion chapter, chapter six, to elaborate and explain the findings and link it them to the literature, and eventually the conclusion and recommendation for future research.

CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

Advancements in information technology have enhanced the capacity of managerial activities within many firms. The BI&A solutions have enabled the management accountants to utilise the massive amount of data to enhance the decision-making process from internal and external sources. Internally from almost all organisations' functions and externally from published datasets such as government sources, websites and social networks (Rikhardsson & Yigitbasioglu 2018). The use of BI&A has become increasingly significant in modern management accounting (Spraakman et al. 2020). In this context, the ability to analyse vast amounts of data and obtain valuable insights has become essential for informed decision-making. BI&A may provide an opportunity for managers to track performance metrics, identify areas where resources can be better allocated, and evaluate the effectiveness of management accounting strategies (Geddes 2020; Torres et al. 2018). It is essential to show what has been covered so far by researchers and the gaps and criticisms raised by researchers. Consequently, this review endeavours to undertake a comprehensive evaluation of how MAPs respond to the escalation and integration of BI&A within the business environment. The primary objective is to ascertain the potential ramifications of such a development on the operational efficiency and effectiveness of the organisations operating within the UAE. The current study investigates the impact of BI&A adoption on organisational performance in the UAE context, mediated by enhancements in MAPs. The literature review synthesises key findings, limitations, and gaps in extant research on this topic.

2.2 BUSINESS INTELLIGENCE AND ANALYTICS (BI&A)

2.2.1 Introduction and Historical Evolution

The concept of BI&A has gained significant importance in recent times, owing to the emergence of '*big data'* and advancements in machine intelligence. Initially, the progression from BI to BI&A is an ongoing phenomenon propelled by technology progress, evolving company requirements, and an increasing acknowledgement of the significance of data-driven decision-making in the contemporary competitive environment. This evolution has resulted in a significant transformation of BI from a tool mostly used for retrospective reporting to a proactive and forward-looking strategy. This shift enables firms, regardless of their size or industry, to effectively utilise data for strategic advantages. The literature has used some other terms to describe and refer to BI&A, for example, business analytics, big data analytics, data mining and data warehousing. BI&A systems have garnered significant attention from both academic and industrial sectors (Trieu 2017). These systems are currently being widely employed in various business domains that require decision-making to generate value (Bordeleau et al. 2020). The current research deals with BI&A as one variable as they are integral and developmental, following the literature (Chen et al. 2012; Elbashir et al. 2021; Peters et al. 2016; Ramakrishnan et al. 2020; Rikhardsson & Yigitbasioglu 2018; Spraakman et al. 2020; Youssef & Mahama 2021).

2.2.2 Integration of BI and BA into BI&A

Business Analytics (BA), often referred to as Data Analytics (DA), builds on BI by applying statistical, predictive, and prescriptive analytics to generate insights from data. While BI tells what happened, BA aims to explain why it happened and predict what will happen next (Schneider et al. 2015).

While BI and BA have traditionally been treated as separate concepts, their convergence into BI&A is increasingly recognised in both academia and industry. BI provides the infrastructure and tools necessary for data collection and processing, while BA transforms this data into actionable insights. Without BI, BA lacks structured, high-quality data; without BA, BI remains a static, descriptive tool with limited decision-making impact (Torres et al. 2018). Organisations today implement BI&A as an integrated system rather than separate entities. Research shows that companies adopting BI&A holistically achieve better firm performance, enhanced decision-making, and competitive advantage compared to those using them separately (Chen et al. 2020). BI&A systems now include automated data pipelines connecting BI storage with BA models and real-time analytics dashboards that integrate descriptive (BI) and predictive (BA) capabilities (Hurbean et al. 2023). In other words, while BI and BA originated as distinct disciplines, their functional interdependence and increasing technological convergence justify their treatment as a single construct, BI&A. The integrated approach aligns with contemporary business needs, enhances empirical research validity, and provides a more accurate representation of data-driven decision-making in organisations. The integration of BI and BA creates a comprehensive ecosystem where BI provides the data infrastructure and basic reporting capabilities, while BA delivers deeper insights through advanced analytical techniques (Chen & Lin 2021). This combined approach enables organisations to not only understand past performance but also predict future outcomes and optimise decisions (Elbashir et al. 2021).

2.2.3 BI&A Functions

BI&A has been described as a process and product; the process part refers to the methodology, and tools firms apply to produce profound and momentous information by processing the existing internal and external data. While the product part refers to anticipating and forecasting market trends, customers, rivals, suppliers, resources, strategic decisions, acquisitions, and product and service development. Currently, BI&A is used excessively in a corporation, especially medium and large corporations, which are affordable in their cost to strategise and solve complex problems (Trieu 2017). For example, organisations that deploy enterprise resource systems with a single-centralised data architecture are eager to develop BI&A solutions that heavily rely on the ERP systems' generated data. ERP collects corporate data, whereas BI&A analyses enterprise data and employs dashboards and other interfaces to display that data in a manner that is easily understood and aids in identifying opportunities for action.

There is a semi-agreement in the accounting information system's literature that companies are ineffectively utilising the data engendered from the enterprise systems (e.g., enterprise resource planning); accordingly, their investment in business intelligence is questionable (Appelbaum et al. 2017; Elbashir et al. 2013; Rikhardsson & Yigitbasioglu 2018). Business intelligence is a primary term for decision support systems that exploit data generated from the integrated systems to promote business decision-making; it is broadly used on applications that conduct analytics functions to support the organisations' different functions (Watson & Wixom 2007).

Organisations deploy BI&A systems to enhance decision-making through systematic data management and analysis. Modern implementations focus on data identification, classification, storage and analysis capabilities that drive improved decision quality (Bordeleau et al. 2020; Mikalef et al. 2020). Contemporary BI&A architectures integrate multiple components that work in synchronising approaches. The OLAP functionality enables strategic monitoring and multidimensional data analysis, whilst ETL processes ensure data quality through systematic extraction, transformation and validation procedures. Data warehousing provides centralised storage and supports exploration of business relationships, complemented by data mining and visualisation tools that surface insights (Chen & Lin 2021; Ramakrishnan et al. 2020).

Research demonstrates that effective BI&A implementation delivers significant organisational performance benefits at both strategic and operational levels. Key impacts manifest in process efficiency gains, enhanced decision quality and strengthened competitive positioning (Peters et al. 2016; Spraakman et al. 2020). The integration of traditional business intelligence capabilities with advanced analytics has created comprehensive platforms that support both historical analysis and forward-looking insights (Youssef & Mahama 2021). This evolution reflects the maturation of BI&A from basic reporting tools to sophisticated decision support systems that combine real-time monitoring, predictive capabilities and prescriptive recommendations. The result is a more nuanced and complete approach to data-driven decision-making across the enterprise (Elbashir et al. 2021).

Increasingly, the BI&A has been found to force businesses to avoid relying on intuitive-based decisions and primary support fact-based decision-making. Therefore, firms can significantly enhance and improve their competitive advantage by investing in BI&A infrastructure and functionality if the appropriate BI tools are used with expanded data sources (Peters et al. 2016). Usage of BI&A components becomes an integral part of the management accountant’s tasks since he/she provides the analysis and forecast to the management. Hence, and with the recent advancement and the integration of big data analytics, MAs are expecting to leverage big data and the capacity of BI systems to support the use of advanced analytics and drive it. However, it is not clear the extent to which MA is affected by the implementation of BI systems (Rikhardsson & Yigitbasioglu 2018).

The literature also has shown some of the challenges that face the BI&A systems presented in the ERP systems, which affect the MAPs. Those challenges have been raised by Teittinen et al. (2013) based on qualitative research that is built on a case study of a manufacturing entity. Those challenges include the making entries by employees in different departments that include too many steps in the entry process, which take time and increase the probability to generate incorrect entries. Hence, the data that the management accountant will use is flawed and may generate ineffective decisions. In addition, the high complexity of the system requires people who are more competent to handle and manipulate these BI&A systems, people who have only basic skills to use ERP, cannot solve this kind of problem. The unpredictability of the manufacturing processes, such as breaking down machines or changing production lines, would add pressure on the predefined process in ERP systems.

The developed BI&A tools and applications by software providers such as SAP, Oracle, IBM, and Microsoft contain functions that assist the management accountant to conduct the MAPs. Those functions have been summarised by Chugh and Grandhi (2013) in the following table:

Table 2.3 BI&A functionalities to assist the management accountant.

Categories	Function
Data consolidation	Integration of internal and external data Simplified extraction, transformation, and loading of data Deletion of unwanted and unrelated data
Data quality	Sanitise and prepare data to improve overall accuracy
Reporting	User-defined and standard reports generated at any level Personalized reports for any level of management
Forecasting and modelling	Supports analytics used in predictive and prescriptive analytics, which use historical and real-time data, qualitative or quantitative
Tracking of real-time data	Monitor current progress with defined project objectives/KPIs Prioritise scarce system resources
Data visualisation	Interactive reports and graphics, possibly with real-time updates Scorecards and dashboards
Data analysis	What-if analysis Sensitivity/optimisation analysis Goal seeking/goal supporting analysis Descriptive analysis
Mobility	Portability to multiple devices and formats
Rapid insight	Drill down features that enable many layers of analysis Dashboards that are interactive and that can monitor trends and outcomes
Report delivery & Share-ability	Deliver reports in standard formats such as Microsoft Office Email reports in different formats
Ready to use applications	Pre-built meta-data with mappings defined considering performance & security needs

	Pre-built reports, and dashboards to support management
Language support	Multiple language support

This puts some pressure on MAs to acquire highly analytical IT skills, which were initially believed to be directly connected to data scientists and data analysts. Accordingly, the current study examines the similarities between the current management accountant skillsets affected by the implementation of BI systems and the traditional roles of business and data analysts. So far, no studies in MA have considered the link between BI&A and MAPs, which motivates the current study to investigate this phenomenon. In terms of their impact on the quality of MAP outputs, these functionalities are becoming increasingly vital to the execution of various MAPs. In other words, the BI&A's aforementioned features will affect the ability of MAPs to generate more reliable information and, thus, more reliable decisions; nevertheless, this must be evaluated (Chugh & Grandhi 2013).

2.2.4 BI&A as one integrated variable

BI and BA seem almost identical, and the literature has used them as one term, and often used interchangeably or combined as "BI&A" as well as the current research (Appelbaum et al. 2017; Bergmann et al. 2020; Bordeleau et al. 2020; Bronzo et al. 2013; Chen et al. 2012; Chen & Lin 2021; Elbashir et al. 2008, 2013; Rikhardsson & Yigitbasioglu 2018; Schneider et al. 2015; Uyar & Kuzey 2016; Wamba et al. 2017). While BA offers advanced analytics, it strongly relies on BI to answer complicated queries and create estimates. This study operationalises BI&A as a unified construct, aligning with the prevailing academic perspectives and contemporary research paradigms in this domain. -The literature including conceptual and empirical highlights the functional interdependence of BI and BA in driving data-driven decision-making, organisational performance, and business value. The seamless integration of BI’s data management capabilities with BA’s advanced analytical techniques establishes a unified capability that organisations leverage for competitive advantage. Thus, treating BI and BA as separate variables would create an artificial distinction that does not align with how these technologies are implemented and utilised in practice. The following points can justify this approach:

a. There is an evident overlapping between the two solutions in which many scholars have been using the two terms interchangeably (Appelbaum et al. 2017; Bergmann et al.

2020; Elbashir et al. 2013; Elbashir et al. 2021; Llave 2017; Mikalef et al. 2018; Nielsen 2015; Rikhardsson & Yigitbasioglu 2018; Schneider et al. 2015; Spraakman et al. 2020).

b. The integrated nature of BI&A is evident in the study by Ramakrishnan et al. (2020), which presents a holistic model of BI&A abilities and their impact on organisational performance. The authors identify four key dimensions, innovation infrastructure capability, customer process capability, B2B process capability, and integration capability, that collectively determine the effectiveness of BI&A. These capabilities do not operate in isolation; rather, they form an interdependent system that transforms raw data into actionable insights, facilitating strategic decision-making and operational efficiency. The study empirically demonstrates that BI&A effectiveness is a function of its integration across business processes, reinforcing the notion that BI and BA must be studied together rather than separately (Ramakrishnan et al. 2020).

c. The systematic review by Paradza and Daramola (2021) further strengthens this argument by examining the relationship between BI and business value (BV). The study highlights how BI tools, such as reporting and dashboards, work in tandem with BA techniques, such as predictive modeling and machine learning, to create value. The authors emphasise that BI&A is not merely a technological investment but a strategic resource that enables firms to achieve sustainable competitive advantage. Importantly, the study finds that firms deriving the highest business value from BI investments are those that integrate BI with analytics capabilities, suggesting that separating BI and BA in research models would overlook their synergistic effects (Paradza & Daramola 2021).

d. The empirical study by Bergmann et al. (2020) on digitisation in budgeting further illustrates the necessity of treating BI&A as a single construct. The research finds that organisations using BI for data storage and retrieval alone do not achieve significant improvements in budgeting accuracy. However, when BI is combined with BA-driven forecasting models, firms experience higher satisfaction with the budgeting process due to greater accuracy and automation. This finding aligns with industry practice, where business intelligence platforms increasingly incorporate advanced analytics as a core function rather than a separate toolset (Bergmann et al. 2020).

e. Similarly, Llave et al. (2017) examine the role of BI&A in small and medium-sized enterprises (SMEs) and find that firms adopting BI without analytics struggle to extract meaningful insights. The study suggests that SMEs should view BI&A as an integrated investment rather than adopting BI tools first and adding analytics later. The iterative and agile nature of BI&A adoption in SMEs underscores the functional inseparability of BI and BA, as firms need both capabilities to compete effectively in data-driven markets (Llave et al. 2017).

f. Furthermore, Grytz and Krohn-Grimberghe (2018) highlight the cost implications of BI&A, showing that firms that implement BI without analytics often experience inefficient resource allocation. Their service-oriented cost allocation model reveals that BI investments yield the highest returns when paired with analytics capabilities, as organisations can leverage real-time insights to optimise operations and strategic planning. This finding further supports the argument that BI and BA should not be treated as separate variables, as their financial impact is realised through integration (Grytz & Krohn-Grimberghe 2018).
g. Collectively, these studies provide strong theoretical and empirical evidence that BI and BA function as a single system rather than two distinct constructs. RBV theory supports this integration, as BI&A constitutes a firm-wide capability that drives sustained competitive advantage when properly leveraged. Additionally, the dynamic capabilities perspective suggests that firms must continuously adapt their BI&A infrastructure to extract maximum business value, a process that inherently requires BI and BA to function together (Paradza & Daramola 2021; Ramakrishnan et al. 2020).
h. From an industry perspective, leading technology providers such as Microsoft, SAP, and IBM no longer market BI and BA as separate solutions. Instead, they offer integrated BI&A platforms that combine data management, visualisation, and advanced analytics in a unified ecosystem. This practical alignment further supports the conceptual and empirical justification for treating BI&A as a single research variable rather than separating them into distinct constructs (IBM 2022).

To fully understand the justification for treating BI&A as a single variable, it is essential to examine its key components. BI&A is not merely a collection of isolated technologies but rather an integrated system that combines data management, reporting, and advanced analytics to support decision-making. The synergy between BI and BA enables organisations to transform raw data into actionable insights, enhancing strategic and operational performance. By analysing the core components of BI&A, we can further illustrate how its functionalities are inherently interconnected, reinforcing the necessity of a unified research approach rather than separate constructs. These components are also an integral part of the research instrument, as each represents a tool or function used to conduct MAPs, further reinforcing the necessity of a unified research approach rather than separate constructs.

2.3 BI&A COMPONENTS

BI&A comprises of two integrated technologies BI and BA. BI has been defined as the collection of methodologies, techniques, processes, architectures, and technologies that utilise the collected raw data and transform it into meaningful and presentable information, an efficient base for the decision-makers to make timely decisions (Evelson & Norman 2008). BI's main components are online analytical processing, data mining, data warehousing and data visualisation. While the BA is defined as "*the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their operations and make better fact-based decisions.*" (Appelbaum et al. 2017). BA's is classified into four main types, which are descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. BI primarily addresses retrospective inquiries, concentrating on historical data to elucidate past events, their timing, and methodologies. Its functions encompass reporting, automated monitoring, and data visualisation tools. Conversely, BA adopts a more forward-looking and investigative approach, exploring causal relationships, predictive scenarios, and novel data insights. BA's toolkit includes advanced statistical analyses, data mining, and predictive modelling. While BI facilitates decision-making for current operations through backward-looking analyses, BA informs future operational decisions through forward-looking methodologies. This dichotomy highlights the complementary yet distinct roles these analytical approaches play in organisational decision-making processes (Nerkar 2016; Velu 2021). The BI&A components in this study are derived through a comprehensive review of conceptual and empirical literature, ensuring their alignment with established frameworks and practical applications in MAPs. The selection process involved identifying core BI&A functions commonly used in financial decision-making, reporting, and strategic planning. Conceptual studies provide a theoretical foundation for these components. Dedić and Stanier (2016) classify BI as encompassing data collection, processing, and reporting, while analytics involves pattern recognition, prediction, and decision support. Fink et al. (2017) highlight that BI&A capabilities contribute to organisational learning and value creation, particularly in financial decision-making. These frameworks guided the identification of key components such as data warehousing, OLAP, data mining, and various levels of analytics.

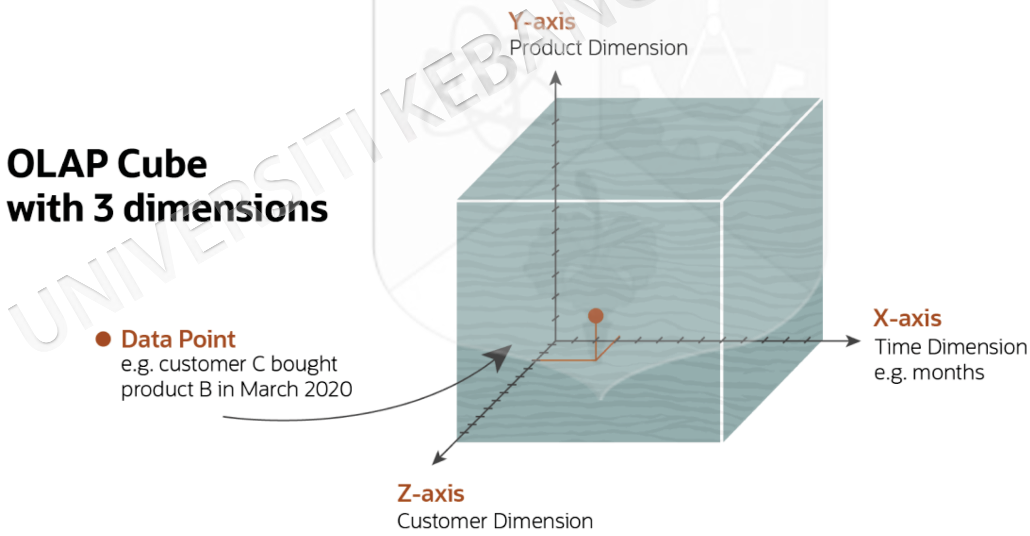
Empirical studies validate these components by demonstrating their practical application in MAPs. Lauría and Greco (2010) illustrate how OLAP enables financial analysis and planning, confirming its role in budgeting and forecasting. Ramakrishnan et al. (2020) empirically assess BI&A's impact on performance, reinforcing the inclusion of descriptive, diagnostic, predictive, and prescriptive analytics. By integrating insights from both conceptual frameworks and empirical evidence, the study ensures that each BI&A component is grounded in literature and aligned with financial professionals' decision-making needs.

Additionally, the BI&A components in this study were systematically derived through established theoretical and empirical frameworks from Youssef and Mahama (2021). The study employed measurement scales from Davenport (1998) and Rom and Rohde (2006), which were based on material from major enterprise software vendors (SAP, Oracle, and Microsoft Business Solutions), ensuring industry relevance and practical applicability. The seven BI&A modules specifically included: data warehouse, activity-based costing, performance measurement/balanced scorecard, executive portal, data mining, planning and simulation, and consolidation. These components were operationalized using a five-point Likert scale measuring the extent of application from 1 (did not apply at all) to 5 (systematically applied). This derivation approach aligns with contemporary BI&A frameworks that encompass the full spectrum of analytical capabilities from basic reporting to advanced analytics, reflecting the integrated nature of modern business intelligence systems as confirmed by vendors' comprehensive software suites.

2.3.1 OLAP (Online Analytical Processing)

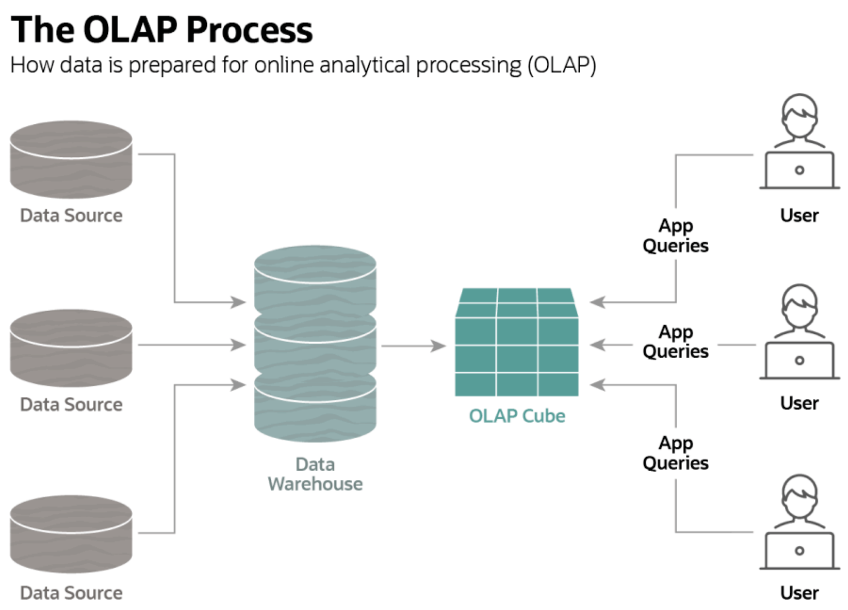
This component of the BI is a technique that is used to analyse the data to look for insights and gives multidimensional, summarised views of business data; these insights are highly crucial to augmenting the business through the modelling techniques, reporting, and analysis. OLAP works interactively with data warehouses in the enterprise intelligence systems to process queries in order to discover trends and analyse critical factors. OLAP, or the hypercube, allows users to interactively and dynamically query and summarise multidimensional information. In other words, users conduct a multidimensional analysis of corporate data and enable users to perform complex calculations, trend analysis, and sophisticated data modelling. The multidimensional feature of the OLAP is highly significant in decision-making, especially in management accounting, where there are always cross-functional decisions that must be taken, such as decisions those related to budgeting and forecasting for business functions, performance management, financial reporting, or simulation models (Andreassen 2020; Cristescu 2017). For example, the sales data can be analysed by a management accountant by regions, salespersons, allocated targets, or time periods. They use multidimensional data to identify trends for particular categories of products.

Figure 2.1 OLAP Cube with three dimensions of data



This figure is an example of one cube with three main dimensions that shows the sales of a certain product at a certain time. OLAP provides a multidimensional cube to allow different analytical processes especially when it comes to financial planning and analysis (Wittmann 2022)

Figure 2.2 OLAP Process



OLAP cubes are used to organise, process, and visualise data. OLAP cubes are beneficial for distribution, marketing, performance reporting, business process management, budgeting, forecasting, and billing analysis, as well as database analysis. OLAP cube-based software systems may automatically search for information about a certain event, product, service, or project. Relational data banks are used to define the relationships. This cube was constructed with the intent of providing key performance indicators (KPIs) and reports for demonstration purposes and hence getting pertinent data (Cristescu 2016). As a result, OLAP is an advantageous tool for performance management because, as it facilitates the tracking of cost and variance metrics, responsibility centres and reporting segments, and common cost allocations.

2.3.2 Dashboards and Visualisation

This part of the BI is highly specialised in the reporting function, where the sophisticated systems use its reporting mechanism to show an overview of the organisation from a multidimensional perspective. Dashboards and visualisation techniques use highly aggregated reports, comprising a multitude of key performance indicators with trend analysis. Dashboards are used to visualise scorecards that represent the KPIs to gauge the achievement of short- and long-term objectives. It is also a crucial tool to highlight the gaps in performance in certain areas of each function (Arkhipova et al. 2024).

2.3.3 Real-time BI

This is one of BI's powerful techniques. It allows the decision-makers to receive information up to the minute by feeding the business operations' transactions into a real-time data warehouse. The generated processed data will be circulated and disseminated through different mediums, such as the visualisation dashboard emailing system and interactive visualisation systems. A manufacturing corporation, for instance, may track things like electricity consumption, raw material prices, and labour hours in real-time. If this works, MAs will be able to see cost overruns faster, giving the business more time to fix them (Dedic and Stanier 2016).

2.3.4 Data warehouse

A data warehouse is an extensive database or repository that contains an organisation's historical data. This repository presents different subjects that are integrated; it fuels the decision support systems. It works as a storage and retrieval source, but it involves data cleaning, data consolidation, and data integration. One of the features of data warehouse is the data's non-volatility; it means that the previous and old data are not erased or overwritten, making it different from the operational database. Increasingly, the frequent changes in the operational database are not reflected in the data warehouse. Therefore, the data warehouse is a valuable source for decision-makers for analysis (Duan & Xiong 2015).

Furthermore, data warehousing is a technique of gathering, pooling and managing data. Then the turn comes to data mining, which benefits from these collected data by analysing and discovering anomalies, patterns and correlations in large data sets to predict outcomes using algorithms hypothesis formulation and forecast testing. The discovery and analysis are made jointly with machine learning, statistics, neural networks, data visualisation, image and signal processing, and database systems (Ahmed et al. 2019).

The technical literature has classified the BI into four main areas (Chaudhuri et al. 2011; Troyansky et al. 2015):

- Infrastructure, such as cloud-based infrastructure
- Data management, which refers to disciplines and practices used to process, store and run data.

- Data analysis: this includes different statistical models and techniques; besides, artificial intelligence.
- Information delivery or data visualisation, such as the dashboards

The four disciplines, or as (Evelson & Norman 2008) called it, "*the architecture stack*" of BI&A, are interrelated and iterated in which the achievement of one area requires the achievement of the others. For example, the data visualisation and information delivery would not be possible with only raw data; but this data must be cleaned, processed and analysed where it can be presented and understood to the decision-makers in presentable and meaningful formats and designs. Simultaneously, analysing data requires proper collection, organisation, and adequate storage. Without a crucial infrastructure, achieving all the aforementioned elements will ultimately prove impossible.

Simultaneously, data could not be analysed without properly collecting, organising and adequately storing the data. Eventually, all the above elements will not be achieved without a vital infrastructure. This classification is highly connected with the MAPs in some facets; for example, the management accountant decision analysis or deferential analysis must process and clean the raw data, such as variable cost ratios, fixed cost and selling prices, before implementing the different statistical models and techniques to find the optimal results for each scenario,; and when the analysis is completed the information will be delivered and visualised. In their study, Vukšić et al. (2013) examined service industry firms' utilisation of the potential of BI in performance management, which is one of the main functions of MA. They classified their sample into early adopters and late adopters. They have found that the business performance management (BPM) tasks have been digitised by resembling logs to enable MAs to track the execution of processes and obtain the data to eventually measure the business unit performance. However, due to the lack of sophisticated functionalities to analyse log data and only be a source to collect data, BI has been used with the BPM to conduct data analytics. It has been found that Integrating BPM and BI for performance management is an essential tool for improving business performance. Accordingly, this needs to be expanded to other functions of the MA, such as budgeting and forecasting, decision analysis, and cost management, which is already the main focal point of the current research.

There are some earlier foundations or conceptions that cannot be neglected when discussing the BI elements, which are (Chen et al. 2012):

a. Decision Support Systems (DSS): These systems reflect the applications used to support the decisions taken by the firm's decision-makers; however, some scholars argued that the DSS comes under the umbrella of the BI (Turban & Aronson 2001); while others see that the BI is the newest version of the DSS where operators are using more sophisticated models to generate better decision instead support the decisions.
b. Executive Information Systems (EIS): these systems come under the DSS, which focuses on supporting the executives in decision-making. According to these systems, executives are given easy access to the company's required data based on the identified goals. These systems provide a user-friendly graphical display for senior managers. EIS mainly uses external, unstructured, and uncertain information for the executives' impromptu and impulsive strategic decisions.
c. Management Information Systems (MIS): the MIS is the central infrastructure where the daily operating records from the daily transactions will be stored. This system should be flexible and reliable enough to respond to daily queries. Thus, managing transactional information is the central core of MIS. On the other hand, the analytical information is the BI's central core, where data is collected from the transactional activities and compiled to connect the dots to analyse the performance in certain areas and answer questions raised by management.

2.3.5 Descriptive analytics

This type of analytics is the most common type in which it focusses on the past to view what already happened (IBM 2021). It has a different name and different forms in the business environment. These include KPIs dashboards, and descriptive statistics, where results are compared to benchmarks or fixed objectives (Dilla et al. 2010). Visualisation comes under descriptive analytics, which is very common in the business environment presented in dashboards and menus; it has been implemented in the BI systems and is already quite common in business use (Dilla et al. 2010). The BSC is the most common and omnipresent measure involved, and embedded in the BI-based visualisation systems is the BSC, since BI intersects with BA in the descriptive part. Organisations use and digitise the BSC model to understand their performance and analytically describe their overall performance from many dimensions: financial, internal process, market and customer, and learning and growth. The model shows real-time results based on the updated inputs and hence visualises these simultaneously to for decision-makers. Visualisation techniques are highly appreciated by the top management, especially when they show simplicity and presentability, and provide the intended information in glances such as geo-maps, pie charts, or heat maps (Davenport & Harris 2017).

2.3.6 Diagnostic analytics

Diagnostic analytics elucidates the "Why did this happen?" query. Diagnostic analytics is the practice of analysing data in order toto ascertain the underlying causes of trends and correlations between variables. It may be considered a natural progression following the use of descriptive analytics to discover patterns. Diagnostic analysis can be performed manually, via the use of an algorithm, or through using statistical software. One use of diagnostic analytics is to ascertain the drivers of product demand. For instance, a catering firm collects millions of data points from global consumers, such as geographic location, reported demographic information, meal type, taste preferences, and normal order cadence and time. This data is used by the company's staff to establish links between trends in consumer traits and behaviour. As a hypothetical example, suppose the company's team notices an increase in orders for fish-based recipes. After doing diagnostic analysis, they discover that the factors most strongly associated with ordering fish recipes are female identity and coastal residence.

2.3.7 Predictive analytics

Once the obtained data is analysed to develop descriptive statistics, it becomes essential for data analysts to use this result and predict what would happen in specific areas and characteristics (Bertsimas & Kallus 2020). There are various models to be implemented in predictive analytics, such as the probability and forecasting models. Predictive analytics depends on the historical data generated over time to find out and create a pattern between them and hence provide a forecasted result. Most organisations are less reliant on predictive as their primary focus is on descriptive results; however, organisations have started to use predictive models (Appelbaum et al. 2017).

2.3.8 Prescriptive analytics

Prescriptive analytics predominantly focuses on the actions and responses to the facts that have been revealed from the descriptive statistics and the forecasts. These techniques are responsible for developing solutions and alternatives based on probabilistic models (Bertsimas & Kallus 2020). People may be confused when it comes to the comparison between prescriptive and predictive analytics. Still, when it comes to using a massive amount of data, or big data, the techniques have a prescriptive nature. Prescriptive -oriented techniques depend not only on quantitative data but also on qualitative data from internal and external sources. The data used in the prescriptive analysis can take many shapes and forms, such as social data grabbed from social media, videos, audio, and even pictures (Basu 2013). Prescriptive analytics include mathematical simulation models as well as operational optimisation models, which provide better solutions to mitigate and alleviate the consequences of uncertainties.

MAs can use and practice business analytics and benefit from ample data available to generate alternative solutions for decision-makers, especially when implementing prescriptive analytics that suits the sophisticated nature of the management's objectives and limitations. One notable example in this discipline is the data gathered from social media platforms, which is used to set the optimal marketing budget and reduce any uncertainties that might affect the market segment. MAs who apply the BA techniques could use other exogenous data besides the social media data that reflect the changes in the business environment, competition, regulations, economic conditions, and even the risk events. Appelbaum et al. (2017) argue that management is always reluctant to deal with complex analysis and reporting; hence, MAs can efficiently communicate the complex optimised system's findings to be visually presentable for the decision-makers.

Schneider et al. (2015) confirm that analytics improves the tasks that provide inference, prediction and assurance for accountants and auditors; for example, MAs can work with operational managers to infer any operational inefficiencies. Accountants and auditors also use it to predict future tax liabilities, identify fraudulent financial reporting, and flag risky transactions. However, there are concerns about the confidentiality and integrity of the collected and analysed data, which could potentially lead to bias. We must initiate the current research to fully understand the impact of BI&A on MAPs, particularly their tasks and techniques. Increasingly, Schneider et al. (2015) found that accountants' qualities and skills are highly aligned and coherent with the analytical-based technologies since they are already detail-orientated, frequently conduct analytical-based tasks, and are identified as trusted advisors.

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Another classification has been added by Appelbaum et al. (2017)

- Qualitative and quantitative
- Structured, semi-structured and unstructured
- Exploratory and confirmatory
- Deterministic and statistical

Table 2.4 The orientation and techniques of business analytics in the managerial accounting domain

Orientation	Technique type			
Descriptive (D) Predictive (PD)	Exploratory (E) Confirmatory (C)	Structured (S) Semi-structured (SS)	Quantitative (QN) Qualitative (QL)	Deterministic (D) Statistical (S)

Prescriptive (PS)					
			Unstructured (U)		
	Basic accounting analysis				
D	Ratio Analysis	C	S	QN	D
	Unsupervised				
D	Clustering Models	E	S	QN	S
D	Text Mining Models	E	SS, U	QL	S
D	Visualisations	E	SS, U	QL, QN	S
D	Process Mining: Process Discovery Models	E	S, SS	QN	S
	Supervised				
PD	Process Mining: Process Optimisations	C	S, SS	QN	S
PD	Support Vector Machines (SVM)	C	S	QN	S
PD, PS	Artificial Neural Networks (ANN)	C	S	QN	S
PD, PS	Genetic Algorithms	C	S	QN	S
PD, PS	Expert Systems/Decision Aids	C	S, SS, U	QN, QL	S
PD	Bagging and Boosting Models	C	S	QN	S
PD	C4.5 statistical Classifiers	C	S	QN	S
PD	Bayesian Theory/Bayesian Belief Networks (BBN)	C	S	QN	S
PD	Dempster-Shafer Theory Models	C	S	QN	S
PD	Probability Theory Models	C	S	QN	S
	Regression				
PD. PS	Log Regression	C	S	QN	S
PD, PS	Linear Regression	C	S	QN	S
PD, PS	Time Series Regression	C	S	QN	S
PD, PS	Auto-Regressive Integrated Moving Average (ARIMA)	C	S	QN	S
PD, PS	Univariate and Multivariate Regression Analysis	C	S	QN	S
	Other statistics				
PD	Multi-criteria Decision Aid	C	S	QN	S
PD	Benford's Law	C	S	QN	S
D	Descriptive Statistics	E	S	QN	S
PD	Structural Models	C	S	QN	S

PD	Analytical Hierarchy Processes (AHP)	C	S	QN	S
D	Spearman Rank Correlation Measurements	E	S	QN	S
PD	Hypothesis Evaluations	C	S	QN	S
PD, PS	Monte Carlo Study/Simulation	C	S	QN	S

The techniques that are traditionally applied in the accounting field are based on statistical techniques that use structured data and follow the quantitative approach. The analytical techniques have been enhanced and modernised by using algorithms such as machine learning (ML), artificial intelligence (AI), deep learning, text mining, and data mining, which come under the category of prescriptive analysis (Warren Jr et al. 2015). The above table summarises the different techniques under each category of descriptive, predictive, and prescriptive analysis.

The BI&A components identified in this study are directly reflected in the questionnaire, where management accountants and financial professionals are asked to evaluate the extent to which they apply these tools and functions in MAPs. Each component represents a distinct function of BI&A, aligned with different stages of data processing, analysis, and decision-making. The questionnaire employs a five-point Likert scale to measure how frequently respondents utilise BI&A functionalities, ranging from basic data management to advanced analytics. For instance, OLAP, data mining, and data warehousing assess how respondents manage and structure financial and non-financial data, forming the foundation of BI. Visualisation and descriptive analytics examine how professionals interpret and present data for tracking and performance evaluation. Meanwhile, diagnostic, predictive, and prescriptive analytics evaluate advanced decision-support capabilities, helping accountants understand trends, causation, and optimal financial strategies. By integrating these BI&A components into the research instrument, the questionnaire captures the full scope of BI&A application in MAPs, reinforcing its treatment as a single variable. Rather than assessing BI and analytics separately, the survey reflects their synergistic role in data-driven financial management, ensuring a holistic evaluation of BI&A in organisational decision-making.

2.4 BI&A THREE ERAS

BI&A has been developed and evolved over the years in three main phases: BI&A 1.0, BI&A 2.0 and BI&A 3.0 (Chen et al. 2012).

Table 2.5 BI&A Evolution, applications, and research

Eras	BI&A 1.0	BI&A 2.0	BI&A 3.0
Features	RDBMS-based and structured content	Web-based and unstructured content	Mobile and sensor-based content
Applications	E-commerce and market intelligence	Science and technology Smart health and wellbeing	Security and public safety
Emerging research	Big data analytics and text analytics	Web analytics and network analytics	Mobile analytics

In BI&A 1.0 phase or era, the content is structured and distributed by several data sources. It depends on relational databases, which allow users to identify and access data in relation to another sort of data in the same database. Accordingly, it requires a program to administer these relational databases, Relational Database Management Systems (RDBMS). Another dominant feature of this era is the high dependency on Data Warehouses (DW), which are vital for integrating and consolidating enterprise data. The DW compilation uses ETL or Extraction, Transformation and Loading, which permits gathering data from multiple sources and consolidating it into a single, centralised location. This phase also employed Online Analytical Processing (OLAP) which enables the analysers analysts to analyse information from multiple sources and extract the required query data from different views. It also compiles reporting tools that are supplemented with statistical methods and data mining algorithms for advanced data analytics.

BI&A has entered into a new era, BI&A 2.0, when new methodologies have been introduced and employed by the Internet and the Web of data collection and analytics. BI&A has entered into a new era, BI&A 2.0, when new methodologies have been introduced and employed by the Internet and the Web of data collection and analytics. These new methodologies have enabled business and data analysts to use the generated data from the user interactivities, such as the data collected from cookies and server logs, and IP-specific user search. These outcomes of these interactivities would allow exploring customers' needs and lead to identifying new business opportunities. BI&A 2.0 relies on the unstructured data utilised by text and web analytics, web mining, and social network analysis (Chen et al. 2012).

The third era of BI&A 3.0 starts with the excessive usage and embedment of smartphones, tablets, sensor-based devices, and radio-frequency identification technology that allows items to be identified and tracked wirelessly through radio waves using IoT. Here, the data collected are massive, where many new insights are collected and individualised. From this perspective, Bronzo et al. (2013) stated that adopting the latest analytical techniques and BI will most probably lead to massive changes in the business processes. Accordingly, the organisations must equip themselves with the adequate capacity to constantly update procedures and tasks. This can be reflected in the MAPs, especially when Moll & Yigitbasioglu (2019) have concluded that the MA literature lacks attention to internet-related technologies such as Big Data analytics and BI, cloud artificial intelligence and blockchain. They urge researchers to study the impact of those technologies on different accounting disciplines, including the MA and determine the new skills and competencies accountants may need to master to remain relevant and add value. In the same vein, Chartered Global Management Accountant (2013) has surveyed to investigate the impact of Big Data analytics by collecting the opinions from over 2000 CFOs and financial professionals; it has been found that approximately 87% view big data as likely to transform the way business is done in the next ten years; however, this transformation is not clear in which practices (Moll & Yigitbasioglu 2019).

2.5 MANAGERIAL ACCOUNTING PRACTICES (MAPS)

Management accounting is the primary process and techniques of generating, updating, assessing, analysing, rendering, and communicating financial information to decision-makers. The primary purpose of management accounting is to provide financial and non-financial information to internal users to support strategy development, decision-making, and monitoring within an organisation. Key MAPs include budgeting, cost optimisation, performance measurement, analytics-driven decision support, and internal controls (Horngren et al. 2021).

International Federation of Accountants (1998) conceptualises MA as a functional discipline within the broader accounting landscape, with a particular emphasis on data relevant to the strategic planning, strategic assessments, and regulation of managerial activities within organisations. MAPs as tasks and functional activities encompass a range of persistently developed tools and methodologies. These are specifically designated to strengthen managerial operations, therefore promoting the improvement of operational efficiency and the achievement of optimal organisational performance.

Since MA does not report to external users and is exclusive to internal users, it does not require to meet the GAAP standards. It can be adjusted to meet the needs of internal users; for example, the operation manager's requirement may differ from the HR director for reporting. MAs need to provide information for decision-makers in the organisation in whatever format or structure meets the users' needs (Burns et al. 2013; Collis et al. 2017; Horngren et al. 2021).

Organisational planning is one of the most significant and predominant tasks and functions in MA. MAs use management's strategic and operational objectives to forecast the different financial values using forecasting and probabilistic models, for example, simple and multiple regression and learning curve analysis. Decision analysis is one of MA's core tasks, where the managerial accountant conducts marginal analysis to reach a proper decision that enhances the business value and decreases or eliminates the non-value-added activities. CVP, or cost-volume-profit analysis, is used to determine how changes in costs and volume affect a company's operating income and net income. It also assists the company in pricing decisions. The MA undertakes some other decisions, maybe not regularly, such as selling or processing further decisions; adding or dropping segment decisions; making or buying decisions, leasing or buying decisions, and special orders decisions. Another area where the MA focusses is performance management, where the managerial accountant specifies the responsibility centres and reporting segments using transfer pricing techniques. Cost and variance measures are the most common and known ones that help decision-makers know the weaknesses and strengths of the operations and resources, some of the techniques are residual income, stand-alone methods, and incremental methods (Horngren et al. 2021).

The capacity of MAPs to generate both financial and non-financial data, crucial for the survival and sustainability of businesses, underscores their importance, making them a valuable field of study in accountingThe importance of MAPs is underscored by their capacity to generate both financial and non-financial data, which are vital for the survival and sustainability of businesses, making MAPs a value-laden field of study in accounting (Senftlechner & Hiebl 2015). Operational managers have attested to the enhancement in their business processes attributable to MAPs. Resonating with this perspective, Ahmad (2012) asserts that the strategic implementation of MAPs can contribute to heightened increased business profitability by facilitating continuous minimisation of waste and optimally utilising resources.

Nishimura (2005) along with other contributors to the literature such as Hiebl et al. (2013) who explained that MAPs could change due to the challenges faced by businesses, both internally and externally. Internal and external factors have been examined by those authors which include the which include but not limited to the Management Control Systems (MCS), size and change in top management personnel, market competition, and the technological state of art (Azudin & Mansor 2018).

Changes could be seen in the management accounting tasks and techniques, such as how "*the process costing*" is applied or advanced performance measurement systems are done (Burns & Scapens 2000). It becomes crucial for an organisation to understand the nature of the change; for example, if the changes in technology, the organisational change follows, including the management accounting (Robey et al. 2002). AISs have been used to undertake the MA tasks and practices using the ERP systems that are fundamentally tied to accounting work. There is an agreement that the ERP enhances transaction processing, positively impacts the quality of the information, and supports ad hoc reporting (Granlund & Malmi 2002).

The current accounting information systems such as ERP still lack business analysis and decision support for MA. Unexpectedly, the ERP has shown little impact on dealing with the new updates and changes in MA tasks and techniques; in other words, the more the techniques and models used become more sophisticated; the ability of ERP to manipulate information becomes questionable. For example, some of those techniques are the ABC systems, balanced scorecard, value-chain analysis, etc., where their support remains limited by the ERP systems (Granlund & Malmi 2002). Booth et al. (2000) have justified this deficiency as organisations do not use the complete set of modules in the ERP system. Hence, the company is not reaping the benefits of the system. Besides, there is a high probability that companies that implement the ERP system require a longer time to obtain the benefits to benefit from the learning curve. According to Nawawi et al. (2020) research findings, the use of BI&A systems and the implementation of ERP systems result in significant transformations in MAPs, particularly in organisations that have recently adopted BI&A systems. The research findings of Nawawi et al. (2020) indicate that the utilisation of BI&A systems and the implementation of ERP systems result in substantial transformations in MAPs, particularly in organisations that have recently adopted BI&A systems. The authors have determined that the most commonly adopted MAPs subsequent to the comprehensive system implementation are KPIs. Conversely, the least frequently employed techniques, in descending order of significance, include target costing, lifecycle costing, activity-based costing, benchmarking, balanced scorecard, and customer satisfaction surveys.

Based on their survey of 138 practicing MAs in the UAE to discover from their perspectives variables that encourage innovation in management accounting, Halbouni & Nour (2014) observed that conventional management accounting procedures are more commonly practiced than innovative ones. In other words, traditional and innovative MAPs are currently practiced by MAs in the UAE, but the traditional ones are more dominant than the innovative MAPs as shown in Table 2.6. Other data also reveal that globalisation, access to intelligence-based technologies, and business size have a major effect on management accounting innovation, but other factors such as market dynamics and staff credentials do not have a significant influence. The finding that ICT is a key driver of management accounting innovation suggests that more investments in BI&A are needed to update management accounting systems and practices, and more information technology training is needed to empower MAs with skillsets necessary to implement innovative techniques.

Table 2.6 innovative MAPs vs Traditional MAPs

Traditional MAPs	**Innovative MAPs**
Budgeting for planning and control	Financial and non-financial performance evaluation
Variance analysis	Customer satisfaction measurement
Return on investment measurement	Economic value added (EVA)
The use of accounting systems and financial reporting	Providing specialised reports/shareholder value (e.g., about growth possibilities) to stockholders
Short-term budgeting process	Providing other non-standard reports for general use
Using traditional cost accounting systems	Analysing and designing computerised accounting information systems
Financial analysis	Troubleshooting, revising, and enhancing existing systems
Preparing reports for a government agency (e.g., labour statistics)	Managing and supervising accounting information systems

Source: (Halbouni & Nour 2014)

Prior studies have used some techniques such as budgeting (Bergmann et al. 2020), performance management (Chen et al. 2016), ABC method (Youssef & Mahama 2021). Some contributions in BI&A have viewed MA from its attributes such as management control systems, and management cost systems (Elbashir et al. 2021; Gomez-Conde et al. 2019;

Youssef & Mahama 2021), and some other articles examined MA as a broad scope (Ahmed et al. 2019; Möller et al. 2020; Uyar & Kuzey 2016), this current study view MA from its ability to infer accurate insights which is all viewed as management accounting capability, justifications are provided in section 2.9.

2.6 IMPACT OF BI&A ON THE MAPS

2.6.1 Evolution from ERP to BI&A in MAPs

Before moving into BI&A, it is better to highlight the impact of the related technologies to on BI&A and apply them in the MAPs contexts. In their qualitative study (Granlund & Malmi 2002) to study the impact of ERP on the MAPs (Cost and profitability accounting, performance measurement, strategic management accounting implications, managerial control, budgeting and forecasting, MAs role and new challenges), they found that the impact of ERP was minimal as there were no recorded improvement of applying it in different industries, except it allows more time for analysis and lighten the burden of routine reporting. In the same vein, other contributors found a notable enhancement in collecting and reporting accounting data to positively conduct those tasks, enable better control, and positively affect organisational performance (Hunton et al. 2003; Velcu 2007). Others (Spathis & Constantinides 2004) indicated that responding companies for their surveys have increased the use of non-financial performance measures and profitability analyses when the ERP system is implemented.

However, this impact does not create significant upgrades or rejuvenate the tasks and techniques (Granlund & Malmi 2002; Rom & Rohde 2007; Scapens & Jazayeri 2003). Here, the need for a new framework for accounting information systems becomes essential to cope with the sophisticated processes and various data sources and data types. The latest approach in information technology involves collecting necessary data from an ERP system and transferring it to a data warehouse. This data is then connected to BI&A tools such as OLAP, data mining, query and reporting. For example, the OLAP's working mechanisms has been tested on produced financial data and provided real analysis of historical and current data, as well as conducted financial planning activities such as budgeting and budgetary management. The interconnection of the three financial statements, income statement, balance sheet, and cash flow statement, their time dependence, and the demand for various types of financial data consolidation and analysis (temporal, geographic, or across product lines, customer groups, and multiple planned scenarios) make OLAP technology an ideal delivery platform for performing complex multidimensional analysis on financial data (Lauría & Greco 2010). This was well recognised by the Corporation's project management team, which set out to select OLAP systems that met the organisation's needs for flexibility, speed, and adherence to budgetary limitations (Lauría & Greco 2010). However, the sophisticated solutions of BI&A which deal with diagnostic, predictive and prescriptive analytics were not part of the study scope.

2.6.2 BI&A Impact on Strategic MAPs

BI&A has been found to enhance the collection of strategic practices under MAPs such as reporting and analysis. However, only a limited impact on budgeting activities was uncovered. Indeed, there were companies that had only recently initiated the revision of their budgeting process, as they were still reliant on spreadsheets for their financial planning and analysis (Mehdi et al. 2022; Spraakman et al. 2020). These findings are quite similar to the (Rom & Rohde 2007), study which was based on 401 Danish companies were applying ERP and BI&A to conduct MAPs. The ERP has an impact on data collection and the organisation of MAPs, while the BI has relatively more implications upon for the related analysis and reporting practices, where the budgeting activities and tasks were lagging behind in terms of analysis and reporting. In a similar vein, the impact of BI&A on the efficacy of contemporary MAPs has been investigated in the literature by Al-Zubi et al. (2014) who conducted a comprehensive investigation into the impact of BI&A on the efficacy of contemporary MAPs within a sample of 32 industrial firms listed on the Amman Stock Exchange and a total of 40 questionnaires. The study highlighted the ability of BI components to effectively assimilate large amounts of valuable information, particularly in the context of budgeting tasks. The study underscored the capacity of BI components to effectively assimilate substantial quantities of valuable information, particularly in the context of budgeting tasks. Overall, the findings provided substantial support for the working hypothesis positing a positive influence of BI&A tools on the enhancement of modern MAPs. The study sheds light on the advantages conferred by BI&A systems in terms of strengthening decision-making efficiency, saving time, and promoting budgetary economy. However, it seems the sample size was one of the limitations in their study besides, they did not cover the other sophisticated analytical techniques which comes under predictive, diagnostic and prescriptive analytics.

In similar context (Bergmann et al. 2020) argued that BI&A would overcome the main criticisms of the traditional budgeting system for being too time-consuming, costly, and inflexible. Based on their survey for 115 German organisations they investigated the determinants of applying the BI&A in the budgeting process and how those determinants affect the overall satisfactions within the budgeting process from the financial professionals. They proposed three main determinants of sophisticated data infrastructure and two major functions of budgeting (the planning and the evaluation function). They found that the application of BI&A is favourably correlated with a sophisticated data infrastructure. On the one hand, the findings demonstrate a favourable correlation between the usage of BI&A in the budgeting process and the planning function's importance. Because of this, it appears that using BI&A in the budgeting process is especially ideal for companies that place a high value on planning, forecasting, coordination, and resource allocation. However, they do not discover any statistically significant correlation between a company's usage of business analytics in the budgeting process and its emphasis on the budgeting process' evaluation role. Ultimately, they discover that a higher degree of budgeting process satisfaction is correlated with a larger use of BI&A. It appears here that (Bergmann et al. 2020) have focused only on one of the MAPs which is budgeting under two dimensions of planning and evaluation. This would urge researchers to expand the scope of (Bergmann et al. 2020) research to include more MAPs and focusing on other dimensions.

2.6.3 Motivations and Transformations in MAPs

Based on a case study of 10 BI&A consultants from Italian consulting companies with more than 300 BI&A projects in the Italian market run by Nespeca and Chiucchi (2018), they summarised the main reasons to implement BI&A in the context of MAPs as following:

The main reasons to for adopting BI&A systems, as identified in the given passage, can be summarised as follows:

- Improvement in information timeliness: Companies implemented BI&A systems to ensure that information is available when needed, without delay. This enables decision-makers to make timely and informed decisions. The consultants highlighted the importance of having access to information at the right moment.
- Enhancement of information reliability: Implementing BI&A systems addresses the concern of data manipulation by data owners. Without these systems, the risk of using

inaccurate or manipulated data for reporting exists. Without such systems, there is a risk of inaccurate or manipulated data being used for reporting. BI&A systems provide a more reliable framework for data gathering and reporting, reducing the potential for manipulation.

- Information gathering and analysis: BI &A systems are implemented to enable analysis of new dimensions or to enrich the existing information system. MA professionals may require specific information that cannot be generated by existing tools or systems. BI&A systems provide the necessary proficiencies to produce the required information and offer a satisfactory level of detail for analysis.
- Support for cost accounting practices: Some companies implemented BI&A systems to support cost accounting practices on new cost objects. By accurately accounting for costs and revenues and allocating them to specific cost objects, such as bus lines in the case of public transport, companies gain insights into which areas are profitable, and which ones result in losses.

These reasons reflect the motivations behind implementing BI&A systems, specifically in the context of MA. The study also revealed changes in the MAPs due to applying BI&A; The implementation adoption of BI&A as resulted in significant transformations in management accounting techniques. Companies have experienced greater flexibility in reporting, allowing for customised dimensions of analysis and enriched information. Advanced management accounting techniques, particularly the Performance Measurement System (PMS), have been introduced and automated through BI&A, enabling real-time data updates and frequent analysis. Budgeting practices have also been influenced, with BI systems providing IT support throughout the budgeting process, resulting in improved efficiency and structure (Bergmann et al. 2020). Moreover, the implementation of BI systems has preceded the adoption of the BSC, facilitating the extraction of real-time data for dynamic BSC measurement. These changes have enhanced management accounting practices and decision-making processes within organisations. However, most of the focus of (Nespeca & Chiucchi 2018) were on the reporting and processing of the data as well as the descriptive part of the BI&A ignoring the predictive and prescriptive part of the data analytics.

This motivation and transformation in MAPs are supported by the idea of Integrated Information Systems (IIS). In another research run by (Pervan & Dropulić 2019), to check the impact of integrated information system on the MAPs, they collected their data from 108

Croatian firms and concluded that the four assessed dimension of the MAPs have shown dramatic changes. With regards to the data collection aspect, the implementation of IIS has demonstrated advantages in terms of enhanced data scope, accuracy, and timeliness. Specifically, in the context of internal reporting utilising IIS, notable reductions in report production time have been observed, accompanied by increased frequency and quantity of management-oriented reports. Furthermore, positive effects have been identified in relation to budgeting processes facilitated by IIS. Additionally, IIS has the potential to support the implementation of contemporary accounting techniques such as Activity-Based Costing (ABC), Balanced Scorecard (BSC), Target Costing (TC), Benchmarking, and Key KPIs. Combining BI&A with the IIS to conduct MAPs (Pervan & Dropulić 2019) found higher support for forecasting, data mining, business planning and simulations, real time project control, business analytics trough Dashboards, control of key financial indicators, control of key non-financial indicators, business process analysis and ABC, control of key financial and non-financial indicators for business segments. However, authors have not standardised the capabilities between the MAPs, they customise the change factors; for example, for data collection (as one of the MAPs) they added data accuracy and data scope. At the same time, they have not studied the BI&A as self-contained entity of single variable, they studied it as a combination of the IIS. Accordingly, the current study shed light on covering more MAPs and use one change factor which is inference.

2.6.4 Visualisation as BI&A Component

How the BI&A plays a mediating role between ERP and MAPs, has been assessed by Youssef and Mahama (2021). The findings of the study demonstrate that BI&A partially mediates the substantial connections between ERP and the three distinct categories of MAPs: costing, budgeting and performance measurement. This result is consistent with the literature review's expectations because the implementation of a BI&A system, as an extension of ERP, aims to enhance analytical proficiencies. These results show how important it is to include both ERP and BI&A parts in research models that look into how information systems affect the management accounting functions. This result is consistent with expectations of the LR since the implementation of a BI&A system, as an extension of ERP, aims to enhance analytical capabilities. These findings highlight the importance of incorporating both ERP and BI&A components into research models investigating the impacts of information systems on the management accounting function. By considering both ERP and BI&A, future research can gain a more comprehensive understanding of the relationships at play. Youssef and Mahama (2021) have not included in their research the different categories of data analytics (descriptive, diagnostic, predictive and prescriptive), they used only some of the components of the BI such as data warehousing and data mining. Iin addition, the capabilities, or the change factors of the MAPs were not assessed.

In order to bridge this gap, (Spraakman et al. 2020) have followed employed qualitative approach to investigate how the data analytics would enhance predictions and assurance in the MAPs. Based on 20 interviews in different industries, they found data analytics (DA) supports inference, prediction, and assurance in management accounting tasks through several means. Firstly, DA simplifies the analytical process by eliminating complexities inherent in advanced analysis and improving the presentation of results. It enables the simplification and customisation of financial statements for analysis using tools like Excel, facilitating in-depth comparisons and detailed dives into various accounts.

DA also supports self-serve analytics, allowing users to create their own reports with drag-and-drop interfaces, making inference, prediction, and assurance tasks more accessible to analysts. Additionally, DA enables the analysis of different types of data, overcoming challenges posed by large data sizes and facilitating the understanding of the full organisational picture. Furthermore, DA provides a variety of analytical tools for MAs and embedded skillset to detect exceptions, patterns, and non-compliance more readily. Various roles of MAs, such as budgeting, internal control, and financial reporting, benefit from different types of DA analysis, including forecasting, modelling, cost exception reports, variance analysis, and drill-down analysis.

Moreover, drill-down tools and variance analysis in DA allow for detailed insight into costs and their behavior, improving assurance on the validity of financial numbers and facilitating the identification of irregularities and potential areas of fraud. While predictive analytics is still in its infancy in management accounting, DA has the potential to support prediction and forecast analytics, trend analysis, and future-orientated decision-making. Although some organisations have started embracing predictive analytics, there is still room for growth and adoption in this area. However, the study has a limited sample and very restricted geographical area. In addition, the focus of the study was only on the analytics part, which is applicable to be conducted using some available software, such as MS Excel, as it is a repeatedly used tool in the questions and the revealed answers by the respondents.

Visualisation tools, as integral part of the BI&A, have a notable impact on MAPs where performance dashboards, an emerging area whose design is based on scorecards and the presentation of multidimensional financial and non-financial data, are among the visualisation tools. Managers tend to disregard non-financial variables when analysing data in scorecards, scholars suggest using performance markers to prevent bias toward financial performance measurements (Chen et al. 2016; Yigitbasioglu & Velcu 2012). Chen et al. 2016 contend that a manager's understanding of strategically connected performance metrics is more significant than the balanced scorecard's framework for improved decision-making (Chen et al. 2016). In the same contribution of (Chen et al. 2016), they explored the influence of visual attention in management judgements during balanced-scorecard performance assessments.

Eye tracking was used to determine how much time managers spent paying attention to visual cues, and they found that managers paid more attention to measures of performance that were linked to the strategy than to unconnected measures, even when the presentation format of the strategy information didn't play a big role. In other words, they discovered that knowledge of strategically related performance metrics, but not their presentation, appeared to be essential in assisting managers to make better choices. Performance dashboards are successful when their goals are matched with their functional and aesthetic design characteristics, and when they are adaptable (or customisable) and adapted to the particular kind of user (Yigitbasioglu & Velcu 2012). Specific visualisation tools or dashboards perform well with large time series data or probabilistic forecasts. The use and efficacy of visualisation approaches or methodologies other than tables and standard graphs in MAPs for complicated data (big data) have to be investigated. Specifically, planning and control-relevant strategies for qualitative data visualisation.

In addition, given the significance of fit in visualisation, it would be beneficial to map the needed characteristics of a system to the different activities in management accounting. To elaborate, some tasks, such as budgeting, may need more interaction or system recommendations, but performance monitoring may not. Considering the potential for BI&A when advocating the presence or absence of a given feature, future studies might emphasise the characteristics that are most suitable for certain activities, while considering the possibility of BI&A when recommending a particular feature or its absence. In addition, visualisation with intelligence feedback paves the way for linking artificial intelligence to the display of information, both in selecting an appropriate visualisation that fits the user (e.g., the functionality of solutions such as Tableau and Qlik) and the task, as well as aiding with the visual analysis and interpretation of the data (Chu & Yong 2021).

2.6.5 Contemporary Applications and Future Directions

Performance measurement, as one of the MAPs, have been covered in the literature. It was in the attention of (Ocañas & Cruz 2018) but only in terms of the visualisation and reporting tools. Their case study of Mexican brewery plants led them to the conclusion that decision makers and end users' preferences should guide the development or application of visualisation techniques and tools. Based on her case study of Mexican brewery plants, they found that applying the visualisation techniques and tools must be used or developed to suit the end users' preferences as well as decision makers. They set a group of rules for the visualisation reports, such as When creating visualisation reports for performance measurements, it is important to consider end user preferences. This includes respecting the colour code and symbology of the company, ensuring that the report uses terms in the local language to enhance understanding across all levels of the organisation. The report format should be easily distributable via email to all employees. Utilising a dashboard-style layout allows for an overview of the most relevant indicators from each area, providing insights into the organisation's current status and performance. Regular monthly updates should be conducted to ensure that management can make informed decisions on how each area can contribute to achieving global indicators. Additionally, including a comments section for each indicator enables users to delve into the details and gain a comprehensive understanding. Although this conference paper sheds the light over on the performance measurement; however, it partially covered the performance measurement from the perspective of the MA and focussed only on the visualisation of the descriptive statistics, similar to (Vallurupalli & Bose 2018).

PMS would bring substantial improvements; this has been investigated by Vallurupalli & Bose (2018) who proposed an innovative PMS utilising BI&A for a large manufacturing company in India. The project was initiated due to the limitations and challenges associated with traditional dashboards, characterised by complex data tables comprising numerous rows and columns, which hindered effective decision-making. The implementation of the new PMS brought about substantial improvements, enabling employees to monitor and track their performance using BI-based dashboards. Managers can now engage with employees, addressing deviations and managing actions directly through the interactive dashboard interface. Furthermore, the introduction of the new BI systems enhanced overall transparency in setting performance targets, facilitating comparative analysis. Notably, the authors discovered a significant enhancement in the productivity of management meetings, a key driver behind the PMS implementation. Additionally, the incorporation of rich visualisation features has considerably improved analysis and communication among employees, enabling faster and easier interactions through interactive graphical representations such as graphs and maps. The marketing and sales departments particularly benefitted from the utility of these visual features.

Peters et al. (2016) have advanced a comprehensive perspective on the usefulness of BI&A systems when employed for performance measurement and balanced scorecards. BI&A systems offer extensive capabilities for measurement and analysis, serving as the basis for implementing integrated and comprehensive management control systems. This broad capability to enable such systems is facilitated by the multitude of pre-designed scorecards and key performance indicators embedded within modern BI software. Consequently, these pre-designed scorecards and key performance indicators represent distinct attributes of a BI system that significantly enhance its capacity for improved performance measurement capabilities. In the same vein, (Zóltowski 2022) have has conducted a bibliometric analysis of the BI in the balance scorecards and found that the domain of BI&A and its utilisation of tools to bolster the balanced scorecard framework are revealed to be more of a generic notion rather than a distinct and operationally implemented set of tools, the consequential effects of which require meticulous investigation. Despite the potential advantages associated with the incorporation of BI&A tools within the Balanced Scorecard framework, the proportion of scholarly articles devoted to this subject remains relatively meagre when compared to the overall corpus of literature pertaining to the Balanced Scorecard. Both domains are characterised by perpetual advancement, although such progress is not readily apparent in the literature. Consequently, forthcoming research endeavours could focus on identifying the factors contributing to this circumstance or attaining a deeper comprehension of the determinative yet unexplored domains.

Accordingly, the MAs' Analytical Skillset will be affected by such changes in the tasks and techniques applied in the MA context. It has been agreed that the accounting information system and the digitisation of the MA process have made MAs' roles more strategic-oriented and more consultancy-based roles (Caglio 2003; Rom & Rohde 2007). MA tasks become applied in other functions in the organisation, such as but not limited to supply chain and procurement, operations and risk management, etc., since the enterprise systems are applied in the MA context. In other words, MAPs implementation becomes more decentralised; hence, the MA function's decentralisation is perceived. For example, the MAPs become accomplished and completed in other functions in one company (Granlund & Malmi 2002; Quattrone & Hopper 2005).

BI&A is complementing the ERP in that which the ERP collects, organises, and reports the enterprise data while the BI&A analyses and interprets the data in a presentable, understandable, and actionable way (Chen et al., 2012). In their study, (Korhonen et al. 2020) discovered that not all MAPs are programmable. They have found that not all the tasks and techniques of MAPs can be programmed. Additionally, they discovered that cost-related expertise can be surprisingly nonprogrammable, and the entire pricing-related tasks and only parts of the cost specialists' pricing task can be programable if the sales configuration is programmed. Automating the MAPs using robotic process automation (RPA), machine learning, and AI must be done with discretion due to the un-programmability of some of the tasks that require human cognitive interventions. However, BI&A is not a fully automated solution; it requires necessitates human interventions and even judgement and employs their expertise and MAs knowledge along with the market and business understanding. Therefore, knowing the MAPs that can be affected but the BI&A is highly crucial before pouring investment to achieve full automation of the MAPs. While existing research demonstrates BI&A's positive impact on MAPs, several contradictions emerge. Spraakman et al. (2020) suggest that accountants' roles remain largely traditional despite BI&A adoption, while Oesterreich and Teuteberg (2019) argue for fundamental role transformation. These contradictions may reflect varying organisational contexts and implementation approaches, highlighting the need for more nuanced understanding of contextual factors affecting BI&A's impact on MAPs.

2.7 MAPs INFERENCE CAPABILITY

Although existing literature has explored the influence on MAPs, there is a lack of empirical study testing its particular impact on the ability of MAPs to make inferences. The present study focuses on the dimension of inference capability of MAPs as an organisational capability, which is a crucial factor that can be significantly impacted when organisations implement BI&A models. The inference capability of MAPs refers to the ability to derive meaningful insights and conclusions from accounting data to support decision-making as synthesised from (Appelbaum et al., 2017).

MAPs inference capability represents a distinct organisational capability that extends beyond individual accountant competencies. It encompasses the systematic processes, technological infrastructure, and organisational routines that enable firms to derive meaningful insights from accounting data (Oesterreich et al. 2019). This capability manifests in the organisation's ability to transform raw accounting data into actionable intelligence through established procedures, automated analytics, and standardised interpretation frameworks (Moll & Yigitbasioglu 2019).

Like other organisational capabilities under the RBV, MAPs inference capability develops through deliberate investment in systems, processes, and routines (Peters et al. 2016). It represents a firm-specific capability that can create competitive advantage through superior information processing and decision support (Elbashir et al. 2021). This distinguishes it from individual management accountant skills, as it is embedded in organisational processes and technology infrastructure rather than residing solely in human capital."

The justification for MAPs inference capability as an organisational capability is further reinforced by Schneider et al. (2015), who categorise inference as one of the three key tasks in accounting, alongside prediction and assurance. Their study highlights how data analytics has fundamentally changed accounting task processes, particularly in inferring insights from financial and operational data to support decision-making. The study aligns with the conceptualisation that inference is not an individual accountant’s skill, but a function embedded in MAPs through BI&A-enabled processes, systems, and data infrastructures.

Examining MAPs inference capability as a mediating mechanism between BI&A and organisational performance reveals how firms systematically transform accounting data into strategic insights. Organisations implementing BI&A develop enhanced inferential capabilities through sophisticated analytical and visualisation functionalities that augment traditional accounting methods (Rikhardsson and Yigitbasioglu 2018). This organisational capability enables systematic evaluation of BI&A's impact on decision support processes.

MAPs inference capability represents a critical organisational process for value creation from accounting information. While data collection and reporting provide the foundation, organisations develop systematic routines for generating actionable insights that drive performance improvements. As Bhimani and Willcocks (2014) note, the evolution of data analytics and decision support technologies fundamentally transforms how organisations derive insights from MAPs.

The organisational capability to draw meaningful inferences remains underexplored in information systems research, with most studies focusing on technological impacts on specific accounting procedures (Rom and Rohde 2007). Understanding inference as an organisational capability provides deeper insights into how BI&A enhances firms' systematic ability to generate valuable insights across management accounting domains.

This organisational capability encompasses standardised processes for deriving conclusions from management accounting activities through systematic analysis of facts, calculations and observations. For instance, organisations develop structured approaches to performance measurement that maintain competitive positioning while controlling costs. The systematic nature of these processes, enabled by BI&A, allows organisations to generate consistent, timely insights that may not be achievable through conventional methods.

Increasingly, examining the influence of BI&A on MAPs inference capacity could result in several significant findings. BI&A may demonstrate how it improves particular inferential procedures within MAPs. For instance, it has been shown that BI&A significantly enhances the capacity to recognise causal connections, discover irregularities, or establish precise predictions based on accounting data (Appelbaum et al. 2017). This can provide organisations with guidance on how to effectively utilise BI&A functions in order to optimise the development of insights.

This study has the potential to reveal possible obstacles or constraints in employing BI&A to facilitate inference in MAPs. Challenges such as data quality issues, absence of integration, or complexities in comprehending intricate analytics can arise as obstacles (Rikhardsson and Yigitbasioglu 2018). The identification of these factors can facilitate the development of solutions to surmount barriers to the efficient usage of BI&A usage. Moreover, investigating the intermediary function of inference ability in the relationship between BI&A and performance helps illustrate the process by which BI&A generates value. Should it be demonstrated that improved inference acts as a mediator in the relationship, it would emphasise the need of prioritising the development of insights rather than only deploying business intelligence and analytics technologies (Peters et al. 2016).

The conceptualisation of MAPs inference as an organisational capability aligns with contemporary understanding of management accounting as a system of interrelated processes and technologies rather than merely a set of individual activities (Möller et al. 2020). This systemic view emphasises how organisations institutionalise their ability to derive insights through standardised processes, automated analytics, and established decision support frameworks. While individual accountant skills contribute to this capability, the organisation's ability to consistently generate meaningful insights depends on its systematic processes and technological infrastructure (Spraakman et al. 2020).

In another study, Elbashir et al. (2021) found that management control-oriented BI&A enhances the integrated management control information and shows a significant indirect relationship with business process improvement and organisational performance. However, they focused on their sample at the executive level who might be interested in the visualisation domain of the BI&A and ignoring the financial professionals who are experiencing and undertaking the daily MAPs. Another study by (Peters et al. 2016) investigated the impact of BI&A quality from three main dimensions (infrastructure, functionality and self-services) on management control and how it enhances performance measurement capabilities, and how it is related to the competitive advantage. They found that BI&A quality enhances the performance measurement capabilities and are positively associated with competitive advantage. Thus, they have focused only on a limited aspect of MAPs which is the performance measurement.

AIS and its related applications, such as BI&A and ERP, give more insights and understanding of the financial numbers through various analytical techniques (Spraakman et al. 2020). Data analytics produce more accurate information that boosts and optimises managers' and decision-makers' understanding of the financial and operational details. Accordingly, data analytics enhance inference and prediction (Spraakman et al. 2020). This inference adds value to the firm in two ways; firstly, the MAs become more aware of and mindful of the financial numbers in terms of causal explanations that improve any evaluation. Secondly, the decision-makers perceived understanding of the situations in different contexts and paved the path for understanding and assimilating the predictions (predictive analytics) and what recommendations and actions to do (prescriptive analytics).

Wamba et al. (2017) demonstrate how process-oriented capabilities enable organisations to leverage detailed information through analytical methods. This aligns with MAPs inference capability, where established organisational routines and systems enable consistent derivation of insights from accounting data. Mikalef et al. (2020) further support this view, showing how organisational capabilities mediate between technological resources and performance outcomes.

The framework proposed by Rikhardsson and Yigitbasioglu (2018) positions MAPs as organisational processes that generate value through systematic analysis and interpretation. This organisational capability perspective helps explain why similar BI&A investments yield different results across firms, the ability to derive meaningful insights depends on organisation-wide processes and routines, not just individual competencies. Rikhardsson and Yigitbasioglu (2018) emphasise that BI&A technologies are transforming management accounting by enhancing decision-making through data integration, analytics, and visualisation tools. The authors argue that inference capability in MAPs emerges from an organisation's ability to collect, structure, and analyse accounting data systematically using BI&A. This aligns with Elbashir et al. (2021), who found that BI-integrated MCS facilitate the assimilation of financial insights into business processes, significantly improving performance measurement and strategic decision-making.

Geddes (2020) highlights that BI&A has become an essential component of management accounting, as it enables accountants to move beyond retrospective reporting towards real-time analysis and predictive insights. This supports the conceptualisation of inference as an organisational capability that allows MAPs to process vast amounts of data, detect trends, and identify causal relationships. Similarly, Wamba et al. (2016) argue that big data analytics enhance firms' ability to extract insights from complex data, reinforcing MAPs' capacity for inference and strategic alignment.

2.8 MAS' ANALYTICAL SKILLSET

2.8.1 Current State of MA Analytical Skills

The digital transformation in management accounting has led to an evolution in the skillset required MAs. Spraakman et al. (2020) categorised organisations in Canada into three tiers based on their integration of DA: 20% adhered to traditional practices relying on trend analysis; 55% employed basic DA tools like Excel for data extraction and analysis; and 25% fully embraced data science, integrating statistical models and IT for predictive analytics. Despite this, the core responsibility of MAs, supporting senior management with traditional analysis, has remained largely unchanged. However, their roles have expanded to include data preparation and presentation, signifying a shift towards more data-driven support functions. The study also identified five dimensions of evolving MAs responsibilities: (1) from serving only senior management to broader managerial support, (2) from direct service to client self-service, (3) from purely financial to both financial and statistical/mathematical skills, (4) from isolated MA units to IT-integrated teams, and (5) from traditional MAPs to DA-enhanced capabilities. Nevertheless, the study's reliance on a limited sample from central Canada and interviews constrains its generalisability. Similarly, Oesterreich et al. (2020) observed that while DA adoption is reshaping expectations of MAs and controllers, current job roles still heavily involve traditional practices, with minimal emphasis on DA or data science. Their text analytics of 2,331 German professional profiles revealed a skill gap: the anticipated future roles demand IT and data science skills, yet current requirements reflect traditional tool proficiency (e.g., ERP, Microsoft Office). This mismatch suggests a lag in skill development relative to technological advancement.

2.8.2 Evolution of Skills Requirements

The findings of Steens et al. (2024) are in the same line of Oesterreich et al. (2020). Steens et al. (2024) who has a sample of 453 senior controllers and MAs in the Netherlands have found that these controllers considered their existing digital skills to be inadequate and expected substantial growth needs. Nevertheless, the anticipated future levels of competence continue to be modest, even for technology that is dedicated to tasks such as analytics and visualisation. A positive correlation was observed between higher levels of present knowledge and increased predicted competency growth, indicating that acquiring knowledge is an essential first stage in skill development (Steens et al. 2024). Controllers prioritised technological competencies associated with business control activities of higher expectation. Steens et al. (2024) emphasise a possible discrepancy between controllers' low assumptions of future digital competency requirements and the higher levels presumably needed in progressively digitised financial operations. This underscores the importance of proactive skill development to sustain relevance.

Madsen and Stenheim (2016) have given two possibilities regarding these Analytical Skillset gaps: the first possibility is that many organisations have yet started their digital transformation process; for example, the actual adoption rate of big data, cloud computing, BI&A is still low;

accordingly, financial controllers and MAs are not required to possess the data analytics and data science skill profile and do only their traditional roles and responsibilities. The second possibility refers to those companies that which adopt and invest in the BI&A, and big data analytics might favour dedicated people as data scientists and data analysts instead of improving their MAs or burdening them with extra tasks and responsibilities. This is reflected in the increasing demand for data scientist jobs in the market, and it is expected to further increase in the upcoming years.

In their case study, Nespeca and Chiucchi (2018) found that the implementation of BI&A systems has brought about changes in the roles of MAs. The sample revealed that BI&A systems have enabled MAs to reduce time spent on routine activities like data gathering and report preparation, allowing them to allocate more time to data analysis. The system's automated data control capabilities have shifted the focus towards analysis. Furthermore, consultants highlighted that the implementation of BI&A systems has pushed MAs to enhance their knowledge of the company's business. However, it was noted that this enhancement typically occurred when the MAs were the driving force behind the BI project.

2.8.3 Emerging Roles in Digital Environment

Franke and Hiebl (2023) found that the availability of a wide range of big data sources and the establishment of a data-driven organisational culture enhance the effectiveness of decision-makingthey found that the effectiveness of decision-making is enhanced by the availability of a wide range of big data sources and the establishment of a data-driven organisational culture. However, it is crucial for MAs to possess advanced data analytics skillset in order to fully capitalise on these resources. The findings of this study findings highlight underscore the significance of MAs within an organisation and their proficiency in converting large volumes of data into well-informed judgements, an aspect that has not been thoroughly investigated thus far. They approved the moderating role of the MAs' analytical skills between the available sources of Big Data and the quality of the decisions. The main skillset that they found are the skills to handle processing and cleaning big data with different types, visualise the data using different platforms, skills of transforming the raw data into business intelligence, produce insights from unstructured data. The achieved mean values range from 5.5 to 5.7 in a 7-point Likert scale.

BI&A has a drastic impact on the MAs' Analytical Skillset in the different business environments (Andreassen 2020). Andreassen (2020) conducted a case study at an insurance firm in a Nordic country, highlighting the lack of comprehensive empirical investigations that have examined the impact of digital technology on MAs' responsibilitiesAccording to Andreassen's (2020) case study conducted at an insurance firm situated in a Nordic country, there is a scarcity of comprehensive empirical investigations that have examined the impact of digital technology on the responsibilities of MAs. The research paper outlines a transition in the responsibilities and expectations of divisional MAs, resulting in more specialised jobs.

Conversely, business-oriented roles at the group level are observed to have broader responsibilities and higher expectations. The integration of digital technology into BI&A has the potential to facilitate more focused and specialised responsibilities for MAs. This is achieved through the utilisation of digital tools that enable the performance of duties such as customer accounting, pricing, and product evaluations to be more specialised. Moreover, the utilisation of BI&A for the purpose of gathering data and offering decision-making assistance has the potential to enable the emergence of novel specialised positions within the Customer Relationship Management (CRM) and the analytics, product, and price departments.

The author elucidates that the alterations brought about by digital technology, as discussed in the context of BI&A, might serve as intermediaries in the identity-related efforts of MAs. This mediation occurs through two distinct mechanisms. One potential benefit of BI&A is the ability to provide MAs with greater autonomy and freedom in their employment. This allows them to pursue areas of personal interest that are closely aligned with their professional identity. For MAs, this can be seen as a highly desirable outcome, analogous to the realisation of a long-held aspiration. Furthermore, BI&A have the potential to impact positions by diminishing their influence, increasing the prevalence of monotonous duties, and perpetuating a constant cycle of fulfilling information requests. Consequently, this can result in issues about one's identity and a perceived disassociation between the role of a management accountant and their own sense of self.

In the same vein, Kokina et al. (2021) discovered that all accountants, including the MAs, will play five roles in the digitisation era. Within the realm of digitalisation, there exist various pivotal functions that play a significant role in augmenting organisations operational efficiency and overall effectiveness of organisations. The identifier role utilises a range of cognitive abilities, including critical thinking, problem-solving, process mapping, and project management skills, in order to discover potential areas for digital transformation. This involves identifying manual processes that are suitable for automation, employing technology such as BI&A. The Explainer role possesses a set of abilities, including communication, change management, and stakeholder management. Based on this role the accountant aims to clarify the benefits of digitalisation to various stakeholders. Specifically, they provide examples to senior management and other decision-makers, illustrating how digitisation such as robotic process automation and BI&A may save expenses, improve operational effectiveness, and enhance precision.

The trainer role, possessing specialised knowledge in the areas of training and development, coaching, and mentoring, assumes a vital role in imparting employees with the requisite information and abilities to foster efficient collaboration using digitalisation technologies and data. In addition, the sustainer's role expertise in programming and data analysis, coupled with their strong analytical and problem-solving abilities, plays a crucial role in maintaining and enhancing digitalisation systems. This encompasses tasks such as debugging issues and proposing improvements to ensure uninterrupted functionality and ongoing development.

Finally, the analyser possesses expertise in data analysis, data visualisation, and critical thinking. They utilise intelligence-generated data to conduct predictive, prescriptive, and historical studies, and skilfully convey these findings to relevant stakeholders. The combination of these jobs and their respective abilities collectively contribute to the formation of a unified team, which plays a crucial role in facilitating the advantages of digitisation across the entire organisation (Kokina et al. 2021). Nevertheless, there has been a lack of attention from authors about the correlation between skills and management accounting practices. This correlation is influenced by the industry in which a company operates, as well as the operational capabilities of the company within that industry.

2.8.4 Technical Competencies Development

The functions and competencies of MAs were investigated by Rouwelaar et al. (2021) in the context of Dutch healthcare organisations. The study involved a survey of 215 controllers. The researchers investigated the perception of MAs regarding the necessity of possessing interpersonal skills, conceptual skills, and technical skills in order to exert influence and achieve effectiveness in their expanded role. Interpersonal skills refer to the ability to constructively challenge and question assumptions, numbers, and their meanings. Conceptual skills involve the capacity to make and lead decisions that align with the organisation's business environment and strategy. Technical skills encompass proficiency in computer usage, accounting, and data modelling.

It can be inferred from the literature that the perceptions observations of MAs regarding their influence on management decision-making are linked to their possession of interpersonal and conceptual abilities. Furthermore, it is evident that the efficacy of MAs is associated with the presence of all three skills. It is also observed that the influence of MAs is jointly connected with both technical and conceptual skills, whilst while their effectiveness is jointly associated with conceptual and interpersonal skills (Rouwelaar et al. 2021). However, authors have neglected the mapping of those skills with the MAPs that varies depending on the industry and even in the operation capacity of the companies within the industry.

In their study, Wadan et al. (2019) conducted a comprehensive examination of interviews and job advertisements to gain insights into the progression of competencies among MAs in Germany. Observations indicate a shift from conventional analysis approaches to statistical analysis methods. It has been observed that a transition is occurring from conventional analysis approaches to statistical analysis methods. The implementation of personalised production and process control relies on the utilisation of forecasts and predictive analytics. This approach enables the early detection of market fluctuations and facilitates the ability to proactively anticipate such changes. It has also been discovered that the existing IT skills possessed by MAs are inadequate in meeting the demands of the emerging Industry 4.0, which involves the handling of vast amounts of data and various data formats. The demand for data scientists is on the rise; however, it is not replacing the need for those with a MAs. The examination of job advertisements provided empirical support for the assertion that there is a growing demand for professionals in the field of data science. Nevertheless, the available information does not support the existence of a positive correlation between a MAs and the occupation of a data scientist. Therefore, it may be inferred that the role of a data scientist will evolve separately from that of a MAs. The extent to which the actions of MAs have been thoroughly examined in regard to their potential applications in forecasting, early detection, and scenario assessments remains insufficient. Due to this rationale, their study serves as a preliminary documentation and categorisation of the existing role of the MAs within the framework of Industry 4.0 (I4.0) (Wadan et al. 2019).

In a study conducted by Szukits (2022), the author examined the perceptions of senior managers in Hungarian small and medium-sized firms towards the utilisation of advanced analytics. The findings of the study revealed that the adoption of advanced analytics has resulted in an increased recognition of the significance of MAs' participation in the decision-making process inside organisations. Furthermore, the researcher discovered that the surveyed executives held the belief that advanced analytics, along with the contributions made by MAs, have the potential to enhance decision-making processes. However, it was also discovered by Szukits (2022) that the aforementioned criteria did not result in a significant rise in the amount of genuine data-driven decision making. The study suggests that the involvement of MAs in utilising data analytics for business decision-making is significant. However, it is crucial to note that Szukits (2022) did not examine the specific abilities possessed by MAs in this context. The existing body of work on management accounting has suggested that the IT and statistical skills possessed by MAs may be highly pertinent (Wolf et al. 2020). As an example, Rouwelaar et al. (2021) study which revealed a favourable relationship between the technical skillset of MAs and their efficacy in performing their roles.

Oesterreich and Teuteberg (2019) urge future research to investigate further how the competence profiles of the MAs and financial professionals as well as data can be defined more deeply in several organisational contexts. In the same vein, the IMA found considerable skills gaps in MAs' business and data analytics proficiency and know-how, based on a distributed survey of 500 financial executives and managers. Increasingly, those firms have found it difficult in finding qualified personnel with the required skills. IMA also concluded that there is an obligatory need for skills in strategic data-driven analyses, which involve the application applying of business analytics techniques and processes. The IMA added that the adoption of BI&A will definitely expand the tasks of MAs and financial controllers, and hence companies must be prepared to close the skills gap. Consequently, this could drive companies to heavily invest in formal education and training to remain competitive in the market. Besides, organisations may embed the data and business analytics skills in the MAs' annual development plan or grant them the opportunities to develop those skills (Brands & Holtzblatt 2015).

Researchers conducted evaluations on the significance of various trends, including business analytics, digital business models, self-service reporting, agile management, and digital literacy. In the year 2017, evaluations were conducted about the significance of many trends, namely 'business analytics,' 'digital business models,' 'self-service reporting,' 'agile management,' and 'digital literacy. Only a small percentage of controller functions, specifically 5% of respondents, make extensive use of business analytics. They found that the majority of controllers lack natural competence in the BI&A. Additionally, the investigation revealed that a limited number of organisations have incorporated data scientists within their financial departments. Inside the investigated firms, it was seen that data scientists predominantly occupied positions inside the IT and operations departments. Furthermore, a mere 22% of the companies that employed data scientists allocated them to roles within the controlling function. The results also suggest a limited level of interaction between controllers and data scientists, irrespective of whether the latter are employed in controlling or other departments. It is observed that a mere 17% of organisations exhibit a close collaboration between controllers and data scientists (Möller et al. 2020).

MAs have been dealing with a variety of data with different categories and different volumes, especially big data. Big data has three main characteristics: volume, velocity, and variety. The volume in this framework refers to the magnitude of data predicted to grow annually by 61% (Oesterreich & Teuteberg 2019). The second element is the velocity, which refers to how fast the data is generated. The faster the data is created, the more opportunities companies can seize; however, this raises an eager need for real-time analysis and decision-making. The last element is the variety of data; this element shows the various types of data received in the business environment regarding structural heterogeneity.

Data is divided into three main categories: structured data, which is available in tabular form and found in relational databases, such as CRM or ERP;, it is characterised by its exact values and has standard rules to process. While the unstructured data is not located in tabular forms and cannot be manipulated by conventional databases,; such as but not limited to multimedia contents (images, audios, emails, phones calls, software updates), social media contents (posts, ads, comments, interactions), machines and sensors' data, etc. (Cai & Zhu 2015; McAfee et al. 2012). The last type is semi-structured, which is a mixture of both structured and unstructured data in which some of the data can be managed by conventional relational databases, and the rest uses sophisticated and advanced analytical (Gandomi & Haider 2015). Those sophisticated techniques are addressed as big data analytics, which is called interchangeably in the market and academia as data analytics, business analytics and real-time analytics; they are part of the BI (Chen et al. 2012). Effective implementation of digital technology in management accounting requires a wide range of technical competencies. The development of competence in data analytics, encompassing the capacity to handle both structured and unstructured data, is imperative for MAs (Arkhipova et al. 2024). While other authors have stated that proficiency in programming and statistics is becoming more crucial (Richins et al. 2017).

MAs have always depended on structured data to conduct the data analysis tasks; for example, the generated data from ERP, CRM, and other customised similar applications and spreadsheets programs (Brands & Holtzblatt 2015). With the massive amount of data of all types, which seems impossible to analyse, big data analytics or DA has the capabilities to elicit patterns and find correlations and hence generate a conclusion. This data includes mMedia and entertainment data, surveillance data, geospatial data, audio, weather data, sensor data, voice mail, email, employees and customer logs, documents and presentations, encrypted files and messages, social networks profiles and posts, customers visits and interactions in websites, blogs and forums, etc. (Beach & Schiefelbein 2014). Accordingly, it becomes insufficient to only depend on historical data to guide the decisions. Still, MAs must implement future-oriented business analytics, which utilises the unstructured data from multiple sources to create patterns and correlations to understand the market trends and customers (Bhimani & Willcocks 2014). Recent studies reveal tensions between traditional accounting skills and emerging analytical requirements. While Kokina et al. (2021) emphasise the need for advanced analytical capabilities, Steens et al. (2024) find significant gaps between current and required digital competencies. This disconnect suggests potential challenges in skill development and role evolution that merit further investigation.

MAs should utilise the increasing amounts of structured and unstructured data and turn it into opportunities to add value to origisnations. It has been proven that data-driven decision-making improves corporate productivity and achieves higher outcomes (Brands & Holtzblatt 2015). Consequently, MAs must acquire DA-related skills, which become professional standards, and update their competence profile to gain the benefits of DA (Bhimani & Willcocks 2014). Seeking and acquiring those skills is part of the professional competence and due care by "*Attain and maintain professional knowledge and skill at the level required to ensure that a client or employing organisation receives competent professional service, based on current technical and professional standards*" (CIMA 2022). As a response to professional awarding bodies in the management accountingMA and professional financial credentials, the Institute of MAs (IMA) has updated the knowledge areas to include a new domain for "Technology and Analytics." in 2018 updates (IMA 2018). Simultaneously, the competence framework was updated to include technology and analytics as a catalyst to utilise the other stated competencies areas: strategy, planning & performance management; reporting & control; business acumen & operations;, leadership; and professional ethics & values. IMA (2023) has listed four main dimensions or tasks under the new “Technology and Analytics” domain. MAs can conduct each dimension or task with different levels of maturity and skills, starting from limited-skilled MA to expert MA, in which the expert MA has the ability to:

Information systems: design a simple form of data warehouse dedicated to a single subject in a business called data marts;, also, the ability to design central repositories of integrated data from one or more disparate sources, known as data warehouses. This ability and role make MAs provide access to information throughout an organisation. Under the exact dimension of the information system, MA can augment operational and financial performance through design system structure and evaluate ERP systems in complex environments.

Data governance: systematise data cleansing practices, processes and policies to store and retain data according to the legal requirement to satisfy stakeholders. Participate in designing internationally recognised governance frameworks such as the COSO model.

Data analytics: uncover patterns and bring insights using advanced statistical models, such as cluster analysis and time-series analysis. Conduct descriptive analytics and implement prescriptive analytics to determine an optimal course of action in different contexts. Ability to use multiple queries, scripted, or interpreted languages, for example, SQL, Python, or R.

Data visualisation: structure custom visualisations using BI platforms, such as Tableau, to answer raised questions by stakeholders. Infer and communicate complex analyses to decision-makers using advanced data visualisation techniques. Show graphical elegance by combining three substantive, statistical, and artistic skills to simplify complex data design.

2.9 ORGANISATIONAL PERFORMANCE

Organisational performance is one company's actual outcome compared to its intended or previously planned goals and objectives. It is the crucial dependent variable of interest for researchers in almost all disciplines under management. Management Functions in organisations are judged based on their contribution to organisational performance (Zóltowski 2022). It is highly crucial for managers and decision-makers to periodically evaluate their performance to measure the effectiveness of their decisions and strategies against their rivals and the intended objectives. However, the literature on organisational performance measurement led by (March & Sutton 1997; Richard et al. 2009) shows a lack of consistency in methodological approaches to formulate the constructs used in the measurement.

There are a variety, and plenty of performance measures have been used under many categories. Richard et al. (2009) have located the achieved outcomes under three main areas, which are the financial performance where the company compares its actual profits and return on investments in specific time intervals; shareholders' return or the contribution to maximising the shareholders' wealth and the economic values added; and the last area is the product market performance presented in the market share. However, Richard et al. (2009) stress maintaining a solid theoretical rationale to choose the appropriate measures that suit the research context.

Furthermore, they asserted that the allocation of dimensions is a crucial step in identifying performance measures. Additionally, they stated that identifying performance measures must be done through the allocation of dimensions. There are some sources of the dimensionality of the performance measures; organisations may choose internal or external stakeholders as a dimension to measure the performance. In other words, the company may choose the customer's value as one dimension where the firm can develop and use measures under this dimension. Each stakeholder has a different motivation, which signifies different measurement needs, either internal or external. Another determinant of dimensionality is the heterogeneous resources and capabilities that organisations possess; for example, large organisations are inclined to use financial and non-financial measures to gauge their performance, while small firms are prominently focused on financial measures, especially profitability-based measures. The last source of dimensionality is the timeframe; there are short-term, medium-term and long-term measures. It is definite to state that most of the measures are time-based measures. In addition, the measures are comparable in different time intervals.

2.9.1 Justifications of BSC

Performance is the primary outcome that organisations seek to achieve, improve and even precisely measure. Kaplan and Norton (1996) responded to the very comprehensive literature with various measuring systems and models, they introduce the balanced scorecard model with a multidimensional framework that almost summarises the literature. The framework is based on the balanced approach between strategies, objectives, and indicators and shows their alignment. Accordingly, this paves the path for organisations to ensure sustainable competitive advantages, making the BSC the most recognised performance management system in the academic and business fields. The BSC model is applicable in public and private sectors as well as industrial and service-based sectors.

The BSC framework remains highly relevant for measuring organisational performance in contemporary business environments. While Kaplan and Norton (1996) established its foundational principles, recent research validates its continued effectiveness and adaptability. Davis and Albright (2004) demonstrate that BSC's integration of financial and non-financial measures provides comprehensive performance assessment, particularly valuable when evaluating the impact of management accounting practices and business analytics. However, the BSC framework has faced criticism. Researchers note its complexity in implementation and potential rigidity in rapidly changing environments (Albertsen & Lueg 2014). Additionally, traditional BSC metrics may not fully capture emerging performance dimensions like sustainability and digital transformation (Akhtar & Mittal 2015). Despite these limitations, extensive empirical evidence supports BSC's effectiveness in capturing performance relationships. Recent studies demonstrate BSC's ability to reveal complex interdependencies between financial and non-financial metrics (Jaiswal & Thaker 2024), operational and strategic outcomes (Gooneratne & Hoque 2021), and short-term versus long-term performance dimensions (Kunz 2023). Meta-analyses confirm BSC's reliability in measuring causal chains between employee capabilities, process efficiency, customer satisfaction, and financial results (Sharma & Sharma 2020). Furthermore, longitudinal studies validate BSC's effectiveness in tracking how improvements in learning and growth metrics lead to enhanced process capabilities and ultimately superior financial performance (Madsen 2025).

Alternative frameworks offer complementary perspectives. The performance prism emphasises stakeholder relationships, while the results and determinants framework focus on service sector performance (Neely et al. 2002). However, BSC's structured approach to measuring intangible assets and value creation (Cheng & Humphreys 2016), combined with its adaptability to digital transformation, makes it particularly suitable for this study's context. Recent adaptations of BSC demonstrate its evolution. Madsen and Stenheim (2016) show how organisations modify BSC to incorporate sustainability metrics and competitive advantage indicators. The framework's ability to synchronise strategic goals with operational metrics while accommodating emerging performance indicators justifies its selection for evaluating BI&A's impact on organisational performance (Hoque 2014).

2.9.1.1 The financial and non-financial performance perspectives

The BSC model is unbiased compared to other traditional indicators, such as the sole reliance on financial indicators such as profitability indicators, operating costs, cash flow, return on assets (ROA), and return on investments (ROI) (Brewer & Speh 2001). The four dimensions of the model are financial, customer and market, internal process capability, and learning, all mapped with firms' long- and short-term objectives (Kaplan & Norton 1996). BSC is a comprehensive model that assesses internal performance through some internal indicators such as internal processes and learning. In addition, it assesses the external performance through some external indicators for financial and customer/market indicators.

Kaplan and Norton have introduced this model as a strategic tool that assists firms to build their strategy map. In other words, the firm follows steps to map the strategic vision with strategic objectives under the four dimensions where the firm can achieve balance in the four areas. Increasingly, some of the intangible values that companies possess, such as employee skills, innovative capabilities and customer relationships, are parts of the strategic objectives and key performance indicators that are mapped with the four dimensions. Looking at the performance from the perspective of the ultimate outcome that a company requires to achieve leads the research to consider adopting the most comprehensive model to measure this performance.

2.9.1.2 Financial perspective

The financial perspective has the most common measures used to evaluate the organisational performance where as it focusses on the financial position of the firm. There are significant measures or ratios used in this perspective where each one has a significant indication of a specific dimension of the financial position; for example, but not limited to return on sales, return on equity, sales growth rate, the market shares, etc. (Kaplan & Norton 1996). Using the descriptive-analytical techniques by applying the financial ratios provides the MAs with valuable insights into the current performance against the company's past performance. Increasingly, MAs can do benchmarking by comparing the data to rivals in the same industry, where visualisation techniques can be easily applied. BI&A would benefit the financial perspective here by not only conducting the descriptive analytics but also providing predictions on the upcoming periods with a variety of scenarios using algorithms such as support vector machines (SVM) and artificial neural networks (ANN). Then the MAs can recommend the ideal solutions or most likely scenario and the outcomes. In their study, Ramakrishnan et al.

(2020) have examined the impact of an integrated model of BI&A on the organisational performance, where they used only the financial performance perspective (financial performance compared to competitors, sales growth and profit growth). They collected data from 154 firms in India to assess the impact of BI&A (BI&A innovation infrastructure capability, BI&A customer process capability, BI&A B2B process capability, and BI&A integration capability) on the performance. They found that the BI&A has a positive impact on organisational performance through the mediator of BI&A effectiveness.

2.9.1.3 Customer perspective

This perspective focusses on the value propositions achieved by the customers; in other words, this perspective covers the feedback from customers regarding the quality of the service, time, and cost. Kaplan and Norton (1996), who invented the BSC model, have classified this perspective into four sections: quality, time, cost and performance and service. The quality perceived by the customer from the acquired product or service is the degree of satisfaction that the standards perceived are the exact expectations of the customers or even better. Time refers to the time required for the company to meet customers' needs. The cost refers to the customer's price paid for the product or service compared to its standards, performance and service measure how the company's products or services create value for the customers. The priority for this perspective becomes very high when it is related to non-for-profit organisations and government departments, compared to profit organisations where the financial and shareholder objectives drive the organisation's strategy.

2.9.1.4 Internal process perspective

The internal process perspective focusses on the employee skills and how it affects the cycle time to complete the product or the service. This perspective employs measures that correlate with the productivity level and process quality. For instance, the time spent on production, the cost of rework, or the processing of orders are some examples of the measures used under this perspective The measures used under this perspective are related to the level of productivity and quality of processes applied. For example, time taken in production, re-work costs, or order processing (Kaplan & Norton 1996).

2.9.1.5 Learning and growth perspective

Learning and growth measure the innovative solutions introduced by the company to improve the company's value. It measures if the company continuously improves and enhances its value. Organisations may present various metrics to assess their capacity to generate value through the introduction of new products or services, the creation of additional value for customers, and the continuous improvement of operational efficiency, organisations may present some measures to gauge their ability to create value to introduce new products or services, creating more value for customers, and continually improving operating efficiencies. This perspective is vast enough to accept many measures in many functions; for example, training expenses and training ROI, market share of new services or products, and new technology adopted compared to the previous year. Significantly, the used measures will be aligned with human resources and information technology along with the strategic requirements from the company's critical internal business processes (Kaplan & Norton 1996).

2.10 IMPACT OF BI&A ON ORGANISATIONAL PERFORMANCE

The relationship between BI&A adoption and organisational performance presents complex patterns. While some studies report direct positive effects (Elbashir et al. 2021), others find mixed results mediated by organisational capabilities (Mikalef et al. 2020). These variations suggest the need to examine specific mechanisms through which BI&A creates value, particularly the role of MAPs inference capability. BI&A effect on organisations' performance has always been discussed in the literature in relation to the business process and business orientation, resulting in a positive relationship between the BI&A adoption and the firm performance with the mediating role of improving the business processes. Scholars have conducted empirical studies to justify the investment in BI&A solutions (Bronzo et al. 2013; Elbashir et al. 2008; Torres et al. 2018). The BI&A is aligned with initiatives of business orientation to streamline organisational performance, which also has been found as an indicator of performance. While some other scholars have connected the business value to the organisational performance and how it is driven by the business process performance, where there are significant differences in the strength of the relationship between industry sectors (A. Ahmed et al. 2019a; Dehning & Richardson 2002; Elbashir et al. 2008b). Some researchers have studied the impact on BI&A and organisational profitability in which the impact was fluctuating and not consistent between different sectors such as (Hou 2012; Mikalef et al. 2018;

Torres et al. 2018), surprisingly, the BI&A has been found to have an adverse impact on organisational competitiveness in the market.

Chen and Lin (2021) have proven their proposed conceptual framework that studies the impact of the BI&A on firm performance. The BI&A were divided into three phases which are the cognitive sensing of issues and environmental changes, then transforming the information gathered in the first phase into actionable plans and upsurging of resource allocation, then driving the decision-making processes into the achievement of the business objectives; authors named it as a sense-transform-drive model. This would contribute to restructuring the business process and reallocating or reconfiguring available resources to dynamically respond to the changing environment and improve operational efficiency and profitability. They have measured the firm performance using financial performance (return on equity ROE, gross profit margin, and return on assets ROA) and market performance measures (Price-earnings ratio P/E and number of annual stock issuance). Torres et al. (2018) have used a similar model, where they viewed BI&A as sensing-seizing-transforming components of dynamic capabilities. Based on this model, the BI&A as a dynamic capability is broken down into abilities to sense the opportunities or threats through analytical systems, then find out a way to seize those opportunities for the purpose of organisational change; and eventually, transform the process of the firm through the execution of the plans reached in the seizing phase. Torres et al. (2018) have examined the relationship between the BI&A presented in the sense-seize-transform model and the organisation performance, depending on 171 received responses from financial professionals and executives from different industries. They have found a positive relationship between BI&A and performance, mediated by business process change capabilities. They have measured both the financial performance and functional performance of the firms. The financial measures that were used returned on investment, sales, profit, growth, general success, return on assets, and competitive position. At the same time, the functional performance measure was efficiency, productivity, cost of effective decision making, operational cost, quality of product or service outcomes.

In their contribution, Aydiner et al. (2019) examine the correlation between BI&A and firm performance, with a specific focus on the mediating influence of business process performance. The research conducted in Turkey focused on a sample of medium-and large-sized enterprises. The findings of the study indicate that the adoption of BI&A has a good effect on the performance of business processes. Furthermore, this improved business process performance subsequently leads to positive outcomes for the overall performance of the organisation. The authors propose that organisations should allocate resources towards the acquisition and implementation of BI&A tools and applications in order to enhance their operational efficiency and, consequently, their overall organisational effectiveness.

Additionally, this study offers valuable insights into the determinants that impact the adoption of BI&A and provides advice for the successful implementation of BI&A strategies. However, this study focusses only on measuring the business process performance without covering other dimensions under the organisational performance. In addition, the main targeted sample are the top executives who are not close enough to the process. Since the literature has examined the impact of the BI&A on the firm's performance using different mediators such as business process orientation (Elbashir et al. 2008; Bronzo et al. 2013) and dynamic and operational capabilities (Mikalef et al. 2020) and organisational learning capacities (M. T. Lee & Widener 2016); this research focusses on the mediating role of the MAPs inference capability and MAs' Analytical Skillset and their role to improve the overall firm's performance.

Ahmed et al. (2019) have suggested that the business performance is highly affected by the BI&A, and this impact depends on some factors, such as how information is delivered by the systems to be used in the business processes to improve decision-making. Additionally, the quality of this information is another factor; the information quality comes under some criteria, which are:

- Comprehensiveness,
- Accuracy,
- Clarity,
- Conciseness,
- Consistency,
- Correctness,
- Currency,
- Convenience,
- Timeliness,
- Traceability, and
- Interactivity

Those criteria can be achieved and assured from the integration system of the data, the available data sources, and verified tools of analytics that are used in the decision-making processes; those are named as a BI System maturity. The authors identified many other factors to effectively use the information in the business processes, such as strategy alignment, a culture of continuous process improvement, a culture of information use and analysis, and decision process management. In another context, Wamba et al. (2017) investigated the impact of BI&A on firm performance, while also exploring the role of process-oriented dynamic capabilities in mediating this relationship. Process-oriented dynamic capabilities refer to the ability to reduce costs within a business process and leverage detailed information and analytical methods to enhance the effectiveness of a business process.

The competences of BI&A encompass three key aspects: BI&A infrastructure flexibility, BI&A management capabilities, and BI&A personnel expertise capability. The BI&A infrastructure flexibility refers to the connectivity, compatibility, and modularity of the infrastructure. The BI&A management abilities involve planning, investment, coordination, and control of the analytics processes. Lastly, the BI&A personnel expertise capability encompasses technical knowledge, business knowledge, and relational knowledge possessed by the personnel involved in the analytics activities.

The data collection for this study was conducted through an online survey, targeting a sample of 297 Chinese IT managers and business analysts who possess experience in the fields of big data and business analytics. The results of the study validate the assertion that the proposed model exhibits substantial support for the enhancement of organisational performance. The findings additionally validate the significant mediating function of process-oriented dynamic capacities in enhancing understanding and improving performance.

2.11 IMPACT OF MAPS INFERENCE CAPABILITY ON THE ORGANISATIONAL PERFORMANCE

The MAPs profoundly influence organisational performance through its critical role in decision-making process. With the increase of competition in the market, the organisation has eager need timely access to information for strategy formulation and implementation. MAPs generate vital information that supports strategic planning, execution, and monitoring, ultimately enhancing organisational performance. Research demonstrates that in the manufacturing sector, MAPs serve as key determinants of productivity levels and drivers of product quality and delivery performance. (Adu-Gyamfi & Chipwere 2020).

It has been argued that MAPs constitute a fundamental component of the structural capital of organisations. Structural capital is a valuable strategic asset such as processes, databases, and information systems as they provide the tools to support the value chain with the required knowledge (Cleary 2015).

Cleary's study on ICT firms in Ireland found a positive correlation between MAPs and organisational performance based on a survey of 88 companies. Interestingly, while advanced MAPs demonstrated a stronger statistical correlation with performance, many Irish ICT firms continued to rely on traditional accounting systems such as standard costing and budgetary control, rather than contemporary tools like activity-based costing and balanced scorecards. The reluctance to adopt advanced MAPs was attributed to employee familiarity with traditional systems, creating resistance to change. However, Cleary emphasised that the contribution of MAPs to business performance can be significantly enhanced by integrating BI&A solutions, facilitating more effective managerial decision-making. While insightful, his study focused solely on one industry, highlighting the need for further research across various sectors. As Warren et al. (2015) argue, the ability to derive meaningful patterns and relationships from management accounting data represents a distinct competitive advantage in increasingly complex business environments, directly contributing to superior financial and operational outcomes.

In the service sector, MAPs have also been examined from a strategic perspective. Alabdullah (2019) explored the impact of strategic MAPs on service companies in Jordan, sampling 127 firms. His findings revealed that MAPs reinforce market strategy development and enhance organisational performance. However, his study relied solely on financial performance indicators such as Return on Equity, Return on Investment, and operating profit, limiting its scope. The author later suggested incorporating non-financial performance measures, including customer profitability analysis, lifetime customer value, customer retention, and service quality assessments, to provide a more comprehensive evaluation of MAPs' impact.

Further research by Gomez-Conde et al. (2019) examined the influence of Management Accounting and Control Systems (MACS) on environmental innovation practices and operational performance in 89 Brazilian hotels. The study measured operational performance using only four indicators: guest satisfaction, service volume, process efficiency, and compliance with deadlines. While this research highlighted the role of MAPs in driving operational improvements, it was limited in scope by focusing only on a narrow set of performance measures.

Empirical studies consistently affirm that MAPs positively influence organisational performance across industries. However, their effectiveness is contingent upon the integration of advanced tools, such as BI&A solutions, which facilitate data-driven decision-making, predictive analysis, and real-time insights. Future research should adopt a broader range of financial and non-financial performance measures to provide a holistic understanding of how MAPs contribute to organisational success.

2.12 CONCLUSION

The literature review reveals several significant gaps in understanding the relationship between BI&A, MAPs inference capability, and management accountants' evolving roles. While existing research demonstrates BI&A's impact on organisational performance (Elbashir et al. 2021; Mikalef et al. 2020), the specific mechanisms through which BI&A enhances MAPs' ability to generate insights remain underexplored. The concept of MAPs inference capability as an organisational capability, distinct from individual accountant competencies, requires empirical validation. Furthermore, contradictory findings emerge regarding BI&A's influence on management accountants' roles and analytical skillsets. While some studies suggest fundamental transformation of roles towards data analytics (Oesterreich & Teuteberg 2019), others indicate persistence of traditional responsibilities (Spraakman et al. 2020). This inconsistency highlights the need to examine how management accountants' analytical skillsets evolve with BI&A adoption, particularly in emerging economies like the UAE where research is limited (Ahmed et al. 2019; Youssef & Mahama 2021).

The review also identifies methodological gaps in measuring MAPs inference capability and its relationship with BI&A. Previous studies have focused primarily on specific accounting practices or individual competencies rather than organisational-level capabilities. This research addresses these gaps by examining MAPs inference capability as a mediator between BI&A and organisational performance, while also investigating the convergence between management accountant and data analyst roles in the UAE context. The literature review summary (Table 2.7) provides a structured synthesis of key studies examining the relationship between MAPs, BI&A, and organisational performance. The reviewed literature highlights that MAPs significantly enhance decision-making, productivity, and strategic planning, particularly when integrated with BI&A solutions.

Table 2.7 Literature review summary

Title	Author/s	Research aim/questions	Research Design	Key findings	Recommended future research
Does business intelligence mediate the relationship between ERP and management accounting practices?	Mayada Yusuf and Mahama Habib (2021)	Investigate the role of business intelligence and analytics (BI&A) in mediating the relationship between enterprise resource planning (ERP) and three sets of management accounting practices (MAPs): budgeting, costing and performance evaluation.	Cross-sectional survey of 82 firms in the UAE.	The level to which ERP systems are used has a beneficial impact on the extent to which MAPs are applied. BI&A systems are also shown to partially mediate the association between ERP system use and the intensity of each of the three MAP sets. This is consistent with the findings of the study.	The potential mediating effect of BI&A in this study could be further investigated in other nations. The sophistication of management and the characteristics of the management control system are two more possible research avenues that may have an impact on ERP, BI&A, and MAPs.
Developing Digital Competencies of Controllers: Evidence from the Netherlands	Steens, Bots, & Derks (2024)	To investigate how advancing digital technologies impact the competency levels of controllers.	Survey of 453 senior controllers in the Netherlands.	Controllers assess their proficiency in digital technologies as insufficient. Domain-specific knowledge is crucial for the advancement of competence.	Investigate how future competency levels can be developed to meet technological advancements.
Big Data and Decision Quality: The Role of MAs' Data Analytics Skills	Franke & Hiebl (2023)	To examine the influence of data analytics skills of MAs on decision quality in firms.	Literature review and conceptual analysis.	Data analytics skills significantly affect decision quality. Accountants with advanced data skills contribute to better decision-making.	Assess the impact of continuous learning in data analytics on decision quality improvements over time.
Digitalization in Management Accounting and Control: An Editorial	Möller, Schäffer, & Verbeeten (2020)	To elucidate the concept of digitalisation and its influence on management accounting and control methodologies.	Editorial review and discussion of digitalization trends.	Digitalisation alters the company model and the function of management accounting. The shift necessitates organisations to reevaluate their strategies.	Investigate the enduring impacts of digitalisation on management accounting functions and methodologies.
Reflections on the Applicability of Business Analytics for Management Accounting	Nielsen (2018)	To identify and discuss how business analytics influences MAPs.	Literature review and theoretical discussion.	The integration of DA into MAPs allows for fact-based decisions and predictions, enhancing decision quality.	Explore different levels of ambition in integrating DA into MAPs.
Business Intelligence Capabilities and Firm Performance: A Study in China	Yansheng Chen, Zhijun Lin (2020)	Explore the three main BI capabilities (sensing capability, transforming capability, and driving	Cross-sectional study to obtain key information on BI practices using distributed	The three BI capabilities operate to enhance competitive advantages and organisational performance.	Future research may incorporate time series with panel data in empirical analysis.

		capability). The study also aims to explain the correlation between those capabilities and firm performance.	survey in southern China.		
Data analytics by MAs	Gary Spraakman and Cristobal Sanchez-Rodriguez, Carol Anne Tuck-Riggs (2020)	How are MAs' roles and responsibilities affected by data analytics (DA)?	Qualitative approach and exploratory research questions	There is no involvement in MAs in the complex analytical activities, and the prime focus is on the descriptive analysis	Assess the same research questions but with a longitudinal study. The study of drill-down practices and tools used classified by industry.
Digitisation of the budgeting process: determinants of the use of business analytics and its effect on satisfaction with the budgeting process	Mareike Bergmann, Christian Brück, Thorsten Knauer Anja Schwering (2020)	Examine whether the use of business analytics in the budgeting process increases satisfaction with the budgeting process.	Quantitative research	The research found that sophisticated data infrastructure is positively associated with the use of analytical methods. Hence, companies need to implement analytical techniques in the budgeting process and resource allocation.	Investigate the different potential outcomes of business analytics in budgeting.
Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective	Katerina Božič , Vlado Dimovski	Responding to calls for study on the specific function of BI&A use in creating organisational value, empirically identify the role of BI&A use in balancing exploitative and explorative innovation activities.	Quantitative research	The findings confirm the hypothesis that the adoption of BI&A is favourably associated with the successful balancing of explorative and exploitative innovation activities, which improves firm performance. The results also indicate that innovation ambidexterity is enhanced in two ways: indirectly through interaction with the firm's absorptive capacity and directly by increasing the likelihood of faster experimentation with offerings of products or services and enhanced predictability of the value of new offerings.	Future research may benefit from gathering business performance data spanning more than three years. Future research could broaden our theory by incorporating operational business value measurements that emphasise the advancement of productivity and cost efficiency.
The Role of BA in the Controllers and MAs' Competence Profiles	Oesterreich & Teuteberg (2019)	To investigate the presence of a skills gap in business analytics competencies among controlling professionals.	Text analytics approach on 2,331 member profiles from a business social network (XING).	There exists a skills gap in business analytics competencies among controllers, varying based on organisational context.	Examine strategies to bridge the business analytics skills gap in different organisational contexts.
Understanding the Changing Role of the Management Accountant in the Age of Industry 4.0 in Germany	Wadan et al. (2019)	To understand the evolving role of MAs in Industry 4.0.	Case study analysis of Industry 4.0 practices in German firms.	The role of MAs is shifting towards more strategic and data-centric functions.	Further research on the specific skills needed for accountants to adapt to Industry 4.0.

Enabling firm performance through business intelligence and Analytics: a dynamic capabilities perspective	Russell Torres, Anna Sidorova, Mary C. Jones, 2018	The aim is to study the impact of BI&A capabilities (sensing, seizing, and business process change capabilities) on the firm performance.	This is quantitative research where data has been gathered using questionnaires from 171 accounting professionals.	There is a positive relationship between BI&A and performance. Also, business process change capabilities has been found as a mediator in the above relationship.	Future research could answer the same question using different sampling method rather than non-probability snowball sampling. Also, expand the measures under BI&A such as technical readiness and types of decisions.
Impact of business analytics and enterprise systems on managerial accounting	Deniz Appelbaum, Alexander Kogan, Mik Vasarhelyi, Zhaokai Yan (2017)	The research discusses the impact of the BA on MA from an enterprise system perspective by proposing a Managerial Accounting Data Analytics (MADA) framework.	Conceptual analysis and framework development.	The researchers have designed a framework to test and measure organisational performance by exploiting the BA to support decision-makers.	The model needs to be used and assessed in different contexts and may include other variables such as other MA tasks.
Business Intelligence & Analytics in Management Accounting Research: Status and Future Focus	Rikhardsson & Yigitbasioglu (2018)	To critically review literature on the relationship between business intelligence & analytics (BI&A) and management accounting.	Literature review of BI&A and management accounting in top journals (2005-2015).	Identified that there is limited empirical evidence on BI&A's influence on management accounting tasks. BI&A impacts management accounting in five themes: information delivery, improvement of tasks, big data, use, and data quality.	Investigate visualization techniques for complex data (big data) in management accounting, and explore how MAs can adapt to BI&A advancements.
Business Intelligence and Organisational Learning: An Empirical Investigation of Value Creation Processes	Lior Fink, Nir Yogev, Adir Even (2016)	the research aims to assess BI assets and BI capabilities to create business value.	The mixed approach has been followed by data collected from three organisations by conducting interviews and cross-sectional survey	Business value is generated from BI assets via two parallel mechanisms, operational and strategic, based on two orthogonal sets of respective capabilities.	Assess the research questions following the longitudinal approach. Examine the moderating role of organisational resources.
Business intelligence systems used in performance measurement capabilities: Implications for enhanced competitive advantage	Matt D. Peters, Bernhard Wieder, Steve G. Sutton, James Wakefield 2016	how BI quality enhances performance measurement practices within a firm and supports its competitive advantage.	This is quantitative research where data has been gathered using questionnaires of 324 CEOs and CFOs.	A positive correlation was found between BI's quality and enhancement of performance measurement capabilities and the competitive advantage.	Investigate the relationship further by testing another moderating variable such as business strategy and environmental uncertainty.
Improving performance aligning business analytics with process orientation	Marcelo Bronzo, Paulo Tarso Vilela de Resende, Marcos Paulo Valadares de Oliveira (2013)	How to align business analytics with process orientation and improve	Quantitative research	The process orientation is a significant mediator that plays a crucial role in BA's impact on organisational performance. Both process orientation and	Expand the sample size and use studies to explore the phenomena better.

		business performance?		BA are significant drivers of performance.	
Measuring the effects of business intelligence systems: The relationship between business process and organisational performance	Mohamed Z. Elbashir, Philip A. Collier, Michael J. Davern (2008)	Measure the impact of BI systems on the business value. Measure the industry's impact on the strength of the relationship between business process performance and organisational performance?	Quantitative research	The results confirm a significant relationship between business process performance and organisational performance for both service and non-service sectors. With the increasing investment in BI systems, it is essential to provide a valid and reliable measure to capture the business value that arises from their deployment.	Other moderator factors need to be included, such as organisational culture, employee resistance and IT infrastructure.

CHAPTER III

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

3.1 INTRODUCTION

This chapter aims to demonstrate the theoretical foundation of this study. The chapter begins by providing an overview of the RBV theory within the context of using BI&A to conduct MAPs in organisations. Subsequently, the study establishes a framework that illustrates the connections between the primary constructs, followed by the formulation of hypotheses. Prior studies on MAPs and MAs' Analytical Skillset highlight that BI&A serves as a value-enhancing asset that enhances a firm's competitive advantage (Bronzo et al. 2013; Oesterreich and Teuteberg 2019). This establishes a connection with RBV theory employed in the literature on MAPs to elucidate the associations between the technological aspects outlined in BI&A and MAPs. Specifically, the ability of firms' MAPs to acquire or utilise BI&A through the inference attribute affect their performance and competitiveness over competitors. In summary, this chapter seeks to establish a theoretical framework that establishes a connection between the adoption of BI&A and its potential impact on the capabilities of MAPs and MAs ultimately leading to the enhancement of companies' competitive advantage.

3.2 THEORETICAL FOUNDATION AND JUSTIFICATION

Technological aspects of accounting have been studied using various theoretical approaches. For example, RBV theory (Beard & Sumner 2004; Elbashir et al. 2008; Elbashir et al. 2021; Fink et al. 2017; Oesterreich & Teuteberg 2019; Yoshikuni et al. 2023); contingency theory (Gerdin 2005; Nicolaou 2000); diffusion of innovations theory (Ruivo et al. 2014); life cycle theory (Moores & Yuen 2001; Qiu et al. 2023); Dynamic Capability Theory (DCT) (Božič and Dimovski 2019; Mikalef et al. 2020; Elbashir et l. 2021); and Knowledge-Based View (KBV) (Grant 2021; Nonaka and Takeuchi's 2019). The choice of the theoretical model is critical when studying firms' boundaries, as the theoretical perspective and design determine how the problem can be discussed and formulated, and what solutions can be suggested (Saunders et al. 2023).

DCT theory has gained prominence in examining how organisations reconfigure their resources in response to environmental changes (Teece 2018). Recent studies have employed DCT to examine BI&A implementation, with Mikalef et al. (2020) demonstrating how big data analytics capabilities influence competitive performance through dynamic reconfiguration processes. Similarly, Božič and Dimovski (2019) applied DCT to investigate business intelligence implementation, emphasising organisational learning as a dynamic capability. However, DCT's primary focus on continuous resource reconfiguration and adaptation to environmental turbulence limits its applicability to this study, which examines how established BI&A systems enhance stable organisational capabilities embedded in MAPs.

KBV presents another relevant theoretical perspective, particularly applicable to examining how organisations leverage BI&A to enhance decision-making capabilities (Grant 2021). Nonaka and Takeuchi's (2019) recent work demonstrates KBV's relevance in understanding knowledge creation processes in digital environments. While KBV complements DCT by focusing on knowledge integration mechanisms, it inadequately addresses how technological resources create sustainable competitive advantages through organisational capabilities, which is central to this study's focus on BI&A as a strategic resource.

Institutional Theory has provided valuable insights into how management accounting practices evolve under institutional pressures, offering a different lens from the resource-focused DCT and KBV approaches. Oliveira and Martins (2024) examine digital transformation in accounting through institutional change perspectives, while Alsharari and Al-Shboul (2019) demonstrate how institutional forces drive accounting innovations. However, institutional theory's emphasis on external pressures and conformity mechanisms does not adequately explain how internal technological resources create performance differentials between organisations, limiting its relevance for understanding BI&A's strategic impact.

Contingency Theory remains influential in management accounting research, providing yet another perspective that intersects with but differs from the previously discussed theories. Granlund and Lukka (2017) applied it to examine how environmental uncertainties influence MAPs in digital environments, while Appelbaum et al. (2017) used contingency theory to study how different organisational contexts affect data analytics implementation. Although contingency theory effectively explains contextual variations in accounting systems and can complement institutional theory's environmental focus, it lacks the resource-heterogeneity focus necessary to understand how BI&A creates competitive advantages through unique capability configurations.

Life Cycle Theory offers a temporal perspective that bridges the gap between the static and dynamic elements present in the aforementioned theories. Moores and Yuen (2001) applied life cycle theory to examine how management accounting systems evolve as firms progress through different developmental stages, demonstrating how organisations transition from informal accounting approaches to sophisticated systems as they mature. More recently, Van Deun and Corbey (2023) extended this work by showing how management control systems adapt across five organisational stages, from cultural controls in early stages to structured administrative controls in maturity. While life cycle theory provides valuable insights into the temporal evolution of accounting systems and could potentially explain BI&A adoption patterns across organisational development stages, it primarily focuses on developmental sequences rather than the resource-capability mechanisms through which technological investments create competitive advantages. Furthermore, life cycle theory's stage-based approach may oversimplify the complex, non-linear processes through which organisations develop BI&A capabilities and integrate them with existing MAPs (Hanks et al. 1994; Phelps et al. 2007).

While these theories offer valuable perspectives, the RBV provides a particularly appropriate framework for studying how BI&A and MAPs create competitive advantage. Gupta and George (2016) used RBV to study how big data analytics capabilities create competitive advantage, highlighting the importance of combining technological and human resources. Recent work by Franke and Hiebl (2023) on digitalisation in management accounting demonstrates the continuing relevance of RBV in understanding how technological resources combine with accounting practices to create value. Their research shows how digital technologies serve as strategic resources that enhance MAPs. These studies suggest that RBV provides a robust framework for understanding how BI&A and MAPs interact to create sustainable competitive advantage. This analysis demonstrates the diverse theoretical perspectives employed in recent research while highlighting RBV's particular suitability for studying the relationship between BI&A, MAPs, and organisational performance.

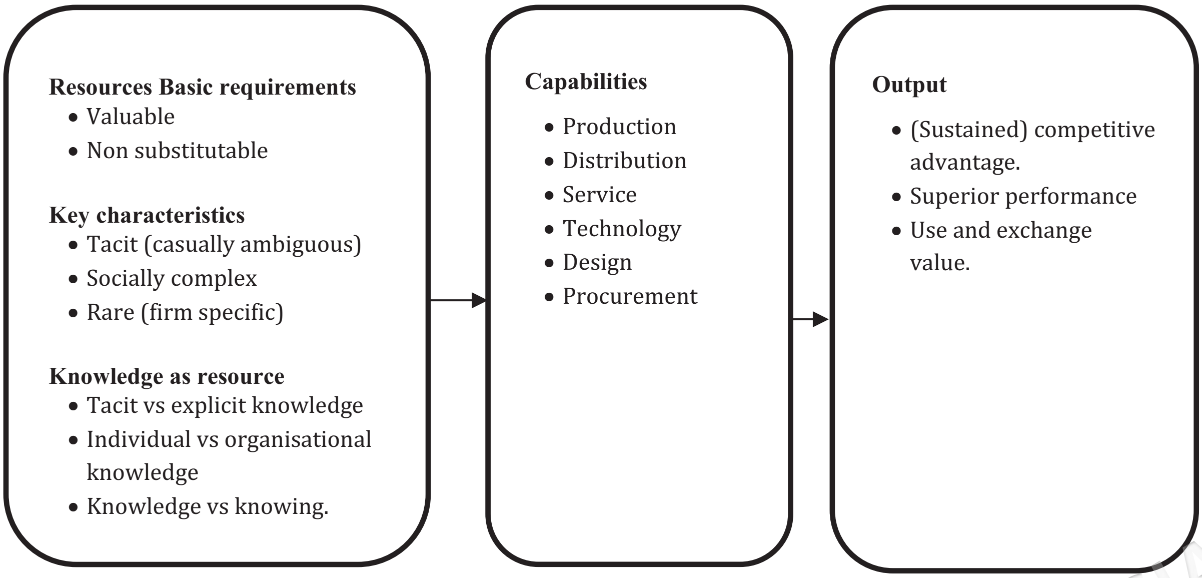

Figure 3.1 Overview of the RBV and the theoretical lens (Bertram & Bertram 2016)

Source: Bertram & Bertram 2016

Bertram and Bertram (2016) outlined the key components of the RBV, including resources, capabilities, and their roles in value creation and sustained competitive advantage. Figure 3.1 highlights the basic requirements for resources, such as being valuable and non-substitutable, and the key characteristics of resources, including being tacit, socially complex, and rare. It also emphasises the importance of knowledge as a critical resource and distinguishes between tacit and explicit knowledge, individual and organisational knowledge, and technology-related knowledge. Additionally, the figure outlines the nature of capabilities, including production, distribution, service, technology, design, and procurement, as a means to achieve sustained competitive advantage, superior performance, and the creation of use and exchange value.

Wernerfelt (1984) first introduced the RBV theory on how companies achieve sustained competitive advantage and enhance their performance through the ownership of resources presented in assets, processes, skills, and knowledge (Douglas Miller 2019). Resources refer to a tangible and intangible assets that firm controls, whereas capabilities refer to a firm's ability to purposefully deploy and coordinate different resources using organisational processes to achieve desired ends. RBV is one of the most commonly adopted theories used to study the relationship between BI&A and business value (BV) (Paradza & Daramola 2021). This has been adopted in the literature by Mikalef et al. (2020) to assess the relationship between big data analytics capability and competitive performance. They split the resources into three categories as follows: tangible resources presented in basic resources, data, and technology;

human skills presented in technical and managerial skills; and intangible skills presented in data-driven culture and organisational learning). According to Ramakrishnan et al. (2020), the four BI&A capabilities (innovation infrastructure, customer process, B2B process, and integration) are proposed as higher-order capabilities that comprise lower-order capabilities. The capabilities are not linked to any specific tangible or intangible resources that would qualify as "resources" under RBV (e.g. data, technology infrastructure, and human skills).

However, these capabilities themselves seem to be the key resources being conceptualised, rather than capabilities leveraging some lower-level resources. They did not identify resources as separate from capabilities, as expected under a pure RBV-driven conceptualisation. In essence, the hierarchy in this study is capabilities leveraging capabilities, rather than capabilities leveraging resources. Aydiner et al. (2019) leveraged RBV theory as a foundational premise to examine the relationships between business analytics adoption, business process performance, and firm performance. Specifically, they discussed BA adoption in terms of the data acquisition and processing resources, descriptive analytics, predictive analytics, and prescriptive analytics. These are considered valuable and inimitable resources under RBV. They defined capabilities as the ability of firms to exploit these BA resources to improve business processes and overall firm performance. Capabilities emerge over time through complex interactions between resources and routines and processes inside the firm.

This theory has been evolved in several studies. For example, Barney (1991) greatly contributes to the theory by classifying firm resources into three categories: physical capital, human capital, and organisational capital. In addition, he stated that the VRIN framework (valuable, rare, imperfectly imitable, and non-substitutable) allows resources to achieve sustained competitive advantage. In the same year, Harrison et al. (1991) stated that resources should be diversified to enhance the value creation process; while Castanias and Helfat (1991) suggested that CEOs are firm resources, and organisational identity is a source of sustained competitive advantage (Fiol 1991). Further contributions include combinative capabilities, emphasising knowledge as a capability (Kogut & Zander 1992), and developing a conceptual spin-off from the RBV called the *natural-resource-based view of the firm* (Hart 1995). It is widely acknowledged as one of the most prominent and powerful theories for describing, explaining, and predicting organisational relationships. The main idea behind the theory of RBV is the significant role of resources used by companies to improve core competencies, or it can itself be the core competencies of the companies. These resources (internal and external) are acquired and applied in the company's different vital activities, which add to or reinforce the firm's competitive advantages and improve its performance.

The RBV has some key assertions which are built on conceptual arguments or empirical evidence; for example, firms possess heterogeneous bundles of resources and capabilities owing to their unique firm histories and accumulated managerial decisions over time. Resource heterogeneity across firms is relatively stable. These firm resource differences persist over longer periods because of resource immobility and imperfect resource substitutability. Resources, such as corporate culture, assets, and capabilities, cannot be traded easily between firms. Heterogeneity in firm's resources and capabilities is a source of performance differences between competing firms. Thus, firms with superior resources can achieve higher efficiency and effectiveness. Firm resources yielding a sustained competitive advantage must be valuable, rare, imperfectly imitable, and non-substitutable, known as VRIN criteria. Resources with VRIN attributes allow firms to gain strategic advantages. The VRIN framework explains success and failure in competitive positioning and helps identify the resource gaps that firms need to address.

Capabilities emerge over time through complex interactions among resources, routines, and processes inside the firm. Wamba et al, (2017) has developed RBV-aligned model that positions Big Data Analytics Capability (BDAC) as a strategic organisational capability that creates value through both direct effects on business analytics outcomes and strengthening process-oriented dynamic capabilities. The multilayered big data analytics construct is a key contribution. A competitive advantage refers to the implementation of value-creating strategies that other firms cannot duplicate. This allows firms to create more economic value than rival firms. Sustained competitive advantage enabled by VRIN resources can persist for longer periods. In addition, some theoretical arguments have led to criticism of the RBV.

These arguments make firm resources and capabilities fundamental units of analysis. Resources are stocks, whereas capabilities are the flows of resources employed in productive activities through organisational processes. The second argument is that firm resource bundles following the VRIN criteria enable the implementation of value-creating strategies that cannot be duplicated by competitors, leading to sustained competitive advantage. Firm performance growth is driven by the ability to acquire, accumulate, and leverage VRIN resources.

The RBV has been criticised for its overly broad and inclusive definitions of the lack of consistency in the definition of its primary concepts such as “resources”. Critics argue that RBV's propositions often become tautological, stating that valuable and rare resources create a competitive advantage without clearly defining what makes a resource valuable or rare. This circular reasoning can limit the theory's explanatory power (Priem & Butler 2001). However, Proponents of RBV argue that while certain aspects of the theory might seem tautological, the theory's strength lies in its ability to guide firms in identifying and leveraging unique resources. The value and rarity of resources can be contextually defined based on industry standards and competitive benchmarks (Amit & Schoemaker 1993).

Bordeleau et al. (2020) employed the theoretical lens of the RBV to conceptualise a model to elucidate the genesis of business value from BI&A activities within manufacturing enterprises. Specifically, they identify three salient BI&A resources: the technical infrastructure, the competent supporting personnel, and the strategic alignment between management and IT. Subsequently, they distinguished between operational capabilities, defined as the exploitation of resources to streamline processes, and strategic capabilities that leverage resources to inform executive decision making. Several testable propositions were then formulated linking the identified resources to the development of capabilities at both levels. Additionally, Bordeleau et al. (2020) recognised organisational learning ambidexterity as a pivotal contingency variable that governs firms' efficacy in translating resources into purposeful capabilities. Ultimately, this conceptual framework serves as an analytical scaffolding to empirically investigate the research question probing the factors driving BI&A-enabled value creation in the manufacturing enterprises context. In their study, from the lens of the RBV, Gupta and George (2016) conceptualise resources as tangible data, technology, and investments; human managerial and technical skills; and intangible data-driven culture and organisational learning that enables a firm to effectively aggregate, analyse, and generate actionable insights from big data. They conceptualised capabilities as the proposed firm-level capability that integrates resources using BA.

3.2.1 RBV Criticisms

Furthermore, the RBV is criticised for its strong focus on internal resources and capabilities, potentially overlooking the importance of external factors, such as market dynamics, industry structure, and competitive forces. This inward-looking perspective might limit a firm's ability to adapt to external environmental changes. In response, although RBV focuses on internal resources, it does not necessarily ignore external factors. Rather, it provides a complementary perspective to external analyses such as Porter's Five Forces. Integrating RBV with other strategic frameworks can offer a more holistic view of a firm's strategy (Danny Miller & Shamsie 1996; Douglas Miller 2019). Another criticism is the challenge of identifying and valuing resources that can lead to sustainable competitive advantage. The ambiguity in determining which resources are truly unique and how they can be sustainably exploited is a point of contention. In response to this, identifying and valuing resources is indeed challenging, but RBV provides a framework to systematically analyse resources. Tools like VRIN (value, rarity, inimitability, and non-substitutability (VRIN) can help firms assess their resources' potential for sustained competitive advantage (Miller 2019). The RBV has also been criticised for underestimating the role of strategic decision making and management in leveraging resources. Critics argue that this theory does not adequately account for how managers identify, develop, and deploy resources to achieve competitive advantage. This is sometimes seen as too static, focusing on the current resource base without adequately considering how firms can develop new capabilities and adapt over time. This makes this theory less applicable to rapidly changing industries. Finally, some critics point out that the RBV often neglects the broader social and environmental context in which firms operate. This includes overlooking the impacts of social capital, societal expectations, and environmental sustainability on resource value and firm performance (Henderson & Cockburn 1994; Makri et al. 2010; Priem & Butler 2001).

Peteraf and Barney (2003) acknowledge the critical role of management in resource exploitation. This theory implies that effective management is necessary to strategically identify, develop, and deploy resources.

3.2.2 RBV as the underpinning theory of the study

RBV provides the most appropriate theoretical framework for this study, as it provides a structured approach to understanding how BI&A, MAPs inference capability, and MAs' Analytical Skillset function as VRIN resources that drive organisational performance. While DCT is primarily concerned with a firm's ability to continuously reconfigure its resources in response to change (Teece 1997), In addition, resources and capabilities in the research framework serve as stable organisational assets that create long-term competitive advantage. RBV asserts that firms gain sustained competitive advantage by developing unique internal resources that are not easily imitated or substituted (Barney 1991). BI&A, MAPs inference capability, and MAs' analytical skill sets align with RBV's resource heterogeneity principle, as these resources collectively enhance an organisation's ability to derive meaningful insights, support decision-making, and improve performance (Miller 2019).

Barney et al. (2021) reinforce that RBV provides a robust framework for assessing how firms create value by leveraging knowledge-based assets, such as BI&A technologies and analytical skill sets, which contribute to a firm's strategic decision-making capacity. In contrast to DCT, which focuses on resource reconfiguration, RBV explains how firms sustain competitive advantage by effectively leveraging existing capabilities. RBV categorises BI&A and MAPs inference capability as firm-wide knowledge resources that enable organisations to process financial and operational data for strategic decision-making (Bertram 2016). Similarly, MAs' analytical skill sets function as a critical human resource, allowing professionals to interpret BI&A outputs, apply advanced analytics, and generate data-driven insights. Schneider et al. (2015) define inference as a key function of data analytics, emphasising its role in interpreting patterns, identifying causal relationships, and predicting financial outcomes. When supported by analytically skilled management accountants, inference capability becomes a strategic organisational asset that enhances business intelligence applications and financial control systems.

RBV recognises that human capabilities, particularly highly skilled professionals with domain-specific expertise, are essential intangible resources that contribute to sustained competitive advantage (Miller 2019). This aligns with research by Elbashir et al. (2021), which found that BI-integrated management control systems improve organisational learning and financial decision-making, further reinforcing the interdependence of BI&A, MAPs inference capability, and analytical skillset of MAs. DCT is primarily concerned with how firms develop new capabilities in response to environmental changes (Teece 1997). However, this study focuses on how established BI&A systems, MAPs inference capability, and MAs' analytical skill sets function as stable firm resources that enhance decision-making. Bertram (2016) explains that RBV remains the dominant theoretical framework in strategic management because it effectively links firm resources to sustained competitive advantage. Similarly, Barney et al. (2021) argue that RBV does not ignore environmental change but instead assumes that firms sustain performance by leveraging their existing resource base rather than constantly reconfiguring their capabilities.

The theoretical framework in this study conceptualises BI&A, MAPs inference capability, and MAs' analytical skill sets as firm resources that mediate the relationship between technology (BI&A) adoption and organisational performance. RBV supports this structure by explaining how these valuable resources enhance performance through their integration into financial and strategic decision-making processes. Miller (2019) highlights that firms with strong knowledge-based resources, such as analytically skilled management accountants, outperform competitors by leveraging internal expertise and data-driven insights. Unlike DCT, which focuses on continuous capability development, RBV highlights how firms sustain competitive advantage through effective resource utilisation.

3.3 DEVELOPMENT OF THE THEORETICAL FRAMEWORK

RBV theory was relevant to accounting research and accounting information system research in several ways. The RBV is a widely recognised paradigm in strategic management that is frequently applied in analysing the value of investments in information technology (Drnevich & Croson 2013). RBV provides a framework to identify and categorise different types of organisational resources related to BI&A that can lead to competitive advantage and performance. RBV allows for systematic testing of the relationships between resources and performance outcomes.

Moreover, it has been actively used in information systems research to assess the strategic value of IT resources (Gupta & George 2016). The RBV theory, as proposed by Barney (1991), emphasises the importance of valuable, rare, inimitable, and non-substitutable resources to gain and sustain competitive advantage. This perspective can be integrated into accounting research and accounting information systems in the following aspects as analysed by Miller (2019): the first aspect is the Strategic management accounting: The RBV theory aligns with strategic management accounting focus on providing information to support strategic decisions. It emphasises the role of accounting information in strategy formulation and implementation, where the RBV can provide a framework for identifying and leveraging a firm's strategic resources. Additionally, management accounting literature (Peters et al. 2016) shows how performance management systems, supported by business intelligence and business process management (BPM), can be enhanced by the RBV perspective. By identifying and measuring key resources and capabilities, firms can better manage and optimise their performance, a concept that is central to both RBV and modern accounting practices.

Furthermore, in the realm of AIS, RBV theory can guide the development and utilisation of information systems to manage and leverage a firm's unique resources. For example, BI systems can be used to analyse data related to a firm's internal resources and provide insights for strategic decision making (Richards et al. 2019). RBV theory suggests that the managerial ability to redesign activities, businesses, and routines efficiently and effectively is vital for better exploitation of specific organisational resources. This implication is directly relevant to BI&A in management accounting, where the strategic use of data and analytics can enhance decision making and operational efficiency (Appelbaum et al. 2017; Bronzo et al. 2013).

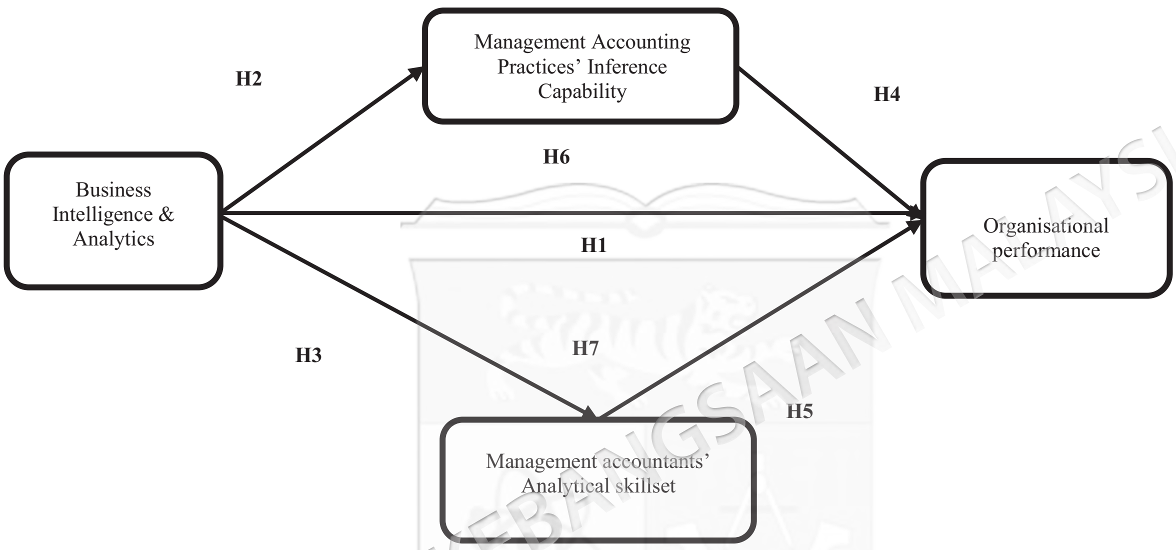

Figure 3.2 Conceptual framework

According to RBV theory, organisations can attain a competitive edge and augment their business value by strategically leveraging their unique resources through the deployment of diverse internal capabilities. This perspective posits that the foundation of competitive advantage and value creation lies in the effective utilisation and orchestration of a firm's distinct resources, which include both tangible and intangible assets. Based on the above framework, BI&A presents the resources in the theory, as BI&A is a significant resource for the company, not less important than physical assets and human resources (Tontiset 2018). BI&A is an IT-based solution and methodology that supports organisations in enhancing their processes, achieving cost reduction, and providing decision-makers and policymakers with accurate information on time. Accordingly, this adds to a company's value and creates a competitive advantage that affects its performance. The relationship between IT as a source and a company's performance is the core idea of the RBV (Wernerfelt 1984). The more the company's resource is valuable and scarce, the stronger the competitive advantage is perceived;

accordingly, the theory concentrates on the valuable resources that would generate value and benefit the firm and improve the corporate performance eventually either in the short or long run (Foss & Knudsen 2003; K. D. Miller & Tsang 2011; Peteraf & Barney 2003).

Companies may seek to diversify their resources to obtain more core competencies, which will eventually be reflected in their performance and competitive advantage in the market, especially in new technological segments that could make a valuable contribution to diversification. However, companies should be discrete when applying this concept as they are combined with extra costs (Prahalad & Hamel 2009).

3.4 BI&A AS VRIN

As a subset of AIS, BI&A possesses the following characteristics: valuable, rare, non-substitutable, and inimitable resources (VRIN), which are the main assumptions in the RBV theory. A resource is deemed valuable when it contributes to the success of an organisation by facilitating the development and execution of strategies that enhance productivity and efficacy. The BI&A fit in the VRIN criteria, where BI&A might be valuable as it contributes to enhancing performance and business value (Elbashir et al. 2021), and is an integral source of financial and non-financial information for present decisions and future predictions (Bronzo et al. 2013). As an illustration, BI&A can provide significant value to an organisation by facilitating improved decision-making, performance optimisation, cost reduction, revenue growth, customer satisfaction enhancement, and more. For example, an organisation may employ BI&A to assess product quality, market trends, customer preferences, competitor activities, and competitor behaviour, among other factors, to formulate and execute impactful pricing strategies, marketing campaigns, and product development initiatives.

A resource is considered rare if it is limited and unique compared to its existing and potential rivals. BI&A may be unique to a firm because of the need for specialised expertise and tools that are not broadly accessible or readily available (Bertram & Bertram 2016). BI&A solutions are tailored to meet and reflect corporate requirements, cross-functional activities, operational processes, cultures, and structures. Accordingly, this makes it rare and unique, especially when they are utilised by various skilled BI&A experts, as they are collectively constrained to one business entity. Consequently, BI&A is inimitable and rare. For example, data analytics includes a variety of techniques, models, and methodologies which are applied based on the context and type of data, such as differential analysis, non-financial analysis, forecasting/trend analysis, and modelling (Spraakman et al. 2020). Additionally, BI&A can provide a unique advantage to a corporation because of the use of intricate algorithms and models that are difficult to imitate or surpass. For example, a company may have created its own exclusive BI&A system that incorporates distinctive functionalities, such as predictive analytics, prescriptive analytics, and sentiment analysis. These characteristics provide companies with a competitive advantage over their rivals (Spraakman et al. 2020).

Finally, a resource is considered non-substitutable when it is indispensable or cannot be replaced by a firm to accomplish its objectives. It possesses the ability to assist firms in identifying potentially advantageous situations and potential risks, assessing different options, and tracking the results. This can improve the synchronisation of management accounting processes with corporate strategies. In addition, the use of BI&A in management accounting can provide a competitive advantage. It can differentiate a business from its competitors by offering unique value proposition. For example, a business that uses BI&A effectively can offer innovative solutions and services that meet the needs and expectations of its customers (Nespeca & Chiucchi 2018) .

3.5 MAPS' INFERENCE CAPABILITY AND HUMAN CAPABILITIES IN THE RBV

The model of this study recognises organisational and human capabilities as the drivers to acquire BI&A, which enhances organisational performance and competitiveness over its competitors. The theoretical framework proposes the MAPs inference capability as the organisational capabilities in the model, and the MAs' Analytical Skillset are human capabilities. A firm's capabilities pertain to its ability to leverage resources efficiently to accomplish its aims and objectives. Capabilities refer to the firm's potential, understanding, and proficiency that empowers it to carry out specific activities or duties more effectively than its rivals. Within the RBV framework of a company, capabilities are regarded as a crucial driver of competitive advantage given their inherent difficulty in duplicating or replicating competitors (Bertram & Bertram 2016). Barney (1991) defines organisational capabilities as a "*firm's capacity to deploy Resources, usually in combination, using organisational processes, to effect a desired end.*" This aligns with the view of MAPs inference as capabilities for information processing and analysis to support resource deployment. MAPs inference capability refers to the processes and structures where MAPs are applied to derive meaningful insights for decision-making. It represents an organisational capability rather than an individual skill, emphasising how MAPs are designed, structured, and embedded within organisational systems to support strategic and operational decision-making. Peteraf (1993) sees capabilities as "*socially complex routines that determine the efficiency with which firms physically transform inputs into outputs.*" The inference capability is the routines in MAPs that determines the efficiency with which firms transform inputs into outputs transform the accounting data into meaningful insights and conclusion to support decision making. Makadok (2001) discusses capabilities as "*a special type of resource—specifically, an organisationally embedded non-transferable firm-specific resource whose purpose is to improve the productivity of the other resources possessed by the firm.*" Based on Makadok's (2001) definition, MAPs inference capability can be understood as a distinct organisational capability because it is non-transferable and firm-specific - the ability to derive meaningful insights from management accounting information is deeply embedded in an organisation's unique processes, systems and context. This capability cannot be simply purchased or copied by competitors (Appelbaum et al. 2017). MAPs inference capability enhances resource productivity by optimising resource allocation through improved cost analysis and forecasting, enhancing decision-making efficiency through real-time insights, improving coordination across functions through integrated performance measurement, and generating actionable intelligence from accounting data to drive strategic choices (Rikhardsson & Yigitbasioglu 2018). Maritan and Peteraf (2011) suggest capability development involves "*complex interactions between the development of knowledge at the individual level, knowledge integration at the organisational level, and deliberate investments set in motion by managers.*" Following Maritan and Peteraf's (2011) framework, MAPs inference capability development involves knowledge development at multiple levels. At the individual level, it requires MAs to develop expertise in analytics tools and techniques, business process understanding, and pattern recognition and insight generation (Spraakman et al. 2020). At the organisational level, knowledge integration occurs through standardised management accounting processes, cross-functional information sharing, and documented best practices and procedures (Elbashir et al. 2021). This is supported by deliberate managerial investments in BI&A systems and tools, staff training and development, and process improvements and refinements (Moll & Yigitbasioglu 2019).

This conceptualisation shows how MAPs inference capability represents a sophisticated organisational capability that requires coordinated development across multiple levels. It enables firms to systematically derive strategic insights from their management accounting data and processes in ways that create sustainable competitive advantage through superior resource allocation and decision-making. The capability view helps explain why some firms are more effective at generating valuable insights from their management accounting systems than others, highlighting the importance of developing and nurturing this capability through sustained investment and focus on both individual and organisational learning.

According to RBV theory, capabilities can be divided into combinative and dynamic capabilities which are distinct capabilities that a company can possess (Kogut & Zander 1992). Combinative capabilities refer to a company's ability to integrate and incorporate current resources and capabilities to generate novel products, services, or processes. Combinative capabilities are crucial for companies operating in stable contexts as they enable them to make incremental enhancements to their existing products or services, which is sufficient to sustain their competitiveness. By contrast, dynamic capabilities pertain to a company's capacity to adjust and react to evolving market circumstances through the modification or reconfiguration of its current capabilities. Organisations operating in dynamic and uncertain contexts rely heavily on dynamic capabilities, which are crucial for success. These qualities enable organisations to innovate and adapt rapidly to changes.

The primary distinction between combinative and dynamic capabilities is that combinative capabilities emphasise the act of merging and integrating current resources and capabilities, whereas dynamic capabilities emphasise the ability to adapt and respond to evolving market conditions. It is crucial to have the ability to combine the different competencies in stable situations. However, in dynamic and uncertain contexts, the ability to adapt and change rapidly is of utmost importance. Combinative capabilities are generally cultivated over an extended period, whereas dynamic capabilities are produced and implemented rapidly in response to evolving market conditions. In conclusion, combinative capabilities prioritise making small enhancements to current products or services, whereas dynamic capabilities prioritise the development of new products, services, or processes that can more effectively address evolving market demands. In the context of RBV theory, Kogut and Zander (1992) introduced the idea of combinative capabilities which refers to the intersection of new knowledge creation and the transfer of knowledge within the organisation.

MAPs inference capability exemplifies Kogut and Zander's knowledge combination routines. They synthesise financial and non-financial data into strategic decision-supporting information. The MAPs inference capability plays an integrative role in resource allocation and coordination. Maritan and Peteraf (2011) discuss the emergence of capability through managerial investments and deliberate learning. MAPs inference capability arises from dedicated investments in management accounting systems and analytical skills as well as standardised management accounting processes, cross-functional information sharing, and documented best practices and procedures. As Peteraf and Barney (2003) note, combinative capabilities occur without major change, in contrast to dynamic capabilities that transform operational capabilities. The MAPs inference capability combines knowledge without radically changing learning routines. In conclusion, MAPs inference capability fits well under the conceptual umbrella of combinative capabilities rather than dynamic ones. They bring together specialised knowledge from various sources to aid decision making without necessarily radically changing operating routines.

Drawing on RBV, prior research has established human resource capabilities as a vital source of sustained competitive advantage. Specifically, Khandekar and Sharma (2005) argue that HR plays a pivotal role in maintaining competitive advantage since it represents the root of competitive strategy. Through the RBV lens, firms possess the competency to evaluate whether employee skills and knowledge are appropriate strategic assets. Therefore, the firm's capacity for innovation fundamentally relies on its employees' knowledge and competencies (Mishra et al. 2019).

However, deficiencies in human capital severely inhibit innovation and achieving competitive advantages. Consequently, human capabilities have emerged as an instrumental facilitator of successful competitive advantage. In summary, extant research convincingly positions human capabilities as instrumental strategic resources conferring durable competitive differentiation. The current research claims that the Analytical Skillset of MAs fit into the theory of RBV as human capabilities. As stated by Barney (2011), the RBV perceives capabilities as organisational routines, processes, and patterns of interaction, leveraging resources to fit the desired objectives. MAs perform analytical routines and information interpretation roles that exploit financial and non-financial data to support strategy and decision making (Barney et al. 2011)

According to Peteraf and Barney (2003), capabilities are defined as socially complex routines that determine the efficiency of the physical transformation of inputs to outputs; MAs' Analytical Skillset can fit as capabilities, as they provide insights that represent such a transformative capability. Grant (1996) discussed the role of integration specialists who support knowledge integration by facilitating organisational members' cooperation and coordination of their specialist knowledge. MAs perform an integrative role by advising on business functions.

The literature has used human capabilities to in the context of BI&A and performance, according to Mishra et al. (2018) human resources is a significant organisational capability which encompasses resources, relationships and decisions that allow firms to take chance to gain an advantage in the market and maintain competition. They used human capability as an enabler of big data and analytics to drive organisational performance. They found that human capabilities have a positive relationship with BI&A diffusion. A significant implication is that the presence of skilled individuals capable of performing business analytics indicates organisational readiness to implement BI&A (Mishra et al. 2018). However, human capability has been measured using non-analytical-oriented skills, such as, business knowledge, idea contributions, commitments, and productivity. Accordingly, this study measures the level of application of analytical skills for MAs.

Using MAPs inference capability along with human capabilities in the theoretical model can be justified as follows: basically, the RBV suggests that sustainable competitive advantage stems from the valuable, rare, inimitable, and non-substitutable strategic resources a firm possesses (J. Barney 1991). As Mishra et al. (2018) argue, MAPs, such as forecasting, planning and decision support, represent valuable organisational capabilities developed over time. Similarly, Spraakman et al. (2021) highlight that MAs possess specialised skills and knowledge regarding an organisation's systems and processes, which constitute human capital resources.

Furthermore, the presence of skilled personnel with the competency to execute business analytics constitutes a salient indicator of corporate readiness and amenability regarding the pervasive propagation of BI&A solutions (Chen et al. 2015). Accordingly, MAs facilitate the contextual and effective application of MAPs. Both sources of advantage are interconnected within the MA context. As Spraakman et al. (2021) state, "*MAs are still responsible for data analysis to support senior management's decision-making*" (p. 14) but now have an expanded role in "*the preparation of data to be used in DA*" (p. 15). This indicates the MAPs rely on the expertise of MAs to prepare inputs, contextualise analysis and effectively communicate insights.

Therefore, the RBV logic of leveraging complementary strategic resources to drive performance, incorporating both MAPs inference capability and management accountant capabilities (analytical skillset) presents a robust way to comprehensively explain how MA functions contribute to organisational performance. The proposed research model reflecting this synthesised, causal chain of strategic management accounting resources driving organisational outcomes is theoretically well grounded from RBV perspective. In essence, RBV recognises the inherent and inseparable connection between organisational capabilities embedded in systems and routines and human capital that animate those routines. Binding these two indispensable resources to explain performance effects better reflects management accounting reality.

3.6 HYPOTHESES DEVELOPMENT

In the following sections, the study's hypotheses are developed and explained in the following three sections to address the research questions. The first section presents the hypothesis related to the direct impact of BI&A on organisational performance, MAPs inference capability and MAs' Analytical Skillset. The second section presents the hypothesis related to the impact of organisational capabilities, that is, MAPs inference capability and management accountant Analytical Skillset on organisational performance. The final section presents the hypothesis pertaining to the mediation effect of MAPs inference capability and MAs' Analytical Skillset between BI&A and organisational performance.

3.6.1 Direct relationship of BI&A to Organisational Capabilities and Organisational Performance

According to Rikhardsson and Yigitbasioglu (2018), "*data-centric decision support for MAs such as planning, performance measurement, and cost management techniques*" is enabled by BI&A analytics and techniques (p.43). They argue that BI&A influences business processes and the way business processes are considered within organisations by supporting planning and strategic management activities, leading to considerable changes in the way business processes are instigated (Bronzo et al. 2013). Specifically, BI&A improves decision support by defining operational goals and action plans (Hsinchun Chen et al. 2012). Thus, BI&A has been claimed to positively influence firm performance by enhancing decision-making, planning, and strategic management. BI&A enables data-driven decision making by allowing managers to base decisions on data-generated insights rather than instinct or intuition (McAfee et al. 2012). Analytical models and simulations in BI&A systems provide actionable recommendations that can guide decision-making related to strategic issues such as pricing, product mix optimisation, make versus buy decisions, and more (Kowalczyk & Buxmann 2015). Additionally, BI&A supports fact-based planning through data analytics and forecasting methods that predict future outcomes in order to inform operational planning and budgets (Bhimani & Willcocks 2014).

The empirical evidence supporting this relationship comes from multiple studies. Aydiner et al. (2019) found that BI&A adoption positively influences business process performance and overall organisational performance. Similarly, Peters et al. (2016) demonstrated that BI&A quality enhances performance measurement capabilities and competitive advantage. Ramakrishnan et al. (2020) showed that BI&A capabilities positively impact organisational effectiveness through improved decision-making and process optimisation. The theoretical relationship between BI&A and performance is further strengthened through three key mechanisms. First, BI&A enhances decision-making quality through real-time access to operational metrics, advanced analytical capabilities for pattern recognition, interactive visualisations, and integration of multiple data sources (Appelbaum et al. 2017; Peters et al. 2016). Second, BI&A strengthens strategic planning and execution through more accurate forecasting, better resource allocation based on predictive analytics, enhanced performance monitoring, and improved strategic alignment across functions (Elbashir et al. 2013). Third, BI&A drives operational excellence by optimising business processes through data analytics, identifying efficiency opportunities, supporting continuous improvement initiatives, and enabling proactive problem detection (Bordeleau et al. 2020; Torres et al. 2018). These operational improvements can be captured through the internal process perspective of the Balanced Scorecard, while enhanced customer relationships and market positioning are reflected in the customer perspective measures (Hoque 2014). The learning and growth perspective further captures how BI&A enables organisational adaptation and innovation. This study adopts a comprehensive approach to measuring organisational performance through the Balanced Scorecard framework, assessing both financial metrics and non-financial indicators across customer, internal process, and learning and growth perspectives (Kaplan & Norton 1996). This multidimensional approach provides a more holistic evaluation of how BI&A impacts overall organisational effectiveness beyond traditional financial measures alone. Accordingly, and based on the research objectives, the following hypothesis has been proposed to be tested in this research:

H1: BI&A practices positively influence organisational performance.

According to Youssef and Mahama (2021), BI&A partially mediates the significant relationships between ERP and three sets of MAPs: budgeting, costing, and performance evaluation practices. They argue that employing ERP systems in organisations not only provides information directly for use in MAPs, but also facilitates integrative and analytical processes in BI&A. Increasingly, the intensity of MAPs applications is highly influenced by the reports generated by BI&A. Similarly, Rikhardsson and Yigitbasioglu (2018) stated that the applied techniques of data mining, analytical procedures, and information delivery in BI&A systems affect MAPs by supporting budgeting, costing, and performance evaluation practices. They provide empirical evidence that BI&A has a positive impact on management accounting tasks such as profitability analysis, reporting, consolidation, and planning, as well as on some contemporary accounting techniques such as activity-based costing and balanced scorecards.

BI&A have emerged as critical tools in enhancing the inference capability of MAPs, facilitating the transformation of raw data into actionable insights. According to Youssef and Mahama (2021), BI&A acts as a bridge between ERP systems and MAPs by enhancing analytical processes, thereby influencing budgeting, costing, and performance evaluation practices. The ability of BI&A to support MAPs extends beyond basic information provision; it introduces integrative and analytical capabilities that significantly impact decision-making efficiency. Rikhardsson and Yigitbasioglu (2018) provide empirical evidence that BI&A enhances management accounting tasks such as profitability analysis, reporting, and planning, as well as contemporary accounting techniques like activity-based costing and balanced scorecards.

A key advantage of BI&A lies in its ability to introduce advanced data analysis techniques that allow MAPs to extract deeper financial and operational insights. These capabilities improve inference by enabling accountants to identify trends, relationships, and causal factors more effectively (Schneider et al. 2015). The availability of interactive dashboards, visual analytics, and predictive modelling tools facilitates not only real-time reporting but also proactive decision-making, enabling MAPs to evolve into a more forward-looking function. Nespeca and Chiucchi (2018) highlight that BI&A increases reporting flexibility, allowing management accountants to tailor outputs to the specific needs of decision-makers. This flexibility enhances the relevance of financial and non-financial data, improving its impact on strategic decision-making.

Predictive analytics allows MAPs to anticipate financial trends and operational inefficiencies, while prescriptive analytics suggests optimal courses of action based on past data (Möller et al.

2020). The predictive and prescriptive functionalities of BI&A contribute to a more comprehensive approach to performance evaluation, helping organisations refine their strategies with data-driven insights. Additionally, BI&A fosters data governance by ensuring data quality, accuracy, and integrity, which are essential for making credible inferences (Appelbaum et al. 2017). The ability to derive reliable insights is contingent on the quality of data sources, and BI&A systems enhance this aspect by integrating structured and unstructured data from multiple sources.

Furthermore, the implementation of BI&A within MAPs requires management accountants to develop advanced analytical skill sets to effectively interpret and utilise complex data models. The integration of BI&A does not merely automate traditional MAPs but redefines them by embedding dynamic analytical techniques into accounting workflows (Elbashir et al. 2021). By leveraging BI&A, MAs are better equipped to explain financial outcomes, detect anomalies, and improve strategic foresight, ultimately driving organisational performance. This enhanced inference capability aligns MAPs with broader business intelligence functions, making them more valuable in supporting corporate decision-making.

BI&A systems are pivotal in introducing advanced MAPs, owing to their multifaceted enhancements (Nespeca & Chiucchi 2018). Initially, the advanced data analysis competencies provided by BI&A systems allowed the MAPs process and workflow to be more efficient to provide more deep insights and conclusion as well as recommendations to MAs, which also allows them to probe into more sophisticated analysis, offering deeper insights into financial and operational data. This enhanced analysis underpins more informed and accurate decision making. Additionally, BI&A systems have brought about notable improvements in reporting flexibility. This adaptability enables MAs to customise reports to fit the specific needs of decision makers, ensuring that the information provided is both relevant and insightful.

Thus, we propose the following hypothesis:

H2: The use of BI&A positively influences MAPs inference capability.

MAs are financial professionals who possess the knowledge and skills to prepare and illustrate financial information and other significant information related to performance, which helps decision-makers plan and control operations and design their policies. They play a crucial role in applying a company's strategic objectives and ensuring that they are processed and fulfilled during a given period. Their roles and skillsets are affected by the application of AIS has been applied, especially ERP systems, which promptly provide integrated information from different functions. However, ERP does not provide analytical functions that enable MAs to conduct their tasks and undertake MA techniques in different contexts (Rikhardsson and Yigitbasioglu 2018).

BI&A potentialities and functionalities could answer questions such as what could happen and what should happen by predicting new trends and sources of new revenue, operational expenses, and timing to make operational changes. BI&A potentialities and functionalities include the use of predictive modelling, propensity scoring, simulation, and optimisation techniques. Accordingly, the implementation of BI&A requires MAs to possess a broad knowledge of the business and methodologies to conduct different BI&A techniques. They must now acquire analytical skills to use financial and non-financial information through sophisticated techniques. Some scholars argue that the new role of MAs may replace the data scientists' role in the company (Rikhardsson and Yigitbasioglu 2018). Brands and Holtzblatt (2015) anticipated that MAs will take over the analytical skills of data scientists, business partners, and business analysts. Accordingly, we propose the following hypothesis:

H3: *The use of BI&A enhances MAs' Analytical Skillset.*

3.6.2 The Direct Relationship of Organisational Capabilities on Organisational Performance

Organisational performance has been significantly influenced by MAPs through various mechanisms. For instance, specific MAPs such as customer profitability analysis, lifetime customer profit analysis, and customer retention analysis have been found to positively impact service firms' performance. These practices enhance managers' strategic decisions by providing a more forward-looking and strategy-focused perspective that drives long-term competitiveness and value creation (Alabdullah 2019; Turner et al. 2017). The resource-based view further supports this relationship by positioning MAPs inference capability as a distinct organisational capacity that drives competitive advantage (Elbashir et al. 2011).

The inference capability of MAPs has become increasingly crucial in today's complex decision-making environment. This capability refers to the capacity to extract meaningful insights from accounting data to facilitate decision-making, which is particularly vital in the age of big data and sophisticated analytics (Schneider et al. 2015). Through effective planning, control, and strategic decision-making, this capability enables the transformation of raw accounting data into actionable insights (Rikhardsson and Yigitbasioglu 2018). For example, empirical research in the manufacturing and services sectors confirms the positive correlations between greater utilisation of certain MAPs and higher financial returns or market growth (Alvarez et al. 2021; Kalifa et al. 2020).

Considerable research in accounting literature has focused on the correlation between MAPs and organisational performance. Given the growing complexity of decision-making environments, the use of MAPs in delivering decision-relevant information has become more crucial (Appelbaum et al. 2017). The inference capacity of MAPs, which refers to the capacity to extract significant insights from accounting data to facilitate decision-making, has become increasingly important in the age of big data and sophisticated analytics (Schneider et al. 2015). Effective planning, control, and strategic decision-making are facilitated by this skill, which enables MAs to convert raw data into actionable insights (Rikhardsson and Yigitbasioglu 2018). The resource-based concept posits that distinct organisational capacities can serve as a key driver of competitive advantage (Elbashir et al. 2011). Given the above, this study posits that enhancing MAPs inference capability leads to improved decision-making and, consequently, stronger organisational performance.

Thus, we propose the following hypothesis:

H4: MAPs inference capability positively influences organisational performance.

Moreover, recent research has emphasised the significance of digital skills in augmenting the value added by MAs (Steens et al. 2024). The growing dependence of organisations on data-driven decision-making suggests that the improvement of inference skills in MAPs can result in higher organisational performance. This correlation serves as the foundation for formulating our assumptions regarding the influence of MAPs inference capacity on organisational success.

Simultaneously, the role of management accountant is highly crucial for enhancing the business value. MAs' analytical skillets significantly impact organisational performance through their support in managerial decision-making and strategy implementation. Traditional roles, such as budgeting, cost analysis, and performance reporting, provide critical data to set targets, allocate resources, and monitor operations, driving profitability and efficiency gains (Brands & Holtzblatt 2015). As business partners, their analytical skills, communication abilities, IT expertise, and interactions with cross-functional teams enable informed decisions aligned with the external environment (Bhatta & Hiebl 2022; Nielsen 2015; Spraakman et al. 2020).

Advanced data analytics competencies allow meaningful insights from increasing volumes of financial and non-financial data to guide competitive strategies (Oesterreich & Teuteberg 2019). In other words, MAs' analytical skills have evolved significantly with the advancement of digital tools, shifting their traditional roles towards data-driven decision-making. Beyond financial reporting, MAs are increasingly required to engage in predictive analytics, data visualisation, and scenario modelling to support executive decision-making (Spraakman et al. 2020). This shift highlights the necessity for MAs to possess advanced data-handling competencies, enabling them to translate vast datasets into meaningful managerial insights (Oesterreich & Teuteberg 2019). Thus, MAs create value through fact-based analysis for planning, risk management, and performance improvement. Continuous skill development is vital to provide decision support in a dynamic business landscape.

Initially, the significance of analytical skills for MAs was emphasised, with surveys indicating their critical role in interpreting large datasets and using new accounting tools effectively, which is crucial for enhancing company performance (Appelbaum et al. 2017). Similarly, expand the skillset of MAs in areas such as data preparation, analysis, and communication/visualisation related to BI&A and data analytics (Spraakman et al. 2020; Youssef & Mahama 2021) equips them with additional skillset that could improve their effectiveness and thereby indirectly benefiting performance. Data analytics supports MAs in variance analysis, drill-down analysis, trend analysis, and predictive modelling to provide better decision support (Spraakman et al. 2020). Recent research emphasises how these analytical capabilities create organisational value in the modern business environment. . The relationship between MAs' Analytical Skillset and performance is further demonstrated through their enhanced ability to conduct sophisticated variance analysis, perform advanced trend analysis and forecasting, develop and interpret predictive models, and create data-driven decision support frameworks. These analytical capabilities enable MAs to generate actionable insights from complex datasets, directly contributing to improved operational efficiency and strategic decision-making effectiveness (Steens et al. 2024).

Therefore, we propose the following hypothesis:

H5: MAs' Analytical Skillsets positively influence organisational performance.

3.6.3 The mediating role of MAPs inference capability and MA’s analytical skills set

BI&A solutions provide extensive measurement and analysis functionalities that can be adopted in many accounting activities (Mehdi et al. 2022; Möller et al. 2022). These solutions enhance MAPs' ability to support financial planning, monitoring and control, performance measurement, and decision support through sophisticated analytical capabilities (Elbashir et al. 2013, 2021). The evolution of BI&A has introduced pre-designed scorecards and key performance indicators that standardise and enhance management accounting processes (Peters et al. 2016). The evolved BI&A solution has a tremendous and positive impact on enhancing the business processes’ elasticity, organisational learning, and organisational performance (Lee & Widener 2016). The mediating role of MAPs inference capability is supported by evidence that BI&A significantly impacts process improvements across various functions, including supply chain, operations, human resources, and marketing (Davenport & Harris 2017). These improvements are intrinsically linked to MAPs due to their cross-functional nature. Uyar (2016) demonstrated that MAPs mediate similar relationships, such as between cost systems and performance, suggesting that MAPs' inference capability could play a similar mediating role between BI&A and performance.

The mediation mechanism operates through enhanced MAPs capabilities in more accurate cost information analysis, improved classification and historical data interpretation, better decision-making support, enhanced financial control mechanisms, and more effective performance monitoring (Youssef & Mahama 2021; Lee & Widener 2016). These enhanced capabilities enable organisations to better translate BI&A investments into tangible performance improvements.

A key component of inference capability is the transformation of raw financial data into strategic insights, which is facilitated by BI&A’s ability to process large volumes of structured and unstructured data in real time. Rikhardsson and Yigitbasioglu (2018) highlight that BI&A significantly improves predictive modelling, variance analysis, and trend identification, enabling MAPs to support proactive decision-making. The availability of interactive dashboards, automated performance scorecards, and AI-powered analytics further enhances the strategic impact of MAPs, ensuring data accuracy, integrity, and relevance (Franke & Hiebl 2023).

Moreover, empirical research suggests that MAPs mediate the link between technology adoption and firm performance, as seen in studies examining the role of costing systems, financial reporting, and management control systems (Uyar 2016). BI&A provides MAPs with decision support mechanisms that bridge operational data with strategic goals, leading to better cost management, resource allocation, and long-term value creation (Lee & Widener 2016). Additionally, by fostering organisational learning and improving financial control, MAPs inference capability reinforces BI&A's role as a strategic enabler of superior organisational performance (Davenport & Harris 2017). Given the strong theoretical and empirical support, this study hypothesises that MAPs inference capability mediates the relationship between BI&A and organisational performance.

H6: MAPs inference capability mediates the relationship between the use of BI&A and organisational performance.

In addition, investments in BI&A solutions provide MAs with enhanced access to data, visual analytics, modelling tools, and automated insights (Franke & Hiebl 2023). These BI&A functionalities improve the way MAs conduct budgeting, cost analysis, forecasting, performance measurement, and other MAPs (Bhimani & Willcocks 2014; Tiron-Tudor & Deliu 2021). For example, access to more customer data allows better sales forecasting and budget projections. The current research endeavours to bridge the gap between BI&A and operational realities will play a pivotal role in enhancing organisational performance. MAs' Analytical Skillset act as crucial mediators in harnessing the full potential of BI&A to drive organisational performance.

The ability of MAs to extract, analyse, and communicate data-driven insights is crucial for improving organisational performance. Enhanced analytical skills allow MAs to engage in risk assessment, business forecasting, and real-time performance monitoring, ensuring that financial and strategic decisions are aligned with corporate objectives (Spraakman et al. 2020). Empirical findings indicate that organisations that invest in upskilling their MAs with BI&A competencies experience improved cost efficiency, operational agility, and revenue growth (Oesterreich & Teuteberg 2019). Recent research highlights that the digital transformation of management accounting has introduced both opportunities and challenges for MAs. While automation and AI-driven analytics have streamlined routine accounting tasks, they have also increased role complexity, requiring MAs to develop expertise in data science, visual analytics, and AI applications (Arkhipova et al. 2024). The ability to bridge technical BI&A capabilities with financial expertise positions MAs as strategic partners in enhancing organisational performance.

Furthermore, BI&A facilitates cross-functional collaboration, enabling MAs to interact with business units beyond traditional finance roles (Wanderley & Horton 2024). This shift towards a more strategic and advisory role enhances organisational decision-making, ultimately driving superior performance outcomes. Given the transformative impact of BI&A on MAs' skills, this study hypothesises that MAs' Analytical Skillsets mediate the relationship between BI&A and organisational performance.

Accordingly, the following hypothesis is developed:

H7: MAs' Analytical Skillset mediate the relationship between the use of BI&A and organisational performance.

3.7 SUMMARY

This chapter has examined RBV theory and its application in the current research to delineate the theoretical framework. The rationale for utilising RBV to underpin the conceptual model has been substantiated in pertinent literature. Moreover, the theoretical framework was formulated by synthesising key RBV concepts from the literature. Additionally, seven hypotheses were postulated based on the theoretical model. This research builds upon and extends previous studies by incorporating contextual and relational factors into a unified framework to produce a more holistic conceptualisation and fulfil the study objectives. The hypothesised relationships depicted in the research model provide testable propositions to empirically validate the connections between the salient constructs. In conclusion, the theoretical grounding and hypothesis development process detailed in this chapter provides an analytical foundation for systematically investigating the research phenomena of interest through a strategy centred on RBV theory.

CHAPTER IV

RESEARCH METHODOLOGY

4.1 INTRODUCTION

The methodology chapter plays a pivotal role in research as it provides a comprehensive account of the methods, approaches, and procedures used to systematically gather and evaluate data. The research method encompasses the processes and tools used to select and develop research techniques (Kothari 2004). This chapter defines the research procedures undertaken to create measures for the constructs and to evaluate the proposed hypotheses. This chapter discusses the adopted research approach, which is the most appropriate method for this study due to the nature of the research questions, research design and procedures. This chapter also describes the data collection method used, sample size, target population, sample techniques, and survey location. It also discusses the software used to analyse the data collected using Structural Equation Modelling (PLS-SEM). PLS-SEM is a multivariate statistical technique that can be used to test a variety of hypotheses, including the reliability, correlation, and regression of measurement models as well as the relationships, coefficients, effect sizes, relevance, and moderating effects of structural models. The chapter is organised into the following sections: first, the research design, unit of analysis, respondents, sampling method, data collection procedure, and statistical analytical procedures used to examine the models.

4.2 RESEARCH PHILOSOPHY

The overall objective of this research is to investigate the impact of BI&A on MAPs and MAs' Analytical Skillset and how those capabilities mediate the relationship between BI&A and organisational performance. The literature review chapter in the previous sections has shown the research gaps and seven hypotheses proposed in the study. The hypotheses were tested throughout the research using statistical data collected through a quantitative method. Saunders et al. (2023) explained upon the conceptual framework of research paradigms, which embodies the underlying cognitive framework that demonstrates the rationale for data acquisition.

Diverse scholars have advocated various research paradigms, each asserting its own suitability, thereby generating ongoing contention among these conflicting notions. Typically, four primary research paradigms are delineated: positivism, realism/post-positivism, constructivism, and critical perspectives. The current research follows the positivist philosophy, as it is working with observable social reality to produce law-like generalisation. The researcher views reality as a single reality where the sampled MAs understand the context from which the researcher is collecting the data and draws conclusions about reality after statistical analysis. In other words, the research chooses to adopt the positivist approach because of its inherent merits. Positivism promotes the use of rigorous scientific methods, enabling researchers to gather empirical evidence, analyse data objectively, and establish causal relationships. It emphasises replicability and generalisability, enhancing the validity and reliability of the findings. Moreover, emphasis on objectivity and value neutrality reduces the potential for bias, ensuring a more objective understanding of social phenomena and contributing to the cumulative growth of knowledge in the field (Saunders et al. 2023).

In positivism, the research approach is deductive and involves the formulation and testing of theories through scientific surveys(Cohen et al. 2002). This approach aims to establish causal relationships by employing statistical evidence, conducting experiments, and utilising comprehensive or limited-scale samples with structured survey instruments. The resulting numerical data are amenable to concise or interpretive statistical analysis. Here, the deductive approach is adopted, aligning the research problem, questions, and objectives with established theories with the intention of testing or refining the theory. Using a survey method, primary data were collected to ascertain causal relationships while emphasising quantitative data analysis. Thus, the positivist approach was deemed the most suitable for this study.

4.3 RESEARCH DESIGN

The Research design streamlines the data collection and analysis processes through a valid framework. This framework organises and rationalises the research problem and answer the research questions (Bell et al. 2018). In other words, the research design is the planning process for collecting, processing, and exploiting data to reach a meaningful conclusion. The research follows the quantitative approach, where quantitative data will be collected and analysed. This research uses quantitative data analysis by adopting statistical analysis.

There are some reasons for pursuing the quantitative approach: the quantitative nature of the research questions in the current research where the researcher recognises the variables to find correlations and relationships. The relationship between variables requires a quantifiable approach for the collected data which has a statistical nature that requires analysis to answer the research questions. The quantitative methodologies were drawn from objectivity-based epistemological assumptions. It provides summaries of data that support generalisations about the phenomenon in current research and the hypothetico-deductive logic underpinning quantitative methodology to answer the three research questions. The literature has primarily followed quantitative research (Elbashir et al. 2008; Bergmann et al. 2020; Appelbaum et al. 2017; Richard et al. 2017; Elbashir et al. 2013; Peters et al. 2020; Moller et al. 2020) whereas others followed a qualitative research method (Spraakman et al. 2020).

This study used a cross-sectional design with a quantitative approach to conduct an empirical investigation. Although some limitations are associated with this design, it has been widely acknowledged that it offers numerous benefits. As Bell et al. (2018)note, a cross-sectional design is the most commonly used approach in social research and involves analysing data at a single point in time. Additionally, cross-sectional design is often employed in research to assess the determinants of behaviour. Moreover, this design is deemed appropriate for describing relationships among phenomena at a fixed point in time, and when a theoretical framework guides the analysis (Saunders et al. 2023).

The survey questionnaire was an appropriate data collection method for this study for the following reasons. The research follows a quantitative methodology and positivist paradigm which relies on empirical data that can be statistically analysed. Surveys allow for the gathering of quantifiable data from a sample population (Saunders et al. 2023). The aim is to make generalisable conclusions by testing the theories and relationships between the defined variables. Additionally, surveys support making deductive inferences and generalisations from a sample to a population, which aligns with the deductive approach associated with positivism, which was chosen as the research philosophy.

Furthermore, research questions require obtaining data on MAs' perceptions, capabilities, and behaviours (Rowley 2014). A questionnaire survey is well-suited for capturing self-reported information from a specific target group. The literature reviewed utilised survey instruments, indicating that it is an accepted method in this field. Standardised survey tools allow for replicability. In addition, surveys are an efficient way to collect data from a large sample, enabling robust statistical analysis and increasing generalisability (Kelley et al. 2003). In summary, survey questionnaires are advantageous for this study, as they facilitate the collection of quantitative data from MAs to test theories and relationships and make generalised conclusions in line with the deductive positivist approach adopted. The method matches research aims, questions, and paradigms.

4.4 SAMPLE OF STUDY

This discussion elucidates the sample chosen for the current investigation. This encompasses the unit of analyses, respondents, and population used to identify the ultimate sample.

4.4.1 Unit of Analysis

The choice of unit of analysis refers to the level of data aggregation that will be used in subsequent analysis. In studies related to management and accounting, the unit of analysis may vary depending on the research questions and hypotheses being tested, and can include individual, plant, division, or firm levels. Therefore, it is crucial to specify the level of data aggregation during the data analysis stage (Sekaran & Bougie 2019).

This study examines the role of MAPs conducted by MAs in UAE industries. Therefore, in line with previous research (Uyar & Kuzey 2016; Youssef & Mahama 2021; Youssef & Moustafa 2014).. This research employs a dual unit of analysis, examining both organisational and individual levels. According to Saunders et al. (2023), the unit of analysis represents the level at which research is conducted, and data is aggregated during subsequent analysis. When research objectives span multiple levels of inquiry, a dual unit of analysis approach can provide richer insights into complex organisational phenomena. At the organisational level, this study investigates how BI&A adoption affects firm-level capabilities (MAPs inference capability) and organisational performance, focusing on company-wide BI&A implementation, MAPs inference capability as an organisational resource, and firm performance across multiple dimensions (Elbashir et al. 2021; Peters et al. 2016).

At the individual level, the research examines how BI&A influences MAs' Analytical Skillset and capabilities, including individual engagement with BI&A tools and personal application of MAPs (Spraakman et al. 2020; Oesterreich & Teuteberg 2019). This multi-level approach aligns with Sekaran and Bougie's (2019) guidance that organisational research often requires examination at different levels to fully understand the relationships between variables. They note that while some phenomena are purely organisational or individual in nature, many management practices involve interactions between individual capabilities and organisational systems.

The selection of a dual unit of analysis is particularly appropriate for this study as it enables examination of both the systemic organisational changes brought about by BI&A implementation and the individual-level transformations in management accountants' analytical skillset and capabilities. This approach acknowledges what Saunders et al. (2023) describe as the nested nature of organisational research, where individual actions and capabilities are embedded within broader organisational contexts and systems. The dual perspective provides a more comprehensive understanding of how BI&A influences both organisational capabilities and individual professional practices in management accounting.

4.4.2 Target Population

Initially, the population presents all entities, individuals and groups who share the same features, such as location, size, and type identified by the researcher based on the research objective (Bell et al. 2018). The concept of targeted respondents refers to the complete population that meets the predefined survey criteria, specifically chosen to fulfil the research objectives. In the context of this study, the target population consists of MAs and financial professionals presently employed across the UAE. The research population is the organisations that run their operations in the UAE. The population includes companies in the seven states as illustrated in figure 4.1 (Abu Dhabi, Dubai, Sharjah, Ajman, Al Fujairah, Um Al Quwain, Ras Al-Khaimah).

Figure 4.1 UAE Map[6]

The population includes listed organisations in both markets of ADX and DFM as shown in Table 4.1, and the non-listed companies that operate in the UAE from all industries.

Table 4.1 listed organisations in ADX and DFM (2022)

Sector	ADX	DFM	Total	%
Banking	11	12	22	16
Telecommunication	3	2	5	4
Transportation	0	4	4	3
Real Estate and Const.	12	9	21	16
Industrial and Energy	15	2	17	13
Insurance	16	13	29	21
Services	7	3	10	7
Consumer Goods	3	6	9	7
Investment and Financial Services	6	13	18	13
Total	**73**	**64**	**137**	**100**

The UAE was selected for the following reasons:

[6] World Atlas

First, the UAE is one of the encouraging spheres of investment; it is one of the top oil exporters in the world with 10% of the global supply of oil reserves and the world's fifth-largest natural gas reserves, where its economy has been booming over the last three decades with the highest rate in the Gulf Cooperation Council (GCC). The country has started to diversify its resources to reduce its dependence on oil, and oil exports now account for approximately 30% of the total gross domestic product UAE. This transformation includes a shift towards a knowledge-based economy, which involves the adoption of advanced technologies, such as BI&A.

Another justification is the UAE Digital Economy Strategy, which was launched in April 2022 and aims to double the contribution of the digital economy to the UAE's gross domestic product (GDP) from 9.7 per cent as of April 2022 to 19.4 per cent within 10 years (The official Portal of UAE Government 2022). This diversity and scale of progression require firms to place more emphasis on efficient solutions presented in BI&A and efficiency practices presented in the MAPs to achieve competitive advantages. Evidence has shown the practice of BI&A in MAPs in the UAE, yet little is known about its degree of influence on companies' values and overall performance (Youssef & Mahama 2021). In addition, Dubai Industrial Strategy 2030 aims to elevate Dubai into a global platform for knowledge-based, sustainable, and innovation-focused businesses. It identifies six priority subsectors: aerospace, maritime, aluminium and fabricated metals, pharmaceuticals and medical equipment, food and beverages, and machinery and equipment. These subsectors were chosen based on their importance to the Dubai Industrial Strategy and Dubai Plan 2021, as well as their future growth prospects, export potential, and mid-term to long-term economic impact. The population includes companies from all industries, as studying all industries can provide a more comprehensive understanding of the impacts of BI&A on MAPs. Different industries may use BI&A in different ways, and their impact on MAPs can also vary. Furthermore, the UAE has a diverse business ecosystem with sectors ranging from oil and gas to retail, healthcare, and technology. Studying all of these industries can provide diverse insights into how BI&A is used and its impact on MAPs (Chen et al. 2012).

4.5 SAMPLING DESIGN

Sampling designs in research can be classified into two main types: probabilistic and non-probabilistic. When conducting a quantitative study, it is crucial that researchers carefully consider the sampling design. Probability sampling ensures that every item in the population has an equal chance of being selected, and that the sample members are chosen through a thorough process (Saunders et al. 2023). Probability sampling typically requires a sampling frame, which is a comprehensive list of all population elements, along with their contact details (Sekaran & Bougie 2019). However, this study the researcher applied probability and non-probability sampling. For example, non-probability sampling was applied by selecting all listed companies in both ADX and DFM were included in the sample which count of 137 organisations. This type of nonprobability, sampling called judgment sampling, which involves selecting units that the researcher believes are representative of the population. For example, a researcher may select people who they believe are experts on a particular topic (using BI&A running MAPs in their daily operations). Medium and large enterprises were selected as they are more likely to adopt BI&A due to their advanced technological infrastructure, financial capacity, and strategic orientation. Additionally, these firms typically implement MAPs, ensuring relevant insights into the integration of BI&A within management accounting practices and organisational performance (Uyar 2016).

Non-listed organisations were included in the UAE *yellow pages* as well as the LinkedIn network which included over 42,000 businesses. It has been filtered by industry, employee numbers, and turnover. To ensure the appropriate selection of companies based on size, the study utilised LinkedIn Sales Navigator, a professional networking tool that enabled the researcher to filter firms by country, number of employees, and annual turnover. This approach facilitated the precise identification of relevant companies listed in industry-specific directories such as Yellow Pages. The sampling technique that is followed is stratified random sampling, in which the organisations are grouped based on the industries; for example, energy, manufacturing, Industrials, health care, financials, information technology, telecommunication services, and Transport/Logistics; then, the companies listed under each category are randomly selected. Accordingly, this eliminates the risk of choosing most of the samples from one group (Welman & Kruger 2001). Companies in the sample that did not respond to the questionnaire were replaced with another company from the same category. The total number of organisations that have been contacted are 1562 companies, the researcher increased the sample size to make sure to have higher responses this shows the probability sampling is followed.

There are various definitions and classifications for medium and large organisations, which often vary across different sectors, including trading, services, and manufacturing. In this paper, we adopt the definitions provided by the UAE Central Bank and the Ministry of

Economy. Specifically, we classify a medium-sized organisation as one with an employee count ranging from 75 to 200 and an annual turnover exceeding 10 million AED. This classification considers the average across sectors, providing a standardised approach to defining medium organisations in the UAE context, particularly for the purpose of this study (UAE Central Bank 2022; Ministry of Economy 2022).

According to Bell et al. (2018), nonprobability sampling is a broad concept that encompasses all sampling methods conducted without following a specific procedure for determining sampling probabilities. It is important to acknowledge that in a non-probability sampling approach, results may be susceptible to hidden biases (Sekaran & Bougie 2019). However, non-probability sampling is commonly employed in studies, particularly in market analyses, where a sampling frame may be absent (Saunders et al. 2023). Thus, judgement sampling is used here when selecting all listed companies in the ADX and DFM, as well as when selecting the financial professionals who are undertaking their functions in the UAE. This type of sampling involves selecting units that the researcher believes are representative of the population (Sekaran & Bougie 2019).

4.5.1 Sampling Frame

The sampling frame acts as a source from which the sample can be drawn, ensuring that all eligible units from the population are included. This provides a tangible basis for the selection of participants or units for data collection. In the current research the sample frame includes medium to large companies in the UAE that implement MAPs, use accounting information systems, and adopt BI&A solutions and practices. The sample frame mainly includes companies from the two primary Emirates in the UAE (Abu Dhabi, Dubai) due to their economic power compared to the rest of the emirates. The main justification for focusing on medium and large organisations is the limitation that small firms face in adopting BI&A because of the lack of technical knowledge, inadequate IT infrastructure, and cost constraints (Brands & Holtzblatt 2015).

A sampling frame is a comprehensive list of elements from which a sample is drawn for research purposes (Saunders et al. 2023). An effective sampling frame should be complete, accurate, current, and accessible to ensure representativeness (Sekaran & Bougie 2019). In this research, the sampling frame includes medium to large companies in the UAE that implement MAPs, use accounting information systems, and adopt BI&A solutions and practices.

The sampling frame was constructed using three primary sources:

- Official stock exchange listings - all 137 companies listed on Abu Dhabi Exchange Market (ADX) and Dubai Financial Market (DFM)
- Business directories - companies identified through the UAE Yellow Pages but have been contacted through LinkedIn.
- Professional networks - LinkedIn Sales Navigator was utilised to identify relevant organisations based on specific filtering criteria including size, industry, and location

This multi-source approach addresses the common challenge of incomplete sampling frames in organisational research (Bell et al. 2018). The sampling frame primarily includes companies from Abu Dhabi and Dubai due to their economic significance, with approximately 75% of UAE's GDP generated in these two emirates (UAE Government Official Portal 2021).

The focus on medium and large organisations is justified by their technological capabilities and resource availability. As noted by Brands and Holtzblatt (2015), small firms typically face significant constraints in adopting sophisticated BI&A solutions due to limited technical expertise, infrastructure inadequacy, and financial restrictions. Medium and large enterprises were defined according to UAE Ministry of Economy classifications, with medium enterprises employing 201-500 staff and having annual turnover exceeding AED 10 million, while large enterprises employ over 500 staff.

This carefully constructed sampling frame enabled the systematic selection of organisations most likely to provide meaningful insights into the research questions regarding BI&A adoption, MAPs inference capabilities, and organisational performance.

4.5.2 Sample Size

Since the current research was a multivariate study, the sample size should be large. Three main dimensions must be considered to determine the sample size: population variability, precision level, and required confidence level (Watson 2001). There is no agreed exact percentage required to determine the sample size; however, a formula presented by Sekaran and Bougie (2019) is used to calculate a suitable sample size based on the abovementioned criteria and population size. The formula is as follows:

$$n = \frac{X^2 * N * P * (1-P)}{(ME^2 * (N-1)) + (X^2 * P * (1-P))}$$

Where:

n = sample size

$X^2 =$ Chi-square for the specified confidence level at 1 degree of freedom, the research will follow the (95%) confidence level. It is calculated using the MS excel formula as 3.841.

N = size of population

P = proportion of population = 50%, as Krejcie and Morgan (1970) suggested, the proportion can be 50% since the researcher can't know what this percentage is until you ask for a sample.

ME= Margin of error = P

$ME^2 = (0.50)^2 = 0.0025$

However, applying this equation in the research context is not applicable as it requires a substantial population. At the same time, Krejcie & Morgan (1970) have provided a statistical-based scale that researchers would follow to calculate their samples.

Required Sample Size								
	Confidence = 95%				Confidence = 99%			
Population Size	Margin of error				Margin of Error			
	5.0%	3.5%	2.5%	1.0%	5.0%	3.5%	2.5%	1.0%
10	10	10	10	10	10	10	10	10
20	19	20	20	20	19	20	20	20
30	28	29	29	30	29	29	30	30
50	44	47	48	50	47	48	49	50
75	63	69	72	74	67	71	73	75
100	80	89	94	99	87	93	96	99
150	108	126	137	148	122	135	142	149
200	132	160	177	196	154	174	186	198
250	152	190	215	244	182	211	229	246
300	169	217	251	291	207	246	270	295
400	146	265	318	384	250	309	348	391
500	217	306	377	475	285	365	421	485
600	234	340	432	565	315	416	490	579
700	248	370	481	653	341	462	554	672
800	260	396	526	739	363	503	615	763
1,000	278	440	606	906	399	575	727	943
1,200	291	474	674	1,067	427	636	827	1,119
1,500	306	515	759	1,297	460	712	959	1,376
2,000	322	563	869	1,655	498	808	1,141	1,785
2,500	333	597	952	1,984	524	879	1,288	2,173
3,500	346	641	1,068	2,565	558	977	1,510	2,890
5,000	357	678	1,176	3,288	586	1,066	1,734	3,842
7,500	365	710	1,275	4,211	610	1,147	1,960	5,165
10,000	370	727	1,332	4,899	622	1,193	2,098	6,239
25,000	378	760	1,448	6,939	646	1,285	2,399	9,972
50,000	381	772	1,491	8,056	655	1,318	2,520	12,455
75,000	382	776	1,506	8,514	658	1,330	2,563	13,583
100,000	383	778	1,513	8,762	659	1,336	2,585	14,227
250,000	384	782	1,527	9,248	662	1,347	2,626	15,555
500,000	384	783	1,532	9,423	663	1,350	2,640	16,055
1,000,000	384	783	1,534	9,512	663	1,352	2,647	16,317
2,500,000	384	783	1,536	9,567	663	1,353	2,651	16,478
10,000,000	384	784	1,536	9,594	663	1,354	2,653	16,560
100,000,000	384	784	1,537	9,603	663	1,354	2,654	16,584
300,000,000	384	784	1,537	9,603	663	1,354	2,654	16,586

Figure 4.2 Sample size calculation (Krejcie & Morgan 1970)

The determination of optimal sample size in organisational research necessitates careful consideration of statistical power requirements, sampling frame characteristics, and anticipated response rates (Hair et al. 2019). While the Krejcie and Morgan (1970) formula yielded a baseline requirement of 370 respondents for a population of 7,500-10,000 UAE medium and large enterprises, the actual sampling strategy employed deliberate oversampling to address several methodological imperatives.

Table 4.2 Multi-Source Sampling Frame Construction

Sources	**Contact Attempts**	**Percentage of Total**
ADX & DFM	137	8.8%
UAE Yellow Pages	450	28.8%
LinkedIn Sales Navigator	975	62.4%
Total	1,562	100.0%

Note: Sample size calculation based on Krejcie and Morgan (1970) formula yielded 370 required responses. The 4.22:1 oversampling ratio account for anticipated response rates and ensures adequate statistical power for multivariate analysis.

The implemented sampling approach encompassed 1,562 organisations, as shown in Table 4.2, across multiple channels: 137 publicly listed companies from ADX and DFM (representing the complete population of listed entities), 450 companies identified through UAE Yellow Pages, and 975 organisations sourced via LinkedIn Sales Navigator. This comprehensive sampling strategy was predicated on three critical methodological considerations: first, by optimising response rate. Contemporary organisational research consistently demonstrates response rates between 10-20% for executive-level surveys (Cycyota & Harrison 2006; Baruch & Holtom, 2008). The oversampling ratio of 4.22:1 (1,562 contacted versus 370 required) was designed to accommodate these anticipated response challenges while maintaining statistical validity. Second, the multi-source approach addressed the inherent limitations of individual databases. Listed companies provide audited financial information but represent only a subset of qualifying organisations. Business directories offer broader coverage but may contain outdated information. Professional networks enable targeted identification but require verification of organisational characteristics (Saunders et al. 2019). Third, the expanded sample enabled proportional representation across industry sectors, organisational sizes, and geographic regions within the UAE. This stratification ensures that the final sample reflects the underlying population characteristics rather than being biased toward easily accessible organisations (Fowler 2014).

The adopted oversampling approach aligns with established methodological principles in organisational research. Dillman et al. (2014) emphasise that effective sampling strategies must account for unit non-response, item non-response, and coverage errors. The 4.22:1 oversampling ratio reflects conservative estimates based on meta-analytical findings regarding response rates in management accounting research (Van der Stede et al. 2005).

Furthermore, the multi-source sampling frame addresses the challenge of incomplete population listings common in emerging economy contexts. The UAE's rapid economic diversification has created a dynamic business environment where traditional business directories may lag behind actual market conditions (Khanna & Palepu 2010). The combination of official listings (ADX/DFM), comprehensive directories (UAE Yellow Pages), and professional networks (LinkedIn Sales Navigator) provides triangulated coverage of the target population.

The final achieved sample of 192 usable responses represents a 13.9% response rate, which falls within the acceptable range for organisational research in the Middle East context (Mellahi & Harris 2016). This response rate, combined with the rigorous sampling frame construction, ensures external validity while maintaining the statistical power necessary for structural equation modelling analysis.

This oversampling strategy mitigated the impact of low response rates common in organisational research (Saunders et al. 2023). The final usable responses totalled 192 after data cleaning, representing a 13.9% response rate, which is comparable to similar studies in the field (Youssef & Mahama 2021). The achieved sample size was adequate for the selected analytical approach (PLS-SEM), which according to Hair et al. (2021) requires minimum sample sizes of 10 times the largest number of formative indicators or 10 times the largest number of structural paths directed at a particular construct.

4.6 MEASUREMENTS OF VARIABLES

The research constructs were measured according to the literature. BI&A is measured as the degree of implementation and reliance on the different components and techniques of BI&A. These indicators have been previously identified by Bergmann et al. (2020). The measurements included the degree of use on the different components and techniques of the BI&A as shown in Table 4.3. A five-point Likert scale is used to check the extent of adoption where (1) is never used and (5) is always used.

Table 4.3 measurements of BI&A

BI&A	Source
1. OLAP 2. Data mining 3. Data warehouse 4. Digital dashboarding 5. Descriptive analytics 6. Predictive analytics 7. Diagnostic analytics 8. Prescriptive analytics	(Bergman et al. 2020; Amani & Fadlalla 2017; Youssef & Mahama 2021; Chen, et al. 2012; Appelbaum et al. 2017)

Further instructions are given to participants for every element to provide clarity (Appendix A); for example, the first element Online Analytical Processing (OLAP) is clarified as follows: Use the multiple categories-based data to drill down, roll up, slice, or pivot for presentation, tracking, or analysis.”. These BI&A measures (OLAP, data mining, digital dashboarding, descriptive analytics, predictive analytics, diagnostic analytics, and prescriptive analytics) are supported by the literature. These components exemplify fundamental functionalities of contemporary analytics systems as defined by (Appelbaum et al. 2017; Nespeca & Chiucchi 2018; Rom & Rohde 2007). The methodologies cover the entire range of BI&A capacities, ranging from fundamental reporting to sophisticated analytics, in accordance with the developmental path of BI&A systems as seen by Rikhardsson and Yigitbasioglu (2018). This classification aligns with industry frameworks, such as Gartner's BI&A model (Niu et al. 2021) and represents the software solutions provided by prominent business intelligence suppliers. By incorporating these elements, a thorough evaluation of an organisation's BI&A maturity and capabilities is achieved, aligning with frameworks such as the one suggested by Wamba et al. (2017). By assessing the level of implementation of these components, researchers can determine the complexity of an organisation's BI&A infrastructure, and its ability to facilitate management accounting procedures.

The justification for using BI&A as a single construct lies in the strong integration and convergence of BI and BA within contemporary organisations. According to Rikhardsson and Yigitbasioglu (2018), BI&A may be defined as a comprehensive method of using data to obtain valuable business insights. Segmenting BI and BA/DA separates interrelated activities and technology. Youssef and Mahama (2021) contend that analytics enhances and expands the possibilities of business intelligence (BI). Furthermore, empirical research conducted by Elbashir et al. (2013) revealed a strong correlation between BI and analytics skills, which can be attributed to a single element. Employing a cohesive BI&A framework corresponds to the actual implementation and utilisation of these capabilities in real-world scenarios (Geddes 2020). This methodology offers a comprehensive perspective on an organisation's information-driven decision-making capacity.

MAPs inference capability is usually measured through the ability of management accounting tools to derive meaningful insights and real-time conclusions from analytical processes that support strategic and operational decision-making. For instance, studies by Uyar and Kuzey (2016) measure organisational inference capabilities by asking respondents to evaluate how effectively management accounting practices facilitate extraction of actionable insights from financial and operational data, while Schneider et al. (2015) measure inference capability by assessing how well organisations translate raw financial data into strategic insights through management accounting tasks.

In this study, the research objective indicates that MAPs inference capability represents the real-time conclusions and insights that can be perceived from conducting management accounting practices using BI&A systems, thus, the MAPs inference capability variable was selected to capture how effectively organisations can extract actionable insights from their management accounting activities when enhanced by BI&A technologies.

To measure this variable, following the methodological framework established by Uyar and Kuzey (2016) and validated through extensive literature review, respondents were asked to evaluate "the extent to which the applied MAPs facilitate extraction of meaningful insights and support company's decision-making according to the current setup process" on a five-point Likert scale, where score 1 indicates "very low inference capability" and score 5 indicates "very high inference capability."

Table 4.4 The MAPs inference capability

MAPs inference capability	**Source**
Cost determination and financial control	
Budgeting practices	(Uyar & Kuzey 2016)
Forecasting practices	
Performance evaluation based on financial metrics	(Rikhardsson and Yigitbasioglu 2018; Schneider et al. 2015; Moller et al. 2020; Scapens and Jazayeri 2003).
Provision of information for management planning and control	
Performance evaluation based on non-financial metrics	
Cost-Volume-Profit analysis	
Product profitability analysis	
Discounted cash flow to evaluate investments	
Reduction of waste in business resources	
Activity-based costing	
Cost of quality reporting	
Effective use of resources	
Target costing	
Customer profitability analysis	
Industry analysis	
Value chain analysis	
Product life cycle analysis	

These respondents were asked to assess the inference capabilities of fourteen specific MAPs items along the five scales as shown in Table 4.4. The techniques will be assessed by estimating the degree of inference on implementing the practices under the previously assessed tasks (Bronzo et al. 2013; Uyar & Kuzey 2016; Rikhardsson and Yigitbasioglu 2018).

MAPs inference capability measures are justified by their alignment with fundamental management accounting goals (Brands & Holtzblatt 2015c; Horngren et al. 2021) and their ability to evaluate the impact of BI&A (Appelbaum et al. 2017; Rikhardsson & Yigitbasioglu 2018). Validated by Uyar et al. (2016), these metrics encompass crucial management accounting operations, such as real-time cost analysis, financial control, dynamic planning, and resource optimisation. The influence of BI&A on these domains has been demonstrated by methodologies such as activity-based costing, continuous budgeting (Elbashir et al. 2011), and real-time operational monitoring (Warren et al. 2015). These metrics cover both conventional and strategic management accounting policies, demonstrating the role of business intelligence and analytics in facilitating more flexible and data-oriented management accounting. This approach is consistent with the notion proposed by Elbashir et al. (2011) regarding increased absorptive ability in MA functions, as well as the focus placed by Wamba et al. (2017) on rapid detection and response to changes through BI&A capabilities.

MAPs inference capability derived from the literature as follows: Rikhardsson and Yigitbasioglu (2018) argue that BI&A enhances MAPs by integrating data-centric decision support tools, such as budgeting, cost management, and performance measurement techniques. These tools allow organisations to refine their strategic planning processes and enable MAs to derive actionable insights from complex data structures. The inference capability of MAPs is strengthened by the advanced analytical models, predictive analytics, and data-driven forecasting techniques embedded within BI&A, which facilitate more accurate financial and operational decision-making. While Schneider et al. (2015) define inference tasks as those that provide meaningful insights from accounting data. Their study highlights that MAPs inference capability is a key process through which organisations translate raw financial data into strategic insights. This is especially relevant in the age of big data, where the ability to extract and interpret data patterns determines the effectiveness of financial planning and control systems. The authors suggest that MAPs inference capability is a function of advanced data analysis, BI-based decision models, and statistical forecasting, all of which are reinforced by BI&A tools. In addition, Möller et al. (2020) extend this argument by emphasising that the effectiveness of MAPs is dependent on their ability to integrate multiple sources of financial and non-financial data. BI&A enables MAPs to conduct multi-dimensional data analyses, uncover hidden trends, and support real-time decision-making. The study further suggests that BI&A facilitates dynamic performance measurement, variance analysis, and benchmarking, thereby improving the inference capability of MAPs in predicting future financial and operational trends. Scapens and Jazayeri (2003) provide a foundational perspective on MAPs inference capability, arguing that management accounting processes are inherently dependent on the ability to derive logical conclusions from financial data. They note that ERP systems facilitate MAPs by integrating transactional data across business functions, but these systems alone lack the advanced analytical functionalities necessary for deep inference. BI&A fills this gap by providing automated analytics, interactive dashboards, and AI-driven reporting tools, all of which augment the inference capabilities of MAPs and support proactive managerial decision-making.

MAs' Analytical Skillset is measured quantitatively by measuring the new Analytical Skillset of MAs compared to data analysts' Analytical Skillset (Holtzman 2004; Brands and Holtzblat 2015; Rikhardsson and Yigitbasioglu 2018). The instrument measures the possession and implementation analytical skills and relevant roles of MAs as listed in Table 4.5. A five-point Likert scale is used to check the analytical skills used where (1) is never conducted and (5) is always conducted in the MAPs implementation.

Table 4.5 measurements of MAs' Analytical Skillset

MAs' Analytical Skillset	Source
1. Data collection and preprocessing 2. Data exploration and analysis 3. Statistical analysis 4. Data visualisations, dashboarding and reports to communicate findings to stakeholders 5. Design and implement experiments to test hypotheses and optimize processes or products. 6. Analytical thinking and problem-solving skills contribute to addressing business challenges. 7. Possess domain knowledge relevant to my industry or specific area of operation. 8. Working with big data technologies (e.g. NoSQL) 9. Build predictive models and evaluate their accuracy and effectiveness. 10. Collaborating with cross-functional teams	(Holtzman 2004), (Rikhardsson and Yigitbasioglu 2018), Spraakman et al. 2020; Oesterreich et al. 2020)

This study proposes a comprehensive framework for evaluating this hypothesis by selecting data analyst Analytical Skillset to assess the present competencies of MAs in the field of BI&A. This strategy is consistent with the current research that highlights the increasing significance of analytics in management accounting (Appelbaum et al. 2017; Bhimani & Willcocks 2014). The extensive range of abilities, including techniques such as data preparation and advanced modelling, allows for a detailed evaluation of the changing responsibilities of MAs (Oesterreich & Teuteberg 2019; Rikhardsson & Yigitbasioglu 2018). The incorporation of both technical and soft skills provides a comprehensive perspective on the aptitudes necessary for the digital age (Kokina et al. 2021). Moreover, the emphasis on cross-functional cohesion and specialised expertise demonstrates the strategic change in the responsibilities of management accounting (Brands & Holtzblatt 2015; Wolf et al. 2020). Utilising data analyst' skills as a benchmark, this method offers a measurable indicator of the extent to which MAs have adopted BI&A. This aligns with current studies on the influence of data analytics on the profession (Gärtner & Hiebl 2018; Nielsen 2018).

Finally, organisational performance was measured following the balanced scorecards based on the four main perspectives as shown in Table 4.6: the financial perspective, which will be measured by assessing profitability and increased revenues over the last two years, and cost reduction. Customer/market performance was measured by assessing customer loyalty and market share. Learning and growth will be measured by assessing workforce commitment levels to process performance goals, internal processes and organisational capacity, which was measured by assessing consistency in the promised delivery dates (Bronzo et al. 2013). The instrument evaluates organisation's performance relative to their competitors of the subsequent measures in the last two years. A five-point Likert scale is used to check the perceived performance where (1) is very and (5) is very high.

Table 4.6 measurements of organisational performance

Organisational Performance	Source
Financial performance	Bronzo et al. 2013, Elbashir 2013; (Rikhardssona and Yigitbasioglu 2018)
Profitability and increased revenues over the last two years	
Cost reduction	
Customer/market performance	
Level of Customer Efficiency in customer loyalty	
Efficiency in attracting new customers	
Market share evolution of the company	

Level of customer satisfaction
Insight into customer behaviour and purchasing patterns
Internal process
Reduction in the time for servicing orders
Efficiency of the inter-organisational management processes with suppliers
Efficiency of the inter-organisational management processes with customers
Human capacities aligned with business goals
Technological capacities aligned with business goals
Analyses that can be shared in real-time across departments
Learning and growth
Staff with growth potential for competencies in process management
Levels of workforce committed to the process performance goals
Level of improvement in the management of process know-how

The rationale for utilising the BSC framework and metrics from Bronzo et al. (2013) to evaluate organisational performance is supported by multiple factors. The BSC offers a thorough and multifaceted assessment of performance that goes beyond standard financial indicators (Hoque 2014; Kaplan & Norton 1996). This aligns with the study's emphasis on BI&A by including aspects related to processes and learning/growth (Elbashir et al. 2008). BSC has extensively verified in management accounting research (Hoque 2014; Malmi 2001). Bronzo et al. (2013) metrics were intentionally designed to investigate the connections between business analytics, process orientation, and performance, aligned with the objectives of this study. By using well-established metrics, dependability and comparability with previous research have been improved (Bronzo et al. 2013). Recent literature validates the BSC's adaptability to digital transformation and analytics (Akhtar & Mittal 2015; Albertsen & Lueg 2014). The BSC's four perspectives capture both tangible and intangible outcomes of BI&A initiatives while linking strategic objectives with operational metrics (Cheng & Humphreys 2016).

4.7 DATA COLLECTION

Primary data collection methods include interviews, self-managed surveys, focus groups, emails, and phone discussions (Bell et al. 2018) . In this study, a validated, self-managed survey was used as the data-gathering tool. Self-managed surveys were identified by Tashakkori & Teddlie (2003) as an instrument that facilitates the collection of self-reported information from individuals involved in the research study. Since the research follows a quantitative approach, the method adopted to collect data is using a survey questionnaire.

4.7.1 Questionnaire Administration

A questionnaire, as a common data collection tool in the literature, can be administered using different approaches either distributed electronically through different platforms, personally, or mailed to the respondents (Sekaran & Bougie 2019). Those approaches can be applied to both structured and unstructured questionnaires. The former consists of pre-determined, closed-ended questions, where each participant is asked the same questions in the same order, ensuring uniformity across responses. Respondents select predetermined options, such as Yes/No, multiple choice, or a scale rating, which narrows down the range of possible responses. This simplifies the process of collecting and analysing data. While the later consists of open-ended questions without predetermined answer choices, allowing respondents to answer in their own words providing depth and insight into the respondent's perspectives, motivations, and feelings. A questionnaire is a pre-established written series of questions that respondents use to record their replies, typically within specific choices.

The current research questionnaire is a structured questionnaire distributed via email to the sampled companies in the UAE and through the LinkedIn InMail service to the selected sample. The questionnaire has been sent as Google form link. The structured questionnaire was selected as an effective method to collect data for the analysis for the following reasons: it is a self-administered tool where the participant has the freedom to fill it without any pressure from the owner (Saunders et al. 2023; Bell et al. 2018). It fills the gaps in interviews by reaching a high volume of participants, where it can be delivered physically or submitted via email to a large number of people. It also saves cost and time as it is reachable without the physical existence of the interviewer. The questionnaire was the main instrument used in previous studies. However, vigilance must be considered to address some concerns. Participants may quickly or carelessly respond to the questions without proper focus, ignore some vital questions, or find it difficult to assimilate the questions and apply them to their workplace (Bell et al. 2018).

4.7.2 Questionnaire format

Initially, the questionnaire commenced with a cover page to provide an informative introduction to the purpose of the research, which furnished participants with the necessary background information to comprehend the reasons for their involvement and the importance of their input, thus potentially inspiring them to complete the survey. A clear introductory establishes the credibility of the survey which is particularly important for ensuring a reasonable response rate as participants are more likely to engage with surveys that appear professional and legitimate. The introductory section and the top of each section in the survey includes instructions on how to complete the questionnaire, making it easier for respondents to understand how to answer questions. The cover letter can reassure the respondents about the confidentiality and anonymity of their responses.

The questionnaire was divided into five sections: Section one collects the demographic information where respondents state their job title, level of education, level of experience, the industry type where their companies operate, the location of the organisation, number of employees, and the achieved turnover. Section two measures the independent variable of BI&A which includes the seven components of OLAP, data mining, data warehouse, visualisation, descriptive, diagnostic, predictive and prescriptive analytics. Respondents were asked to rate the extent to which they practiced each part of their firms. A brief description is provided for each part of the BI&A. Sections three measures MAPs inference capability. Respondents were asked to rate the extent of the inference capability while applying the MAPs in their workplace. Section four measures the human capability presented in management accountant roles and skillsets that are currently applied in the current work environment. The last section presents the performance evaluation of the company from four main perspectives: financial, internal business process, customer, and learning, and growth. To prevent the questionnaire from becoming excessively lengthy, it was offered just in one language. The questionnaire was written in English, as it is the predominant language used by UAE business enterprises.

4.7.3 Survey Procedure

The measurements and elements were taken from the literature for each construct. The research objectives and questions streamlined the question formation, where each construct presents a separate section in the questionnaire and assessed using some measurements. The data collected by the questionnaires were refined and coded. To facilitate comprehension and accessibility, the researcher deliberately employed succinct and lucid language. The incorporation of concise and pinpointed enquiries was deemed vital to enhance the efficacy of the study. The researcher crafted easily understandable queries, truncated the length of the questionnaires to mitigate potential fatigue among participants, and provided unambiguous instructions to obviate any potential misinterpretation of the item content. The developed questionnaire was distributed via email using *Google Form* link to a selected sample of 137 listed companies, with the email addresses retrieved from the websites of ADX and DFM, as well as the organisations' websites. Additionally, non-corporate companies extracted from *Yellow Pages*and LinkedIn professional network were also included in the sample. Because of the ease access to companies using Linked Sales Navigation service, all identified companies in *Yellow Pages* have been contacted from the LinkedIn network. This service allowed the researcher to filter existing profiles based on specific functions, namely the CFOs, MAs, financial controllers, financial analysts, and financial managers, which corresponded to the functions listed in the questionnaire. A standardised message was sent to participants using the InMail service and direct messages were sent after adding the participant to the researcher's network. Reminders were sent to the sample via email approximately two to three weeks after the first message. Utilising LinkedIn for academic research facilitates targeted engagement with professionals, ensuring high-quality and relevant data collection. As a global professional networking platform, LinkedIn enables researchers to access industry experts and hard-to-reach populations, enhancing survey response rates and validity. Prior studies have demonstrated its effectiveness in web-based academic surveys (Dusek et al. 2015).

To maximise response rates, the researcher employed a multi-channel distribution strategy. A total of 1,562 potential respondents were contacted through a combination of direct emails and LinkedIn professional networking. This expanded sample size significantly exceeded the calculated requirement to ensure sufficient responses for robust analysis. The data collection process spanned five months from March 2023 to July 2023. In cases where the contacted email was found to be non-working, the research replaced the companies in the sample.

4.7.4 Scaling

The study applies five-Likert-scale method to measure the intended constructs. Scaling is the process of assigning symbols or numbers to the various levels of a particular concept to be measured (Bailey 2008). Despite some limitations of this method, several advantages of the Likert Scale in social research have been recognised in prior studies. The construction of the Likert Scale is rather straightforward, and it is more reliable because all questions included in the survey can be replied to by the respondent. Moreover, the data can be readily gathered, as responders have the ability to select a single answer from the provided choices. Consequently, responses can be collected in a standardised manner, facilitating further comparison and analysis. In this study, construct items were measured using a five-point Likert Scale (Kothari

2004). All sections have the same five-Likert-scale; however, there are different indicators for the constructs; for example, BI&A uses the following indicators (five for *always used* and one for *never used*). MAPs capabilities and performance measures use (five for *very high* while one for *very low*). For management accountant Analytical Skillset (five for *completely applied* and one for *never applied*).

4.7.5 Pre-Test

To establish the validity and reliability of the measurement instruments, a comprehensive pre-test process was implemented. Initially, the questionnaire was subjected to rigorous evaluation by a panel of six academic members from accounting and management disciplines at UAE universities. Concurrently, the instrument was distributed to twelve industry participants representing medium and large companies across various sectors in the UAE. This approach aligns with Bell et al.'s (2018) recommendation to include both academic experts and practitioners in pre-testing to ensure theoretical rigour and practical relevance.

The pre-test yielded valuable feedback concerning the clarity of certain questions and instructions, instances of record duplication, and suggestions for question removal or replacement. For example, respondents highlighted ambiguity in questions related to MAPs inference capability, which were subsequently refined to improve comprehension. Several questions regarding BI&A tools were identified as redundant and consolidated. Following these modifications, the questionnaire was revised and shared again with the original panel, whose responses and additional feedback confirmed that the instrument strongly reflected the research questions and objectives.

Given the thoroughness of this pre-test process, a separate pilot test was deemed unnecessary. This decision is supported by Saunders et al. (2023), who suggest that an extensive pre-test involving both subject matter experts and representatives of the target population can sufficiently validate a research instrument without requiring a subsequent pilot test. Similarly, Sekaran and Bougie (2019) note that when pre-testing incorporates comprehensive expert review and target audience feedback with subsequent refinement, the additional value of a pilot study becomes marginal, particularly when research timelines are constrained. The iterative nature of the pre-test process in this study, with multiple rounds of feedback and refinement, effectively served the validation functions typically associated with pilot testing.

4.8 STATISTICAL TECHNIQUES

4.8.1 PLS-SEM Analysis

For data analysis, sophisticated software tools such as SmartPLS, Partial Least Squares, and Structural Equation Modelling (PLS – SEM) were used. Duarte and Raposo (2010) suggested that this software suite possesses the capability to concurrently examine the relationship among the constructs themselves and the relationships between the indicators and their corresponding latent constructs (Duarte & Raposo 2010). PLS-SEM has garnered significant attention in various fields, such as marketing (Hair et al. 2012), strategic management (Hair et al. 2012), management information systems (Ringle et al. 2012), operations management (Peng & Lai 2012), and accounting (Lee et al. 2011). In alignment with the aim of the study, which is to test a hypothesis, the PLS methodology is deemed the optimal tool for undertaking the analysis (Henseler et al. 2009). The software platform is intuitive, thereby simplifying its navigation. Furthermore, it provides a graphical user interface that harmonises effectively with moderators, enhancing its overall user-friendliness. Prior to employing the SmartPLS algorithm, the data were subjected to a rigorous filtration and cleaning process using spreadsheet software, in accordance with descriptive and demographic data considerations.

4.8.2 Reliability and Validity

The evaluation of the measurement model includes an assessment of both the reliability and validity of the constructs. Composite reliability was used to assess the reliability of all reflective models in this study. In the context of Partial Least Squares Structural Equation Modelling (PLS-SEM), three distinct methods are commonly employed to assess the reliability of measurement instruments. These methods include Cronbach's alpha, composite reliability, and Rho_A. Many researchers in the field of Partial Least Squares Structural Equation Modelling (PLS-SEM) commonly use composite reliability as a method for reporting the reliability of constructs. Jöreskog's (1971) composite reliability (CR) is widely recognised as the benchmark frequently cited among researchers using partial least squares structural equation modelling (PLS-SEM) (Jöreskog 1971).

Increased CR values indicate elevated levels of reliability. Values ranging from 0.70 to 0.90 are indicative of a level of performance that can be considered satisfactory to good. Diamantopoulos et al. (2012) suggest that values exceeding 0.95 indicate redundancy and have an impact on the construct validity. Nevertheless, CR values exceeding 0.95 also exhibit unfavourable response patterns and indicate inflated correlations among the error terms of the indicators. Cronbach's alpha is an alternative metric for assessing the reliability of internal consistency that shares the same threshold value (Diamantopoulos et al. 2012). However, it is considered a less precise measure because of the absence of item weighting. In his influential article titled "*Thanks Coefficient Alpha, We'll Take It from Here*", McNeish (2018) argued that Cronbach's alpha is flawed because of its reliance on unrealistic assumptions. By contrast, the inclusion of items in composite reliability calculations leads to an increase in reliability values (McNeish 2018).

Validity is typically divided into two components: convergent and discriminant validity. The establishment of validity is typically divided into two components: convergent validity and discriminant validity. The average extracted variance (AVE) is a statistical measure used to evaluate the convergent validity of a construct. AVE represents the average squared loading value for each constituent element of the construct. The minimum acceptable AVE level is 0.50 or higher. In their study, (Hair et al. 2019) found that when the average variance extracted (AVE) is 50%, the building accounts for a 50% of the variation in the items.

One of the primary considerations in assessing validity is the establishment of discriminant validity, which involves confirming that each construct is distinct from the others in the conceptual model and addresses a unique phenomenon that is not captured by other constructs. Henseler et al. (2015) introduced a test for assessing discriminant validity, known as the Heterotrait-Monotrait (HTMT) ratio, which offers a practical and convenient approach. The HTMT ratio serves as a reliable estimator of deattenuated construct correlations. The HTMT ratio is a statistical measure that compares the correlations between different constructs with correlations within the indicators of the same constructs. An HTMT ratio in close proximity to one signifies a lack of discriminant validity. If the constructs are conceptually similar, it is appropriate to use a maximum threshold HTMT value of 0.90.

Nevertheless, it is preferable to adopt a more rigorous threshold of 0.85 (Voorhees et al. 2016). The researcher used three methodologies to assess the measurement models of second-and third-order formative constructs as described by Hair et al. (2019). Following the assessment of convergent validity through redundancy analysis, the subsequent procedures encompass VIF collinearity diagnostics and examination of external weight relevance. The concept of redundancy analysis is derived from the presence of redundant data within a model, which is integrated into both formative and reflective structures. The robustness of the route coefficient connecting these two constructs signifies the soundness of utilising the construct of interest within the specified collection of formative indicators. Hair et al. (2017) recommend a magnitude of 0.80, or a minimum of 0.70, for the purpose of establishing convergent validity.

The inclusion of the reflecting latent variable in the data collection process was undertaken to facilitate redundancy analysis during the research design phase. The presence of high levels of collinearity among formative indicators is crucial as it has a significant impact on weight estimation and the determination of statistical significance. In practical applications, the presence of high levels of collinearity can significantly impact the analysis results in two distinct ways. First, it is observed that there is a positive correlation between collinearity and the occurrence of defects. Furthermore, it reduces the capacity to demonstrate significant deviations in the predicted weights from zero. The Variance Inflation Factor (VIF) is the selected metric for assessing the collinearity of formative indicators.

4.9 METHODS OF MEDIATION ANALYSIS

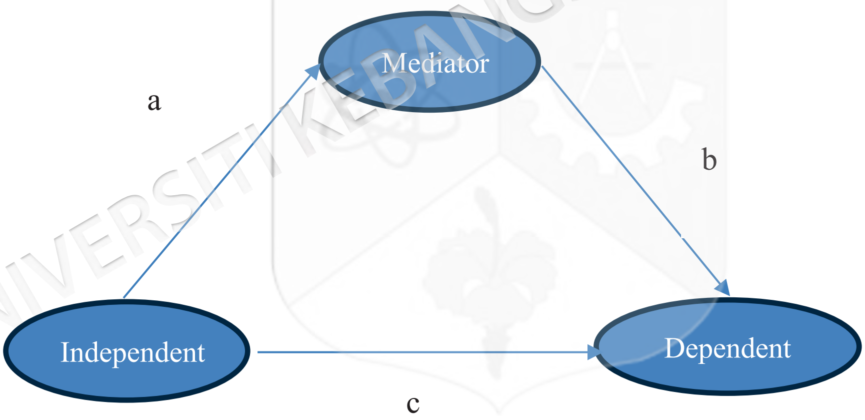

Figure 4.3 Mediation Process

Researchers can effectively conduct the evaluation of mediation by testing the indirect influence of a social effect, as it provides them with comprehensive information. Hence, the use of PLS-SEM for routes *a* and *b* do not require independent testing. The necessity of conducting independent testing for routes *a* and *b* in Partial Least Squares Structural Equation Modelling (PLS-SEM) is debatable, as the testing of these routes is commonly regarded as an integral component of the Barons and Kenny four-step approach to mediation testing. The Barron and Kenny mediation analysis approach involves two distinct steps: first, testing the path from the independent variable to the mediator (route *a*), and second, testing the path from the mediator to the dependent variable (route *b*). There are several limitations associated with the use of the Baron and Kenny's method. In this method, it is imperative that all four steps hold substantial significance before considering mediation. If any of the aforementioned steps lose significance, it is necessary to cease analysis, leading to the conclusion of "no mediation." The methodology employed in this study has faced criticism owing to its limited statistical power, and the inclusion of multiple steps has been found to increase the likelihood of Type I error. Type I error refers to the erroneous conclusion that mediation exists when there is no actual mediation effect (Rungtusanatham et al. 2014). The method proposed by Baron and Kenny does not provide a measure of the magnitude of the mediation effect, nor does it account for models that exhibit inconsistent mediation, as highlighted in previous studies (MacKinnon et al. 2000; Rungtusanatham et al. 2014). The magnitude of the mediating effect is then determined by the extent of the indirect influence exerted by a series.

4.10 DATA ANALYSIS

The data obtained in this study was examined using SPSS 22.0 and PLS 4. The following sections offer concise explanations of the primary analysis methods employed to compile the data, verify the metrics, and evaluate the proposed hypotheses.

4.10.1 Descriptive analysis

Preliminary analysis of the data employed descriptive statistical techniques to characterise the distributional properties of all variables. Measures of central tendency (mean and median), dispersion (standard deviation), and relative frequencies (percentages and frequencies) were computed to discern central trends and rankings within the data. These descriptive indices offer a concise quantitative summary of the data that enables comparisons of variable trends. The percentages and frequencies proved particularly useful for summarising the distributions and comparing patterns across variables. Overall, these descriptive statistics provided an informative initial profile of the key distributional features of the dataset.

4.10.2 Data normality

The normality of the data is a necessary condition for the application of structural equation modelling. The present study involves an assessment of data normality through the examination of both univariate and multivariate normality. Univariate normality was assessed by examining skewness and kurtosis of each variable in isolation. The pervasive nature of the assumption of normality is widely recognised. The reason for its prevalence in both the univariate and multivariate analyses can be attributed to its widespread use. Several statistical methods, such as correlation, linear regression, and t-tests, rely on normal distribution. Nonetheless, deviations from the normality assumption need not be a significant concern for a sizable sample, because of the central limit theorem. According to (Altman & Bland 1995), it has been postulated that the average of a stochastic sample drawn from any given distribution conforms to a normal distribution. However, a universally reliable test has not yet been identified, and multiple tests are required to determine normalcy.

4.10.3 Confirmatory factor analysis (CFA)

Confirmatory factor analysis (CFA) was conducted using SmartPLS 4 to evaluate the measurement model as the initial phase of structural equation modelling (Kline 2023). CFA enabled the assessment of the convergent and discriminant validity of the constructs in the instrument by examining the measurement model. This process confirmed the dimensionality and reliability of the measurement scales, providing evidence of construct validity before evaluating the structural model. Overall, the CFA served as a critical first step in SEM to establish the psychometric rigor of the measurement instruments by investigating their convergent and discriminant validity.

4.11 SUMMARY

This chapter delineates the research methodology adopted for this study. Specifically, it discusses the research philosophy, design, sampling, data collection, and data analysis techniques employed to empirically investigate the hypotheses. This study followed a quantitative, deductive approach aligned with a positivist paradigm. Primary data was collected through a survey of MAs in UAE companies. Participants were selected using probability and non-probability sampling methods. PLS-SEM was used to assess the measurement models and test structural relationships.

A rigorous quantitative research design was implemented by leveraging validated scales from the literature to collect relevant data. Statistical analysis techniques, such as CFA, normality tests, and PLS-SEM were applied to systematically analyse the data. This facilitates the testing of the hypothesised relationships to arrive at empirical conclusions regarding the impact of BI&A on MAPs and firm performance. The methodology provides a sound basis for addressing the research aims and questions through empirical examination.

CHAPTER V

DATA ANALYSIS AND FINDINGS

5.1 INTRODUCTION

This chapter reports the findings of this study based on a comprehensive analysis of the data collected. The discourse and analysis focused on topics such as the response rate, the collected data attributes, and attributes of the sample. The Statistical Package of Social Science (SPSS) was used to present descriptive analysis findings, and further analysis to test the hypotheses was performed using SmartPLS for Structural Equation Modelling (SEM). This encompasses the evaluation of items using the measurement model, which entails examining elements, such as reliability, validity, loading, convergent validity, and discriminant validity.

5.2 DATA CLEANING AND SCREENING

Data cleaning is an essential step in the model analysis and assessment. It is critical to identify and correct errors in the data before proceeding with this study. Therefore, it is essential to plan and execute the research design phase of any project carefully to ensure the highest level of validity and reliability of the collected data related to the research questions. The implementation of a screening code serves the purpose of identifying present or potential issues in the data entry process for each variable. The purpose of this procedure was to ensure the integrity, dependability, and applicability of the data for examination (O'Rourke 2000). In this study, the approaches suggested by Sekaran and Bougie (2019) were used to develop an appropriate instrument for the pre-analysis screening of the code. Additionally, a comprehensive manual check was conducted for each item to verify its accuracy.

5.3 OUTLIERS

An outlier refers to an observation that deviates significantly from the rest of the observations and exhibits exceptionally high or low scores. Such observations have the potential to influence the normality of a dataset (Hair et al. 2021). There are two distinct categories of outliers: univariate and multivariate. A univariate outlier is postulated when the SPSS regression analysis yields a typical value in an independent variable that surpasses the threshold of case acceptance, either falling below -3.29 or above +3.29 (Leys et al. 2019). The data in this study indicates that the range of Z-scores for all research constructs were found to be -2.831 to 1.613 as illustrated in Table 5.1. Thus, the findings indicated that all Z-scores were within the satisfactory range. Table 5.1 presents the outlier results for all research variables in this study.

Another method was used to detect outliers in the dataset using SPSS. Multivariate outlier tests are employed in situations where a dataset contains numerous variables and the observations within the dataset are not mutually independent. These tests are capable of identifying atypical combinations of values among numerous variables, which could potentially signify errors in data collection or measurement, or alternatively, show genuine anomalies within the data. The Mahalanobis distance test was used to measure multivariate outliers. It is a statistical measure that calculates the distance between a point and distribution. It considers the covariance structure of data. The *p-value* was then calculated using the computing function in SPSS using the following equation:

[1-CDF.CHISQ (MAH_1,6)]

(i.e. CDF.CHISQ calculates the cumulative distribution function (CDF) of the chi-squared distribution, MAH_1 is the Mahalanobis value, and 6 is the degree of freedom).

Based on the observations, 12 outliers (cases) were detected which achieved *a p-value* less than 0.001. Observations were excluded to avoid skewness.

Table 5.1 Z-Score Result of Outlier Test

Variable	**Minimum**	**Maximum**
BI&A	-2.21111	1.50958
MAPs Inference	-2.22968	1.2975
MAs' Analytical Skills	-2.83161	1.51079
Performance	-2.80828	1.61309

5.4 RESPONSE RATE

Survey questionnaires were distributed to 1562 companies in the UAE during the 5 months data collection period from March 2023 to July 2023. The researcher increased the sample size to enhance response rates, leveraging the user-friendly LinkedIn Sales Navigator service to send bulk messages to companies that met pre-defined criteria, including employee count, annual turnover, and location. A total of 217 completed questionnaires were returned, with a response rate of 13.9 per cent. The response rate obtained in the current study is comparable to the findings reported by Youssef and Mahama (2021), who recorded 216 responses, representing 16% of the total sample. Furthermore, the current response rate surpasses the figures documented in several other contributions, such as Bergman et al. (2020) with 107 responses, constituting 8% of their sample, and Peters et al. (2016) with 142 responses, reflecting a 12% response rate. Consequently, the response rate attained in this investigation can be deemed satisfactory and within an acceptable range, considering the norms established in the extant literature. Of the 217 questionnaires received, 13 were excluded because of missing data from various sections, and 12 were excluded as outliers. This left 192 usable questionnaires for data analysis. Table 5.5 shows the rate of returned questionnaires.

Table 5.2 Summary of the response rate

Distribution	1562
Returned questionnaire	217
Response rate	13.9%
Unusable questionnaire	13
Outliers	12
Usable questionnaires	192

5.5 UNIVARIATE NORMALITY TEST

Before employing the multivariate data analysis approach, it was important to conduct a preliminary assessment of data normality. Skewness refers to the asymmetry of a distribution, with a spread towards either the right or left tail. On the other hand, kurtosis pertains to the degree of peak intensity in a distribution. According to Hair et al. (2021), the majority of the answers are expected to be located near the centre. According to (Kline 2023), the acceptability of the results is determined by the range of +-3 for Skewness and +-10 for Kurtosis. The Skewness, Kurtosis, and their ratio to their standard errors (Z-values) were calculated for each variable. As shown in Table 5.3, the observed skewness and kurtosis values fell within the permissible range, suggesting that all variables exhibited a normal distribution.

Table 5.3 Result of Normality Test

Constructs	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
BI&A	-0.257	0.175	-0.725	0.349
MAPs Inference	-0.787	0.175	-0.157	0.349
MAs' Analytical Skillset	-0.808	0.175	-0.250	0.349
Performance	-0.450	0.175	-0.108	0.349

5.6 COMMON METHOD BIAS

There is consensus among scholars that the presence of common method bias, which refers to the variance in data that can be attributed to the measurement methods employed rather than the constructs being measured, pose a potential challenge in behavioural research. This issue arises when the evaluation of constructs relies on the responses obtained from a single source (Podsakoff et al. 2003). In this study, efforts were made to mitigate the potential influence of common method bias by adhering to the recommendations put forth by (MacKenzie & Podsakoff 2012). This outcome was achieved through a thorough questionnaire design and systematic arrangement of its components. Furthermore, the research conducted in this study deliberately omitted enquiries pertaining to sensitive personal details and took measures to guarantee confidentiality and anonymity of the individuals involved. Nevertheless, it is important to acknowledge that these processes may not effectively mitigate survey bias. Hence, the present study aimed to investigate the problem of common method bias by employing Harman's single-factor approach, which seeks to ascertain whether a significant proportion of the variation can be accounted for by a single component (MacKenzie & Podsakoff 2012). A factor analysis technique was employed with no rotation, and the number of extracted factors was set to one. According to the findings presented in Table 5.4, the variance extracted is 46.899 percent. This value falls below the established criterion of 50 percent for the extracted sum of squared loadings as outlined by (Podsakoff et al. 2003). This observation supports the assertion that the common method bias does not pose a significant issue, as indicated in Appendix C.

Table 5.4 Result of Common-Method Variance

Total	% of Variance	Cumulative %
435.643	46.899	46.899

5.7 GENERAL PROFILE OF THE RESPONDENTS

The analysis of respondents' profiles is crucial for gaining a comprehensive understanding of the features of the sample. This entails the examination of demographic factors, such as job titles, educational attainment, professional experience, company size, geographical location, workforce size, annual revenue, and industry classification. The job titles of the respondents encompassed the six titles presented in table 5.5. After deleting 12 outliers, the majority of respondents in the sample consisted of MAs, comprising over one-third of the total respondents. CFOs comprise 26% of the sample, while financial controllers represent nearly 19% of the entire population. Table 5.5 illustrates that a notable proportion of the participants, specifically 17%, hold managerial positions and are actively involved in the implementation or engagement of MAPs inside their respective organisations.

Table 5.5 Demographic Profile

Variable	**Level**	**Frequency**	**Percentage**
Job Title	Management Accountant	68	35.4
	Financial Controller	36	18.8
	Financial Analyst	8	4.2
	CFO	50	26.0
	Manager	30	15.6
Years of Experience	1 - 5 Years	4	2.1
	5 - 10 Years	16	8.3
	10 - 15 Years	70	36.5
	Above 15 Years	102	53.1
Industry Type	Agricultural/mining/construction	4	2.1
	Banking/finance/insurance	19	9.9
	Consulting/professional service/IT	36	18.8
	Healthcare	4	2.1
	Hospitality/travel/tourism	26	13.5
	Manufacturing	25	13.0
	Oil and Gas	9	4.6
	Real Estate	10	5.2
	Retail/wholesale/distribution	34	17.7
	Telecommunications	8	4.2

	Transport/Logistics	17	8.9
Employees numbers	100-499	112	58.4
	500-1000	22	11.5
	> 1000	58	30.2
Annual Turnover (AED)	10 million: 99 million	82	42.7
	100 million: 500 million	38	19.8
	> 500 million	72	37.5

Respondents' experiences with their firms are reported over the years. Most of the surveyed respondents (> 53%) had > 15 years of work experience. Different industries were listed in responses based on published categories in both the ADX and the DFM. The highest participation was in the consulting, professional service, and information technology industries, with one-fifth of all the respondents. Retail, wholesale, and distribution companies accounted for almost 18%, followed by hospitality, travel, tourism organisations, and manufacturing at 13.5% and 13%, respectively. Financial institutions present 9.9%, despite being highly regulated, should also be included as they actively utilise MAPs and BI&A to enhance decision-making, regulatory compliance, and performance measurement. Their participation ensures the study captures diverse industry practices, and any regulatory constraints can be accounted for through appropriate analytical considerations. The characteristics of firms may contribute to the improved reliability and validity of the results, as the data encompasses firms from diverse industries.

Participants were requested to specify the magnitude of their organisation by quantifying the number of full-time equivalent personnel. Table 5.5 displays the range of values and the related number of enterprises within each respective range. A diversity of full-time equivalent employees was observed, where almost one-third of the respondents were working in companies with over 1000 employees, and the 60% worked in companies with a headcount of between 100-499 employees. This indicates that the majority of the understudied companies are medium-sized companies. Table 5.5 also reveals that more than one-third of the participants reported achieving an annual turnover exceeding 500 million AED, while almost two-thirds reported a range of annual turnover between 10 million and 500 million AED. According to the adopted definition from UAE Central Bank and the Ministry of Economy, those firms are considered as medium and large companies. Specifically, we classify a medium-sized organisation as one with an employee count ranging from 75 to 200 and an annual turnover exceeding 10 million AED. This classification considers the average across sectors, providing a standardized approach to defining medium organisations in the UAE context, particularly for the purpose of this study (UAE Central Bank 2022; Ministry of Economy 2022).

5.8 MISSING DATA

The quality of the data is crucial and requires detailed attention to ensure reliability and validity. This entails handling missing values and preparing the data before processing them using SPSS. Once the questionnaires were received and examined, it was revealed that 13 responses exhibited multiple missing values across various variables, which were removed. SPSS software was used to analyse the remaining 192 responses, employing several conventional processes including the examination of missing values, outliers, and data distribution. Missing answers to the questionnaire were imputed with the mean values using SPSS. The decision to use mean values as a replacement for missing data was based on the observation that the number of missing values in the dataset was small (Appendix B). One often-employed method for addressing missing values is mean substitution, in which missing values are substituted with the mean value of the observed data for the respective variable (Peng et al. 2023). This was conducted using the SPSS function by replacing the missing value function *series mean* by creating a new variable name with new values replacing the missing values.

5.9 NON-RESPONSE BIAS

Non-response bias refers to the situation in which individuals who choose not to engage in a study, known as non-respondents, exhibit consistent differences compared to those who do participate, known as respondents. The representativeness of the sample can be compromised, resulting in skewed outcomes that impact the reliability and validity of the findings (Fowler 2013). The present survey was distributed to the sample, and reminders were sent to all participants approximately one month following the initial message. To assess non-response bias, Armstrong and Overton (1977) assumed that individuals who responded to a survey later were more likely to share characteristics with non-respondents than those who responded earlier.

Consequently, the study contrasted the respondents who replied to the first submission with those who replied to the second submission (Armstrong & Overton 1977). To accomplish this, the replies were categorised into two groups according to the date the questionnaire was submitted. Questionnaires received prior to the reminder date were classified as early responses. The responses received after the reminders were categorised as late responses and were included in the second group. A total of 156 responses were categorised into the early response group, while 36 responses were categorised into the late response group. A two-sample independent t-test was conducted by assigning the responses to the two groups and coding them as 1 for early responses and 2 for late responses. The results displayed in the table below indicate that there are no significant differences ($p > 0.05$) between the two samples in terms of the study constructs. This suggests that there was no non-response bias in the data.

Table 5.6 Two-sample independent t-test for early and late response

Constructs	***F***	***Sig.***
BI&A	0.201	0.07
MAPs Inference	0.6604	0.23
MAs’ Analytical Skillset	0.5455	0.19
Performance	0.2296	0.08

5.10 DESCRIPTIVE STATISTICS AND CORRELATION MATRIX

This section presents descriptive statistics of the constructs used to assess the validity of the model. Descriptive statistics were utilised throughout the preliminary phase of data analysis, specifically to calculate the many constructs examined in the study, including BI&A, MAPs, MAPs capabilities, and organisational performance.

5.10.1 Descriptive Results for Use of BI&A

Descriptive statistics encompass the presentation of metrics of central tendency and dispersion. These statistical measures included the mean, median, and standard deviation. Table 5.7 presents the results of the descriptive measures for all variables. The data indicate that the average OLAP, data mining, data warehousing, visualisations, and descriptive analytics use were 3.719, 3.729, 3.583, 3.839, and 3.500, respectively. Diagnostic and predictive analytics exhibited a reasonable degree of use with scores of 2.906 and 3.036, respectively. The Perspective Analytics tool exhibited the lowest mean value of 2.705 compared to the other tools; this is most likely due to the highly sophisticated analytical tools involved in prescriptive analytics. It appears that, the participants in the study utilised the recommended elements of

BI&A in their respective work environments, as indicated by the mean values above a threshold of three.

Table 5.7 The respondents' use of BI&A

Variables	Mean	Median	SD	Min	Max
Online Analytical Processing (OLAP)	3.719	4.000	1.4522	1	5
Data mining	3.729	4.000	1.3183	1	5
Data warehouse	3.583	4.000	1.3038	1	5
Visualisation	3.839	4.000	1.2616	1	5
Descriptive analytics	3.500	4.000	1.4580	1	5
Diagnostic analytics	2.906	3.000	1.3190	1	5
Predictive analytics	3.036	3.000	1.3628	1	5
Prescriptive analytics	2.705	3.000	1.4388	1	5

Note: (l = Never Used, 2 = Rarely Used, 3 = Sometimes Used, 4 = Often Used, and 5 = Always Used).

5.10.2 Descriptive Results of MAPs Inference Capability

This section presents the descriptive statistics of the collected insights from MAs and financial professionals on the inference capability of MAPs. Respondents revealed their practical reflection of the 14 examined MAPs on the degree of real-time conclusions and insights that can be perceived from conducting the MAPs. Table 5.8 presents the average values and variability measures of these practices. The MAPs inference capability was evaluated on a 5-point Likert scale ranging from very low to very high. The practices of budgeting, forecasting, performance evaluation using financial measures, performance evaluation using non-financial measures, industry analysis, product profitability analysis, and customer profitability analysis demonstrate a notable level of inference capabilities compared to other listed practices MAPs, with a mean score exceeding 3.5. However, these practices exhibited a slightly higher standard deviation, suggesting that the data points were more dispersed around the mean. Conversely, practices such as value chain analysis, discounted cash flow, and activity-based costing exhibit lower inference capabilities, with mean scores closer to 3.0, suggesting moderate application in real-time decision-making.

Table 5.8 Descriptive statistics – MAPs Inference Capability

Variables	Mean	Median	SD	Min	Max
Budgeting practices	3.865	4	1.4077	1	5
Forecasting practices	3.948	4	1.2893	1	5
Performance evaluation using financial measures	4.073	5	1.1867	1	5

Performance evaluation using non-financial measures	3.719	4	1.1995	1	5
Cost-Volume-Profit analysis	3.313	3	1.4554	1	5
Product profitability analysis	3.724	4	1.3925	1	5
Customer profitability analysis	3.641	4	1.2284	1	5
Discounted cash flow to evaluate investments	2.984	3	1.5194	1	5
Activity-based costing	2.958	3	1.5344	1	5
Target costing	3.063	3	1.5268	1	5
Value chain analysis	2.854	3	1.4933	1	5
Product life cycle analysis	3.166	4	1.5517	1	5
Industry analysis	3.542	4	1.3761	1	5
Cost of quality reporting	3.063	3	1.5405	1	5

Note: (l = Very Low, 2 = low, 3 = average, 4 = high, and 5 = Very High).

5.10.3 Descriptive Results of MAs' Analytical Skillset

The data indicates that the respondents practice the listed Analytical Skillset in table 5.9. However, the level of practice varied among the samples. The most frequent role that has been found is "data collection and processing" with mean value of 4.219 and standard deviation of 0.94. This involves gathering data from diverse sources and performing tasks such as handling missing values, duplicates, and inconsistencies. This function is succeeded by the task of "data exploration and analysis" with an average rating of 4.057, which entails the examination of patterns and trends within extensive datasets to reveal valuable insights and support decision-making processes. The skill of using data visualisations, dashboarding, and reporting tools achieved an average of 4.042, indicating that the majority of respondents demonstrated a tendency to utilise data visualisations, dashboarding, and reporting as a mean of effectively communicating their MAPs. The possession of analytical thinking and problem-solving skills, and the ability to collaborate with cross-functional teams achieved higher means scores of 3.932 and 3.635, respectively. These skills contribute to effective resolution of business difficulties. The lowest mean scores of 2.984 and 2.750 were obtained for the tasks of "working with big data technologies" and "designing and implementing experiments to test hypotheses and optimise processes or products," respectively. While the skill of "Build predictive models and evaluate their accuracy and effectiveness", achieves a mean value of 3.089.

Table 5.9 Descriptive statistics – MAs' Analytical Skillset

Variables	Mean	Median	SD	Min	Max
Data collection and preprocessing	4.219	4	0.9401	1	5
Data exploration and analysis	4.057	4	1.0293	1	5
Statistical analysis	3.448	3	1.2353	1	5
Data visualisations, dashboarding and reports to communicate findings to stakeholders	4.042	5	1.2400	1	5
Design and implement experiments to test hypotheses and optimise processes or products.	2.984	3	1.3282	1	5
Analytical thinking and problem-solving skills contribute to addressing business challenges.	3.932	4	1.2493	1	5
Possess domain knowledge relevant to my industry or specific area of operation.	3.635	4	1.2161	1	5
Working with big data technologies	2.750	3	1.3263	1	5
Build predictive models and evaluate their accuracy and effectiveness.	3.089	3	1.3410	1	5
Collaborating with cross-functional teams	3.927	4	1.1823	1	5

Note: (l = Never Applied, 2 = Rarely Applied, 3 = Sometimes Applied, 4 = Often Applied, and 5 = Completely Applied).

5.10.4 Descriptive Results of Organisational Performance

The performance metrics exhibited mean values ranging from 3.333 to 3.953, indicating relative consistency across the categories. The balanced scorecard framework is divided into four key perspectives, with performance indicators representing each area as presented in Table 5.10. The mean scores for the financial, customer/market, process capabilities, and learning and growth perspectives were 3.849, 3.577, 3.454, and 3.448, respectively. These results suggest a balanced distribution of performance across the dimensions. Appendix D provides a detailed breakdown of the means and standard deviations for all 16 performance indicators used in the study.

Table 5.10 Descriptive statistics – Performance

Performance category	Mean	Median	SD	Min	Max
Financial perspective	3.849	4	1.016	1	5
Customer/market perspective	3.577	4	1.119	1	5
Process capabilities perspective	3.454	4	1.136	1	5
Learning and growth perspective	3.448	4	1.083	1	5

Note: (l = Very Low, 2 = low, 3 = average, 4 = high, and 5 = Very High).

5.10.5 Descriptive and correlations of all variables

The means of the main computed variables are depicted in Table 5.11, ranging from 3.377 to 3.608 which are very close to the median value. The inference capability and performance are very close to the median value of 3.5. If the mean is close to the median, it indicates that the data are likely to be approximately symmetrically distributed but with some degree of skewness. Skewness direction was determined by comparing the mean and median values. If the mean is greater than the median, the data is positively skewed; if the mean is less than the median, the data is negatively skewed. This implies that the data distribution is skewed to the left, with a longer tail on the left-hand side of the distribution. This means that there are more observations with higher values on the right-hand side and fewer observations with lower values on the left-hand side of the distribution. In a negatively skewed distribution, the mean is typically lower than the median value. The perceived results are quite similar to the literature (Uyar & Kuzey 2016) where the mean has been found between 3.48 to 3.71 for the MAPs and the performance ranged from 3.33 to 4.0. The mean of the BI&A is similar to Youssef and Mahama (2021) of 3.7.

Table 5.11 Descriptive statistics – All variables

Variables	Mean	Median	SD
BI&A	3.377	3.500	1.31028
MAPs Inference	3.422	3.500	1.36865
MAs' Analytical Skillset	3.608	3.900	1.17715
Performance	3.541	3.596	1.01424

Table 5.12 displays the correlation coefficients of all variables. Examination of the correlation matrix revealed a statistically significant correlation at the 0.01 significance level for all variables. A moderate-to-strong relationship exists between the primary variables. The BI&A is positively and strongly correlated with the MAPs inference capability with a r value of 0.639. Similarly, this high positive correlation was expanded to include data analysts' Analytical Skillset, with an r value of 0.731. Furthermore, a moderate correlation was found with overall performance, with an r of 0.532. The correlation findings indicate that the assumption of multicollinearity is unlikely to pose a concern in the forthcoming analysis. Furthermore, the issue of multicollinearity was assessed in greater detail by examining the Tolerance and VIF values (Appendix E). While the correlation coefficients indicated the presence of associations

among the variables, none of the coefficients exceeded the threshold of 0.9, suggesting that multicollinearity is unlikely to pose serious concern in the subsequent analysis (Hair, 2014) .

Based on the multicollinearity analysis in Appendix E, the Tolerance values range from 0.121 (Inference Capability) to 0.417 (BI&A). A Tolerance value below 0.1 is generally indicates a potential multicollinearity issue. Accordingly, the Inference Capability variable showed a low tolerance value of 0.121, suggesting no multicollinearity with other independent variables. Considering the obtained VIF values, a value greater than 10 is typically considered an indication of severe multicollinearity. Both the BI&A and MAs' Analytical Skillset variables have a tolerance value of 0.417and 0.369 and VIF of 2.395 and 2.707, respectively, which are within acceptable ranges, suggesting no significant multicollinearity issue (Appendix E).

Table 5.12 Correlation analysis

Variables	**BI&A**	**Inference**	**Analytical Skillset**	**Performance**
BI&A	1			
MAPs Inference Capability	.639**	1		
Analytical Skillset	.731**	.645**	1	
Performance	.532**	.631**	.724**	1

** Correlation is significant at the 0.01 level (2-tailed).

5.11 MEASUREMENT MODEL

The measurement model outlines the associations between observable variables (also known as indicators) and a collection of unobservable variables (sometimes referred to as latent constructs). This statement elucidates the extent to which indicators effectively capture and assess the fundamental constructs they are designed to portray. A measurement model was employed to evaluate the reliability and validity of the indicators and the latent constructs.

5.11.1 Reflective and formative modelling

This section provides an overview of the modelling process for BI&A, MAPs capabilities, and performance before proceeding to the development of the measurement model and the testing of the structural model. It is imperative to comprehend the nature of latent constructs and their corresponding indicators, as they play a crucial role in structural equation modelling (SEM) and validation. In their seminal work, Jarvis et al. (2003) proposed a set of four decision principles that warrant careful consideration when choosing between reflective and formative modelling approaches. The set of rules involves the establishment of a causal relationship between the construct and the indicators, the ability to interchange the indicators, the assessment of covariance among the indicators, and the examination of the nomological net of the construct indicators. It is imperative to comprehend the nature of latent constructs and their corresponding indicators, as they play a crucial role in structural equation modelling (SEM) and validation (Sarstedt et al. 2023; Hayduk et al. 2007).

a. The causal relationship from the construct to the indicators

It is imperative to comprehend the nature of latent constructs and their corresponding indicators, as they play a crucial role in structural equation modelling (SEM) and validation (Sarstedt et al. 2023). In the context of a formative model, a causal relationship is established between indicators (items) and the underlying latent construct. Indicators are commonly regarded as distinctive features that serve to define a construct, with the construct itself being influenced by the particular properties that these indicators represent. In the context of formative models, it is important to note that the construct does not influence indicators. Instead, alterations in the latent construct did not have any impact on the indicators. Utilisation of this particular model is prevalent in cases where the latent construct is perceived as an outcome of its indicators, and it is plausible to posit that alterations in the construct do not result in changes in the indicators (Jarvis et al. 2003).

On the other hand, a reflective model posits that the causal relationship originates from the latent construct and extends to objects. Indicators are regarded as manifestations of the construct and capture their inherent similarity. Modifications in the structure result in alterations in the indicators. Within the context of reflective models, it was observed that the indicators possessed a higher degree of interchangeability and served as more accurate representations of the shared variance inherent in the underlying construct (Hayduk et al. 2007). There exists a significant disparity in the direction of causality between formative models, which proposes that indicators create the construct, and reflective models, which claim that the construct impacts the indicators. Furthermore, it is important to note that indicators exhibit distinct qualities, depending on the type of model used. In formative models, indicators are defined by their inherent properties; however, in reflective models, indicators are considered as manifestations. Additionally, both models concur that alterations in indicators should not result in modifications of the build. This highlights the need to thoroughly consider construct validity and the associations between constructs and indicators in both approaches (Coltman et al. 2008).

The current research constructs of BI&A, MAPs inference capability, and performance should be treated as reflective constructs. These constructs exist independently of their indicators or measures because they do not define their characteristics of the constructs. Furthermore, the perceived changes in BI&A and MAPs inference capability result in changes in their indicators and not vice versa. For example, the increased usage and involvement of MAs and financial professionals in using BI&A tools will lead to new tools and techniques to meet continuous changes in the business environment and information technology. In other words, the complete adoption of BI&A in MAPs, MAs, and financial professionals would use the full capacity of BI&A. In addition, variations in BI&A and MAPs capability will lead to variations in their indicators.

b. Interchangeability of the indicators

In the context of a reflective model, indicators are intentionally constructed to possess interchangeability, thereby exhibiting shared content or themes. This implies that the items are presumed to assess the same underlying construct and are affected by it. Removing an indication from a reflective model does not significantly alter the conceptual domain of the construct as the remaining indicators continue to encapsulate the fundamental nature of the construct. The focal point of this model is to highlight the common variance observed among several measures as well as the causal impact of the construct on these indicators (Jarvis et al. 2003).

By contrast, a formative model does not require indicators that possess interchangeability or a shared thematic element. Each indicator contributes a distinct aspect to the underlying construct, reflecting a broader conceptual domain. The exclusion of an indication from a formative model has the potential to modify the conceptual domain of the construct given that each indicator is regarded as making a unique contribution. Formative models primarily focus on the collective influence of indicators in shaping a construct, as well as the impact that alterations in these indicators have on the construct.

The essence of the comparison is centred on the characteristics of the indicators. Reflective models posit the existence of a unifying construct that influences indicators, whereas formative models argue that the construct is generated by indicators. Reflective models are predicated on the notion of shared variance and the removal of indicators does not significantly affect the fundamental nature of the construct. Formative models acknowledge and incorporate the distinct contributions of indicators, and the removal of an indicator can potentially result in a conceptual reorientation. In this study, indicators within the constructs of MAPs capabilities and BI&A are interchangeable with the same content and theme. Not every construct will be incomplete if any indicator is removed or excluded. For example, the indicator of MAPs inference capability depends on the level of application of MAPs in the industry (Hayduk et al. 2007).

c. Covariance among the indicators

In a reflective model, it is anticipated that indicators will exhibit covariation with one another, as they are perceived as expressions of shared underlying notions (Jarvis et al., 2003; Sarstedt et al. 2022). This suggests that indications are perceived as expressions of shared underlying notions. When a particular indicator changes, it is anticipated that the remaining indicators will exhibit corresponding changes. Nevertheless, a key attribute of reflective models is that alterations in one indicator should not correlate with modifications in other indicators. This implies that the variance accounted for by each indicator is attributable to the common construct rather than to distinct sources of variance from different indicators. MAPs capabilities vary in correlation between themselves. In other words, changes in capabilities level in one MAP tend to be associated with changes in the other MAPs based on the industry. In BI&A, changes in one of the eight indicators used in the study might lead to changes in the other indicators. Descriptive analytics results are inputs to other analytics types. On the one hand, data mining is crucial to produce and implement a reliable descriptive analytics outcome. Accordingly, the researcher claims that the reflection model is quite convenient for research (Jarvis et al. 2003).

Conversely, under a formative model, it is anticipated that indicators will exhibit covariance with one another, indicating a degree of coherence among them. However, unlike reflecting models, it is not anticipated that alterations in one formative sign will be linked to alterations in other indicators. In formative models, individual indicators play a distinct role in contributing to the overall construct, and their collective impact determines the nature of the underlying latent construct (Hayduk et al. 2007). Hence, alterations in one indication may not necessarily signify alterations in the other indicators.

d. Nomological net of the construct indicators

According to Jarvis et al. (2003), a reflective model requires that indicators possess identical antecedents and outcomes. Conversely, the formative model operates based on the principle that indicators exhibit contrasting antecedents and effects. Put simply, the indicators inside a reflective model have a comparable relationship, whether positive or negative, and significant or non-significant, with the antecedents and effects of the construct. By contrast, the need for interconnected indicators is not applicable to formative indicators, as they do not inherently possess a shared theme and, as a result, lack the same types of connections with the antecedents and consequences of the construct (Sarstedt et al. 2022). According to this rule, the main constructs of the current model were reflective. The indicator of MAPs capability is anticipated to exhibit a comparable association with the antecedents and consequences of MAPs, as these indicators are characterised by a shared theme of collaboration and a common objective of enhancing organisational performance. Therefore, it is anticipated that any preceding factor will exert a similar influence on the indicators of MAPs, provided they share the same theme. Moreover, it is anticipated that these indicators will yield similar outcomes, whether positive or negative. Likewise, this line of reasoning can be extended to BI&A indicators, which share a common focus on the application of BI&A techniques and the objective of enhancing organisational performance.

5.12 MAPS' INFERENCE CAPABILITY AS A MEDIATOR

5.12.1 Convergent Validity

Convergent validity refers to the extent to which many measures or indicators of a certain construct demonstrate consistency or exhibit a substantial variance. These measures have good convergent validity if they are highly connected. Poor convergent validity occurs when measures are not highly correlated. Convergent validity proves that the distinct construct measurements measure the same concept. The assessment of convergent validity involved an examination of four metrics: outer loading, Cronbach's alpha, composite reliability, and average variance extracted (AVE). The recommended range for all the measures was established as follows: the average extracted variance (AVE) should surpass the established threshold of 0.50, the composite reliability (CR) should ideally exceed 0.70, and the outer loadings (indicator reliability) for the measurement items should be higher than 0.70 (Fornell & Larcker 1981; Hair et al. 2021). The AVE values in table 5.13 are above 0.5 which shows that the construct explains more than half of the variance of its indicators. Furthermore, it is noteworthy that the constructs exhibited satisfactory reliability, as indicated by the Cronbach's alpha. According to the guidelines of Sekaran and Bougie (2019), a value of 0.60 is deemed to be poor, 0.70 is considered acceptable, and a value beyond 0.80 is regarded as good. Thus, this study demonstrates that the internal consistency dependability of the assessment score employed can be deemed satisfactory. According to the findings presented in Table 5.13, the average of the outer loadings resided in an acceptable range greater than 0.7. The detailed outer loadings for every item under every construct are shown in Appendix F, where it shows outer loadings (for indicator reliability), Cronbach's Alpha (for internal consistency), Composite Reliability (for construct reliability), and Average Variance Extracted (to ensure sufficient shared variance among indicators). Exploratory research suggests varying thresholds forouter loadings, with Bagozzi and Yi (1988) recommending values above 0.6, Chin (1998) propose a 0.5 threshold, and Hulland (1999) suggested that loadings between 0.40 and 0.70 might be justifiable depending on the context (Bagozzi & Yi 1988).

As shown in appendix F, the outer loadings of the indicators were assessed for each construct to determine indicator reliability, following established thresholds. While some indicators exceeded the ideal 0.7 threshold, others fell within the acceptable range of 0.40 to 0.70 (Hair et al. 2019), justifying their retention based on theoretical and content validity considerations. For the BI&A construct, outer loadings ranged from 0.705 to 0.937, with most indicators exceeding 0.7, indicating strong reliability. The lowest loading was 0.705 (Visualisation), which remains within the acceptable range. Given that all items contribute meaningfully to the construct, no deletions were made. The MAPs inference capability construct exhibited a wider range of outer loadings, from 0.431 to 0.999. While six indicators surpassed the 0.6 threshold, others fell below 0.5 (Cost of quality reporting = 0.431, Discounted cash flow to evaluate investments = 0.564). Retaining these indicators was justified to maintain theoretical completeness, as recommended by Hair et al. (2021) and Henseler et al. (2015). The lowest loading was 0.648 (cost reduction), which remains within the acceptable range and does not significantly impact the construct's validity (Hulland 1999).

The MAs' Analytical Skillset construct had loadings between 0.558 and 0.855. While the skill of "Design and implement experiments to test hypotheses and optimize processes or products" (0.558) and the skills of "build predictive models and evaluate their accuracy and effectiveness" (0.671) were relatively low. Overall, despite some lower loadings, all constructs met internal consistency and validity requirements, ensuring a robust measurement model. The researcher avoided item deletion as recommended by (Hair et al. 2021; Henseler et al. 2015) that the elimination of items purely on statistical affects the validity of measurement validity. Beyond outer loadings, the study assessed Cronbach's Alpha, CR), and AVE to ensure internal consistency and construct reliability. Cronbach's Alpha, which measures internal consistency, showed values above 0.7, exceeding the minimum threshold for acceptable reliability (Nunnally & Bernstein 1994). However, excessively high values (above 0.95) were avoided to prevent redundancy among indicators. CR values surpassed the 0.7 threshold, confirming the constructs' overall reliability (Hair et al. 2019). AVE values were also within acceptable levels, exceeding 0.5, indicating that more than 50% of the variance in indicators was explained by their respective constructs (Fornell & Larcker 1981). This confirms sufficient convergent validity, meaning that the indicators effectively capture their intended constructs. Given these results, the measurement model meets the necessary validity and reliability criteria, supporting the robustness of the study's structural model.

Accordingly, there are other procedures that can be followed in the case of lower values of the outer loadings; for example, reviewing the measurement errors for those items. Thus, the Standard error of the mean (SEM) was calculated and found to be lower, which indicates that the sample mean was closer to the population mean, indicating acceptable precision and more reliable parameter estimates (Appendix G).

Table 5.13 Results of Convergent Validity

Construct	Outer loadings	Cronbach's Alpha	CR	AVE
BI&A	0.75225	0.913	0.914	0.567
Inference Capability	0.7345	0.949	0.957	0.562
Performance	0.799188	0.967	0.969	0.646
Analytical Skillset	0.731	0.921	0.925	0.54

5.12.2 Discriminant Validity

Discriminant validity pertains to the degree to which a construct is empirically distinguishable from other constructs; that is, the amount to which the construct accurately measures its intended attribute. The Fornell and Larcker (1981) criterion is a commonly used approach for evaluating discriminant validity. According to this approach, a construct should demonstrate a higher degree of shared variance with its indicators than any other construct. To evaluate this particular criterion, it is necessary for the AVE of each construct to surpass the highest squared correlation with any other construct.

One approach to assess discriminant validity involves analysing the cross-loadings of indicators. According to Henseler et al. (2009), the approach, sometimes seen as more liberal than Fornell-Larcker, necessitates that the loadings of each indicator on its respective construct exceed the cross-loadings on other constructs. Table 5.14 shows the cross loadings for the latent constructs; the table tries to answer the question of "*Does any indicator correlate more strongly with the other constructs than with its own construct?*" (Henseler et al. 2015). In other words, the results in the table show whether the loadings of indicators on a specific latent construct surpass those on all other constructs. A high correlation with their own constructs and low correlation with other constructs would indicate a passing outcome.

The loading of an indicator on its associated construct should be higher than its cross-loadings on other constructs. The square root of the AVE for each construct should be greater than its correlations with other constructs. Based on the cross-loadings table (Appendix H); it is evident that the loadings of BI&A (0.75225) are high than other loadings of inference capability, performance, and Analytical Skillset constructs, indicating adequate discriminant validity. The loading of the inference (0.734429) construct is higher than its cross-loadings on other constructs, suggesting discriminant validity. While the loading of performance (0.799813) is higher than its cross-loadings on other constructs, demonstrating discriminant validity.

For the MAs' Analytical Skillset construct, its loading on itself (0.7308) is higher than its cross-loadings on other constructs, indicating discriminant validity. However, it is important to note that cross-loadings alone are insufficient to establish discriminant validity. In summary, the cross-loadings results in Table 5.15 suggest that the items effectively assessed the construct they were designed to measure, rather than measuring other structures. The correlation between the indicators in one construct is higher than in the other constructs, as indicated in bold in the table below (the detailed cross loadings for every item in Appendix H). However, it's important to note that the cross-loadings alone are not sufficient to establish discriminant validity.

Accordingly, this study implements the HTMT method to assess discriminant validity in variance-based SEM following the recommendations of (Henseler et al. 2015). They argued that neither the Fornell-Larcker criterion nor the assessment of cross-loadings allows users of variance-based SEM to determine the discriminant validity of their measures. Hair et al. (2021) proposed that the HTMT threshold value should fall between the range of 0.85 to 0.90, indicating a clear distinction between the two conceptions. The HTMT values for all the constructs in this study are presented in Table 5.15. Thus, the constructs demonstrated a satisfactory discriminant validity. Hair et al. (2021) proposed that the HTMT value should fall below the range of 0.85 to 0.90, indicating a clear distinction between the two conceptions. The HTMT values are below the conservative threshold of 0.85, which indicates that discriminant validity can be deemed satisfactory, as the correlations observed between different constructs do not significantly exceed the correlations observed within individual components.

Table 5.14 Cross Loadings - Discriminant Validity Assessment

Construct	BI&A	Inference	Performance	Analytical Skillset
BI&A	**0.75225**	0.526375	0.42825	0.599125
Inference Capability	0.519214	**0.734429**	0.502214	0.520143
Performance	0.453125	0.554688	**0.799813**	0.617313
MAs' Analytical Skillset	0.5821	0.5196	0.5656	**0.7308**

Table 5.15 HTMT Method - Discriminant Validity

Construct	1	2	3	4
BI&A				
Inference Capability	0.686			
Performance	0.565	0.669		
MAs' Analytical Skillset	0.795	0.693	0.766	

5.13 STRUCTURAL MODEL

The structural model or the inner model, as named by Hair et al. (2014), uses sample data to derive parameters that effectively forecast endogenous constructions rather than predicting parameters that minimise the disparity between the observed sample covariance matrix and the covariance matrix calculated by the model. Path analysis can be conceptualised as a form of linear regression. Path analysis is often regarded as the preferred analytical approach in social sciences and management. Similarly, path analysis is a widely used approach for simultaneously examining intricate linkages (Tabachnick & Fidell 2007). The primary stage of SEM involves the use of a structural equation model. Hence, the structural model allows for the assessment of the interconnections among all constructs, thereby offering precise insights into the association between exogenous and endogenous variables (Hair et al. 2006).

Structural equation modelling was used to evaluate the research hypotheses. The research framework examines the impact of BI&A and MAPs inference capability with the analytical skillset of MAs on organisational performance. It also explores the mediating effect of MAPs inference capability and management accountant analytical skillset on the relationship between the utilisation of BI&A and organisational performance.

The absence of a standardised goodness-of-fit metric in PLS-SEM necessitates the evaluation of the model's quality through the predictive capabilities of the endogenous constructs. The assessment is facilitated by the following criteria: the academic terms that can be used to describe the concepts mentioned are coefficient of determination (R^2), cross-validated redundancy (Q^2), path coefficients, and effect size (f^2). Parameter estimates for the structural model are summarised the following tables, together with their assumptions and relative pathways, which are used to evaluate the overall model fit. The final section verifies the hypothesised connection to the study, as shown in Table 5.16. This study also incorporates a mediator into its theoretical framework. It is feasible to investigate the direct influence of one or more variables on a third by considering mediation. In the context of structural equations, Hair et al. (2014) identified three effects of correlation that can be used to investigate mediation: two types of influences on a dependent variable, those caused by the independent variable itself, those caused by the independent variable's influence on some other variables, and the sum of direct and indirect impacts.

Table 5.16 Research Hypotheses and Relative Paths

Hypothesis	**Path**
H1: The use BI&A has a positive influence on OP	BI&A → OP
H2: The use BI&A has a positive influence on MAPs inference capability	BI&A → MAPs Inference Capability
H3: The use BI&A has a positive influence on MAs' Analytical Skillset	BI&A → Analytical Skillset
H4: MAPs inference capability has a positive influence on OP	MAPs inference capability → OP
H5: MAs' Analytical Skillset has a positive influence on OP	Analytical Skillset → OP
H6: MAPs inference capability mediates the relationship between the use of BI&A and OP	BI&A→Inference capability →OP
H7: MAs' Analytical Skillset mediates the relationship between the use of BI&A and OP	BI&A→Analytical Skillset →OP

The current model relates to the effects of BI&A, MAPs inference capabilities, and the current Analytical Skillset of MAs on organisational performance, in addition to the mediating effect of MAPs inference capability, and human capability in the relationship between BI&A and performance.

The bootstrapping approach was employed in the first model to assess the hypotheses proposed in this study. Bootstrapping involves the use of random resampling techniques on the initial dataset to generate fresh samples that are equal in size to the original dataset. This methodology not only evaluates the dependability of the dataset, but also examines the statistical significance of these coefficients, and consequently, the margin of error in the calculated path coefficients (Hair et al. 2014). The results of the bootstrapping method are shown in Table 5.17, which shows the p-values for each path and path coefficient. The results showed that the effect of BI&A on MAPs inference capabilities and analytical skillset was statistically significant (β= 0.701, t = 20.450, p <0.001) and (β= 0.796, t = 22.474, p <0.001), whereas the effect of BI&A on performance was negative and significant (β= -0.277, t = 2.456, p <0.001).

Table 5.17 Relative path results and hypotheses

Path	β	t value	p value
Path a			
BI&A → MAPs Inference Capability	0.701	20.391	<0.001
BI&A → OP	-0.277	2.456	<0.001
BI&A → Analytical Skillset	0.796	22.262	<0.001
Path b			
MAPs Inference Capability → OP	0.361	4.746	<0.001
Analytical Skillset → OP	0.740	6.395	<0.001

As shown in Figures 5.1, the standardised path coefficients (β) and p-values, significance of the paths, and R^2 for each endogenous construct were tested.

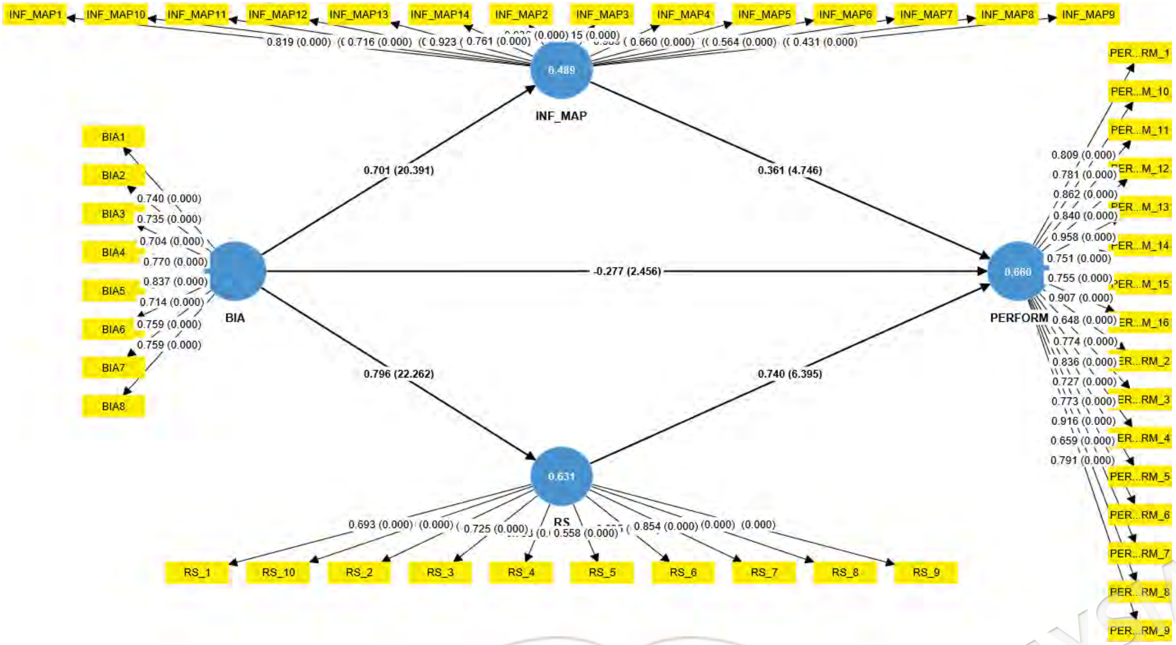

Figure 5.1 Path Model - PLS algorithms (p value, Path Coefficients, and R^2)

5.13.1 COEFFICIENT of DETERMINATION (R^2)

The R-squared (R^2) statistic, also known as the coefficient of determination, quantifies the extent to which a regression model elucidates the variance in the dependent variable by utilising independent factors. In other words, the coefficient of determination, sometimes referred to as R-squared, is a statistical metric used to assess the extent to which a structural model effectively accounts for the variability observed in endogenous variables. The values for this metric range from 0 to 1, with higher values indicating a more optimal fit for the model. This measure quantifies the degree of alignment between the observed data and theoretical model, where larger values indicate a stronger level of alignment. Since R^2 is a measure of predictive accuracy in regression, it lacks fixed thresholds; however, low R^2 implies weak prediction (less than 0.3), moderate values indicate moderate accuracy (0.3-0.5), and high values suggest strong prediction (above 0.7). The R^2 is a valuable tool for assessing the quality of a PLS model (Hair et al. 2014).

The presented R^2 values in Table 5.18 show moderate predictive accuracy of the effect of BI&A on MAPs inference capabilities and MA Analytical Skillset. The achieved R^2 value of 0.492 indicates that 49.2% of the MAPs inference capability can be explained by the adoption of BI&A. The values increased for MAs' Analytical Skillset, and organisational performance.

Table 5.18 Coefficient of Determination (R^2)

Endogenous Latent Variable	R^2	Adjusted R^2
MAPs Inference Capability	0.492	0.489
MA Analytical Skillset	0.633	0.631
Organisational Performance	0.666	0.660

5.13.2 EFFECT SIZE F^2

The effect size f^2 is a statistical measure commonly employed in the analysis of variance and regression. It quantifies the proportion of variance in the dependent variable, which can be attributed to independent variables. The measurement assesses the magnitude of the association and signifies the extent to which the independent variables affect the dependent variable, thereby facilitating an assessment of the practical importance of the findings. f^2 was computed by noting the change in R^2 when a specific construct was eliminated from the model.

f^2 is calculated by replicating the PLS model as specified by the hypothesis that the replicated model excludes the exogenous construct from the model and then calculating the R^2 for this new model. R^2 is compared between the two models (one with the exogenous construct and the other with its exogenous construct omitted). The higher the difference between the two R^2 values (*included* and *excluded*), the stronger the contribution of the exogenous construct to the endogenous construct, leading to a higher f^2 value. The thresholds of f^2 were 0.02, 0.15, and 0.35, representing small, medium, and large effects, respectively (Hair et al. 2014; Hair et al. 2021). The following formula is used to calculate f^2:

$$\frac{R^2\ included - R^2\ excluded}{1 - R^2\ included}$$

The f^2 values were obtained from Smart-PLS and are listed in the table 5.19 for the exogenous constructs which show higher values to the higher threshold of 0.35, signifying the stronger contribution of the exogenous construct of BI&A to explaining an endogenous construct of MAPs inference capabilities and MAs' Analytical Skillset.

Table 5.19 Effect Size (f^2)

Exogenous → Endogenous	f-square	effect
BI&A → MAPs Inference Capability	0.967	Large effect
BI&A → Analytical Skillset	1.727	Large effect
BI&A → OP	0.075	Small effect
MAPs Inference Capability → OP	0.175	Medium effect
Analytical Skillset → OP	0.530	Large effect

5.13.3 CROSS-VALIDATED REDUNDANCY (Q^2)

To measure predictive relevance in the structural model, Q^2 was implemented. The notion of Q^2 is to reuse the sample by omitting a part of the data matrix and then providing estimates of the model parameters, then using those estimates to predict the omitted part, which is called the *blindfolding* procedure. Accordingly, the higher the value of Q^2, the higher the accuracy of the model. The value of Q^2 is then based on the difference between the original (without omitting) and predicted values, where the smaller the difference, the higher Q^2. Values of Q^2 greater than zero for endogenous constructs denote the path model's predictive relevance for this construct and whether it can be predicted. However, a lower value of Q2 than zero indicates a non-predictive relevance model, and the exogenous constructs cannot explain the endogenous constructs (Hair et al. 2014; Hair et al. 2021). As stated by Chin (2009), the main threshold for Q^2 is up to 0.02 is a small predictive relevance, up to 0.15 is medium, and is greater than 0.35 is a large predictive relevance. The Q^2 values in table 5.20 shows higher values above 0.35 which signifies that the independent construct (BI&A) has a predictive relevance for the MAPs inference capability and the MAs' Analytical Skillset.

Table 5.20 Cross-validated redundancy (Q^2)

	Q²	RMSE	MAE
MAPs inference capabilities	0.419	0.771	0.627
Analytical Skillset	0.528	0.695	0.549
Performance	0.271	0.863	0.677

5.13.4 MEDIATION ANALYSIS

To analyse the mediation effect of MAPs capabilities and MA Analytical Skillset, a mediation analysis was conducted. Mediation represents a situation in which a mediator variable to some extent absorbs the effect of an exogenous construct on an endogenous construct in the PLS path model (Hair et al. 2014). Mediation analysis was performed to assess the mediation role of organisational capabilities presented in MAPs inference capability and the current Analytical Skillset of MAs in the relationship between BI&A and organisational performance. Table 5.21 reveals the significant indirect effect of BI&A on organisational performance through the reported MAPs inference capability, as well as the Analytical Skillset (β =0.842, t = 9.356, p<0.001) and (β =0.588, t = 6.410, p<0.001), respectively. The total effect of BI&A and organisational performance was significant when the mediator was included. The direct effect of BI&A on organisational performance shows negative coefficient values but is significant.

Table 5.21 Mediation Analysis – MAPs Capability and Analytical Skillset

	Total effects			**Direct effects**			**Indirect effects**			
	β	t-value	p-value	β	t-value	p-value	β	SE	t-value	p-value
MAPs Inference Capability →OP	0.565	9.532	0.000	-0.277	2.456	0.014	0.842	0.090	9.356	0.000
MA Analytical Skillset →OP	0.356	8.528	0.000	-0.232	2.054	0.049	0.588	0.092	6.410	0.000

Note: SE: Standard Error

The results confirm that MAPs capabilities have an indirect and statistically significant effect on organisational performance. Therefore, it may be asserted that, in this study, MAPs inference capability does mediate the relationship between BI&A and organisational performance. On the other hand, Analytical Skillset of MAs showed full mediation (indirect only).

Based on the model developed by Zhao et al. (2010) p_1 and p_2 refer to the indirect effect of the mediator, while p_3 refers to the direct effect of the exogenous construct on the endogenous construct in the mediation model (BI&A → OP).

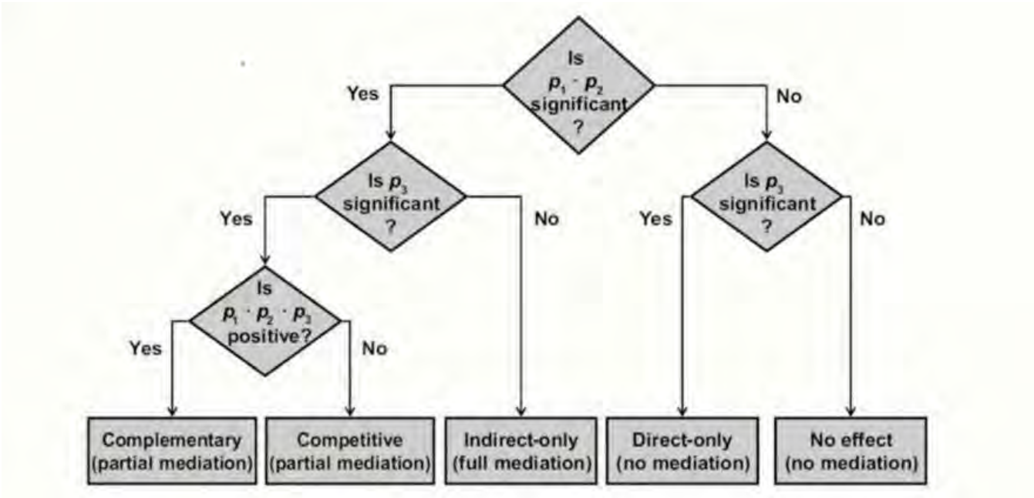

Figure 5.2 Mediation analysis procedure. (Zhao et al. 2010)

Since p_1 and p_2 are significant for the inference capability of MAPs as well as p_3, it may be asserted that, in this study, MAPs inference capability and MA Analytical Skillset mediate the relationship between BI&A adoption and organisational performance in a competitive partial mediation because p_3 shows a negative value. The competitive partial mediation hypothesis posits that the presence of an intermediary variable diminishes the strength of the association between independent and dependent variables. However, the inclusion of an intermediate variable may amplify the strength of the association between independent and dependent variables. The concept of competitive partial mediation has frequently been referred to as a "negative confounding" or "inconsistent" paradigm in the academic literature (Carrión et al. 2017).

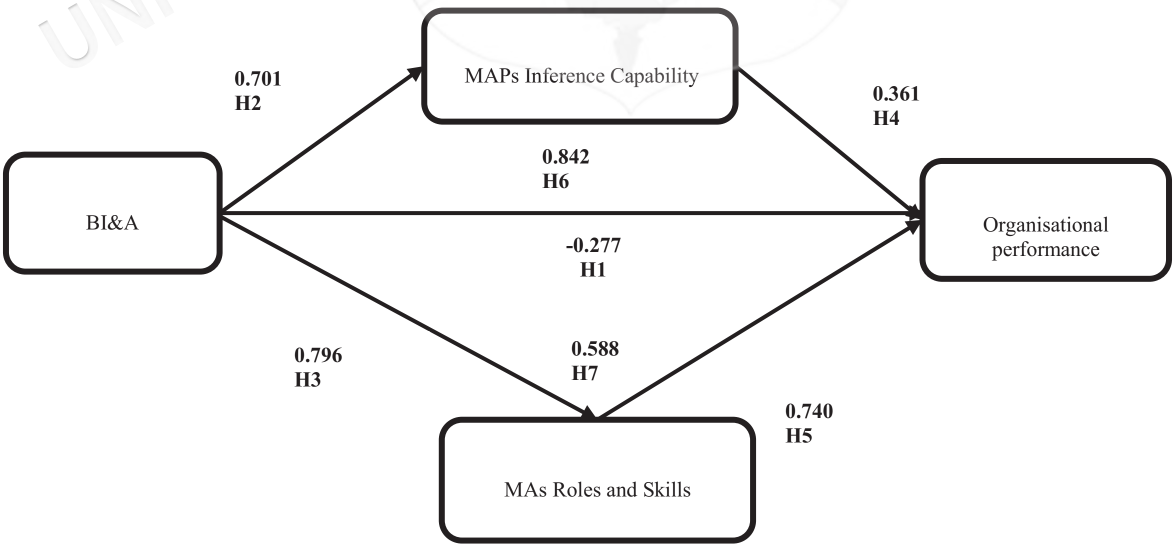

Figure 5.3 Final Framework and Hypothesis Results

The empirical analysis confirms that BI&A creates organisational value primarily through the development of MAPs inference capability and analytical skillsets of MAs rather than through direct performance enhancement, validating the study's resource-based theoretical framework. Figure 5.3 illustrating the empirical relationships between BI&A, MAPs inference capability, MAs' Analytical Skillset, and organisational performance. The path diagram displays standardised beta coefficients for each relationship, revealing strong positive effects of BI&A on both mediating variables (β=0.701 for MAPs capability; β=0.796 for analytical skillset) while showing a surprising negative direct effect on performance (β=-0.277).

Table 5.22 List of Hypotheses and Relative Paths

Hypothesis	**Path**	**β**	***P* value**	**Results**
H1: The use BI&A has a positive influence on OP	BI&A → OP	-0.277	<0.001	Not supported
H2: The use BI&A has a positive influence on MAPs inference capability	BI&A → MAPs inference Capability	0.701	<0.001	Supported
H3: The use BI&A has a positive influence on MAs' Analytical Skillset	BI&A → Analytical Skillset	0.796	<0.001	Supported
H4: MAPs inference capability has a positive influence on OP	MAPs inference capability → OP	0.361	<0.001	Supported
H5: Analytical Skillset have a positive influence on OP	Analytical Skillset → OP	0.740	<0.001	Supported
H6: MAPs inference capability mediates the relationship between the use of BI&A and OP	BI&A→Capabilities →OP	0.842	<0.001	Supported
H7: Analytical Skillset mediate the relationship between the use of BI&A and OP	BI&A→Analytical Skillset →OP	0.588	<0.001	Supported

Table 5.22 provides comprehensive hypothesis testing results, confirming six of seven proposed relationships. Notably, H1 (direct BI&A-performance link) was not supported due to the negative coefficient, while all other hypotheses achieved statistical significance ($p<0.001$). The mediation effects (H6: β=0.842; H7: β=0.588) demonstrate that BI&A's performance impact operates primarily through enhanced organisational capabilities rather than direct mechanisms. These findings suggest that BI&A creates value through capability development, supporting the study's theoretical framework based on resource-based view theory.

5.14 SUMMARY

The research analysis was conducted in this chapter where the results are depicted and interpreted. Initially, the data was coded and cleaned to identify the missing values and outliers and normality of the data. Descriptive statistics and correlation between constructs were also calculated. The measurement model is explained by specifying the relationships between constructs and their underlying latent constructs or factors. This shows the construct validity (convergent and discriminant validity) of the measurement instruments. Structural equation modelling was used to test the research hypothesis and the relationship between the constructs. Due to the concern of multicollinearity between the independent variables, specifically the three mediators of MAPs capabilities, one mediator was used which is the MAPs inference capability in the structural model. Seven hypotheses are tested using this model. Finally, mediation analysis was conducted to test the mediation role of MAPs inference capability and MAs' Analytical Skillset.

CHAPTER VI

DISCUSSION OF FINDINGS AND CONCLUSION

6.1 INTRODUCTION

The main objective of this study is to investigate the influence of the BI&A adopted by UAE firms on the inference capability of their MAPs and on MAs' analytical skill sets. The combination of BI&A adoption and the enhanced capabilities of MAPs and skills of MAs in firms are expected to improve organisational performance. Chapters Two and Three presented an exploratory investigation and involved a thorough examination of the relevant literature. The summary of the literature presented in this study serves as a foundation for constructing the research model by drawing upon relevant theories. In Chapter Three, this research employed a research model based on a RBV to formulate the research hypotheses that were subsequently examined in the empirical investigation. Chapter four discusses the research methodology to elucidate the research design, sampling frame, survey methodology for data collection, statistical analysis, and research measurements of the primary constructs of the study. In Chapter five, the study model was assessed using PLS-SEM. The assessment of the measurement models and the entire model included an examination of convergent and discriminant validity. In the same chapter, the interrelationships between the components outlined in the structural model were analysed, and research findings were objectively produced. The current chapter discusses the findings and provides a comparison of them with those of prior studies to ascertain their level of consistency or contradiction. The current chapter also provides an analysis and elucidation of the outcomes stemming from the interplay between BI&A and MAPs capabilities, MAs' Analytical Skillset, and the overall performance of organisations.

The dual unit of analysis approach employed in this research reveals that BI&A's influence manifests distinctively across organisational and individual levels, requiring differentiated theoretical and practical interpretations. At the organisational level, BI&A primarily enhances MAPs inference capability ($\beta = 0.519$, $p < 0.001$), demonstrating how technological resources create embedded organisational capabilities that transcend individual contributions. Conversely, at the individual level, BI&A significantly transforms MAs' Analytical Skillsets ($\beta = 0.582$, $p < 0.001$), reflecting personal professional evolution in response to technological advancement. The dual mediation pathways (organisational: $\beta = 0.842$; individual: $\beta = 0.588$) suggest that BI&A implementation creates value where individual skills aggregate to organisational outcomes and where organisational capabilities facilitate individual development. This bidirectional relationship underscores that successful digital transformation requires simultaneous investment in organisational capability development and individual competency enhancement, challenging traditional single-level implementation approaches and highlighting the complex, multi-level nature of BI&A adoption in management accounting contexts. The following sections discuss each relationship in detail, beginning with the direct effects of BI&A on organisational performance.

6.2 THE INFLUENCE OF BI&A ON ORGANISATIONAL PERFORMANCE

To understand the influence of BI&A on firms' managerial practices and their performance, this study investigates the direct relationship between BI&A and MAPs inference capability, MAs' Analytical Skillset, and the UAE firms' performance. First, a positive and significant relationship between BI&A and organisations' performance is proposed, as in the majority of the literature. For example, Aydiner et al. (2019) found that adoption of BI&A positively influences business process performance, while Shabbir and Gardezi (2020) found a positive and significant impact of big data analytics applied applications and organisational performance sharing similar findings with other literature contributors (Appelbaum et al. 2017; Chen & Lin 2021; Mikalef et al. 2018; Möller et al. 2022; Peters et al. 2016). In addition, the impact of BI&A on organisational performance is subject to BI&A implementation and integration (Richards et al. 2019). Most prior studies, grounded in the RBV of a firm, suggest that BI&A represents a valuable, rare, and inimitable resource that should enhance firm performance (Appelbaum et al. 2017; Peters et al. 2016; Wamba et al. 2017). The RBV predicts a positive relationship between BI&A adoption and performance. Since BI&A systems constitute a composite organisational resource comprising both tangible elements (technological infrastructure, data repositories, analytical tools) and intangible elements (data-driven culture, analytical competencies, organisational learning capabilities) that collectively satisfy the VRIN criteria (Mikalef et al. 2020; Bordeleau et al. 2020).

However, our results indicate that although BI&A adoption has a significant relationship with organisational performance, the sign of the path coefficient is negative ($\beta = -0.277$). These unexpected results are somewhat consistent with some of the research in the literature, such as Ramakrishnan et al. (2020), who found a significant negative effect of BI&A integration on organisational effectiveness. Our finding of a negative relationship suggests that it is possible that the mere possession of BI&A resources is insufficient to drive performance improvement. Instead, it hints at the importance of effectively integrating and applying BI&A to realise its potential benefits, aligning with the notion of BI&A capabilities (Mikalef et al. 2020). Our findings indicate that the connection between BI&A resources, capabilities, and company performance may be more complex than the RBV posits, influenced by contextual factors and the firm's capacity to convert BI&A investments into improved decision-making and operational efficiency.

Relating these findings to the UAE setting, the negative BI&A performance relationship may reflect the relative immaturity of BI&A adoption in many UAE firms. As an emerging economy, UAE organisations may lack technical infrastructure, skilled personnel, and organisational processes to fully harness BI&A. The UAE government has made significant strides in promoting digital transformation and data-driven decision-making (UAE government Official Portal 2021). However, many local firms may still be in the early stages of this journey, focusing on building foundational BI&A resources without yet seeing performance payoffs. The negative coefficient may capture the substantial upfront costs of BI&A adoption for these firms, which take time to be offset by improved revenue and efficiency. Moreover, realising value from BI&A likely requires a degree of organisational transformation: changes to decision-making processes, job roles, and business models (Mikalef et al. 2020). Such organisational changes are challenging and may meet resistance, especially in the traditionally hierarchical and centralised structures common in the UAE (Suliman 2013). Firms that invest in BI&A without corresponding changes to organisational practices may fail to channel BI&A insights into performance-enhancing actions.

The negative impact could stem from the integration of BI&A on the organisational efficiency of BI&A, which can be attributed to two factors. First, our sample consisted of enterprises from an emerging country, which may have influenced the outcomes. Second, the lack of understanding among these firms regarding the alignment of their BI&A efforts to maximise their effectiveness further contributes to the negative impact. Additionally, it is important to acknowledge that these findings may not be applicable to other settings, such as established companies in developed nations that possess a comprehensive understanding of how to effectively utilise BI&A, or companies that have already deployed BI&A to a sophisticated extent, such as Uber, Google, and Amazon. However, from a conceptual standpoint, we propose that organisations can achieve the efficient adoption of business intelligence by guaranteeing the appropriate integration of their data sources. The efficiency of an organisation's BI&A initiatives is contingent on the quality and availability of its data. Consequently, it is imperative for an organisation to possess the necessary competencies in data acquisition and integration from diverse sources to augment the efficacy of its BI&A endeavours.

6.3 THE INFLUENCE OF BI&A ON MAPS INFERENCE CAPABILITY

Analytical SkillsetThe results show that organisations that apply BI&A enhance the MAPs inference capability (β = 0.701), providing strong support for hypothesis *H2*. This significant positive relationship indicates that BI&A implementation substantially improves the ability of management accounting practices to deliver meaningful insights and real-time conclusions. These findings align with Elbashir et al. (2021), who found that management-control-oriented BI&A enhances MAPs through improved control tools and analytical capabilities. Similarly, Peters et al. (2016) demonstrated a positive impact of BI&A quality on performance measurement capabilities, which represents a key aspect of MAPs inference capability.

The influence of BI&A on MAPs inference capability can be understood through three fundamental dimensions of management accounting processes. In terms of process dimension, BI&A enhances how management accounting information flows through the organisation by enabling real-time data processing, automated analysis sequences, and integrated feedback loops (Granlund & Malmi 2002; Rom & Rohde 2007). From a structural perspective, BI&A strengthens the systematic organisation of MAPs through standardised analytical frameworks, robust data architecture, and enhanced control mechanisms that enable more sophisticated inference capabilities (Scapens & Jazayeri 2003; Möller et al. 2020).

BI&A systems are pivotal in introducing advanced inference capabilities within MAPs through their multifaceted enhancements (Nespeca & Chiucchi 2018). The advanced data analysis competencies provided by BI&A systems have transformed the MAPs process, making it more efficient in providing deeper insights and actionable conclusions. This enables MAs to conduct more sophisticated analysis that reveals patterns and relationships in financial and operational data that would otherwise remain obscured (Spraakman et al. 2020; Bergmann et al. 2020).

From the RBV theoretical perspective, these findings suggest that BI&A serves as a valuable technological resource that enhances organisational capabilities embedded in MAPs. According to Barney (1991) and Peteraf & Barney (2003), competitive advantage emerges when firms develop capabilities that improve resource productivity and coordination. The significant positive relationship between BI&A and MAPs inference capability demonstrates how technological resources can enhance knowledge-based capabilities within organisations. This aligns with Makadok's (2001) view of capabilities as organisationally embedded resources that improve the productivity of other resources. The enhanced inferential capability of MAPs represents precisely such a capability, it improves the productivity of accounting information by transforming it into actionable insights.

Furthermore, the strong relationship between BI&A and MAPs inference capability supports Maritan and Peteraf's (2011) conceptualisation of capability development involving complex interactions between individual knowledge, organisational knowledge integration, and deliberate managerial investments. The implementation of BI&A represents a deliberate investment that enables more sophisticated knowledge integration in management accounting processes.

The magnitude of the path coefficient ($\beta = 0.701$) suggests that BI&A is particularly effective at enhancing inference capabilities in MAPs, more so than its direct effect on performance. This provides empirical support for the RBV tenet that resources create value primarily through enhancement of organisational capabilities rather than directly (Barney et al. 2011). In the UAE context, this finding is especially significant as it demonstrates that companies investing in BI&A are successfully developing enhanced MAPs inference capabilities, even while they may still be in the process of translating these capabilities into overall performance improvements.

In the specific context of UAE businesses, the strong positive relationship between BI&A and MAPs inference capability reflects the nation's strategic emphasis on digital transformation and knowledge-based economic development (UAE Government Official Portal, 2021). The UAE's Digital Economy Strategy and Industry 4.0 initiatives have created a supportive environment for technological advancement in business processes. UAE companies appear to be effectively leveraging BI&A to enhance their management accounting capabilities, consistent with the country's ambition to become a global hub for innovation and technological adoption (Siddiqui & Afzal 2022). This aligns with the RBV perspective on context-specific capability development, where national innovation systems and policy frameworks can enhance firms' ability to develop valuable capabilities from technological resources (Makadok 2001). The relatively high adoption rate of advanced inference capabilities in MAPs among UAE firms suggests that management accounting practices are evolving in tandem with the country's broader digital transformation agenda, potentially positioning UAE businesses for improved competitive positioning as these capabilities mature.

6.4 THE INFLUENCE OF BI&A ON MAS' ANALYTICAL SKILLSET

This study also proposes that the use of BI&A changes MAs' Analytical Skillset to be more data analyst oriented. This hypothesis is supported by the research findings ($\beta = 0.796$, $t = 22.262$), as well as the descriptive statistics of MA Analytical Skillset items which show mean values from 2.7 to 4.2. The substantial influence of BI&A on MAs' Analytical Skillset ($\beta = 0.796$) demonstrates how technological resources facilitate the development of human capital capabilities that satisfy VRIN criteria (Barney 1991). The analytical competencies acquired by management accountants through BI&A exposure represent firm-specific human resources that are causally ambiguous and socially complex, making them difficult for competitors to replicate (Wernerfelt 1984). This capability development process aligns with RBV theory's emphasis on resource heterogeneity, where firms develop distinctive analytical competencies through path-dependent learning trajectories embedded within their organisational contexts (Peteraf 1993). The transformation of traditional accounting roles into data-driven analytical positions exemplifies how organisations leverage technological resources to create sustainable competitive advantages through enhanced human capital productivity and strategic decision-making capabilities. The posted Analytical Skillset represent some of the agreed Analytical Skillset of data analysts in the literature. This positive influence reinforces the assumption that MAs are now practising the role of data analysts while conducting MAPs. These results are highly consistent with the literature, particularly the qualitative research conducted by (Spraakman et al. 2020). One of the pivotal areas in which this convergence becomes evident is data collection and preprocessing. Traditionally, MAs have excelled in gathering and processing financial data.

However, with the advent of advanced analytics, their proficiency has extended to encompass a wider spectrum of data types. This shift seamlessly aligns with the core responsibility of data analysts for data collection and preprocessing, emphasising the complementary nature of their roles (Bergmann et al. 2020). Moreover, MAs and data analysts share a common foundation for data exploration and analysis. Although MAs have traditionally explored financial data to understand an organisation's performance, data analysts employ a similar skill set to uncover patterns, trends, and insights from diverse data sources. This shared competency facilitates harmonious integration of insights from financial and non-financial data, enriching the decision-making process (Andreassen 2020).

Another essential ability in a BI&A environment is statistical analysis, which highlights the convergence of these professions. MAs, with their expertise in financial analysis, are highly knowledgeable in statistical methods that are applicable to cost analysis and forecasting. This level of expertise aligns with the quantitative precision that data analysts use in their analyses, promoting a more profound comprehension of data-driven insights in financial settings (Oesterreich & Teuteberg 2019). Moreover, the capacity to convey results with competence is a shared characteristic of both MAs and data analysts. MAs have conventionally conveyed financial information through reports and presentations, whereas data analysts excel in presenting intricate data-driven insights through visualisations, dashboards, and reports. This collaboration strengthens stakeholders' combines capacity to convert data into practical and useful knowledge (Franke & Hiebl 2023; Oesterreich & Teuteberg 2019; Spraakman et al. 2020). Within the fields of experimentation, hypothesis testing, and predictive modelling, MAs exhibit a reduced inclination to perform experiments aimed at optimising processes or products. Furthermore, they do not align with the data analysts' roles to conduct controlled experiments and prioritise the convergence in their problem-solving methodologies (Demchenko & Cuadrado-Gallego 2020; Mukozho & Seymour 2020). The average scores reported for these abilities are 2.7 and 3.0, correspondingly.

Analytical thinking and problem-solving skills, which are paramount in addressing business challenges, form a cornerstone for both MAs and data analysts. Their ability to dichotomise complex problems, determine patterns, and formulate data-driven solutions serves as a common thread binding their roles. Domain knowledge, a vital attribute, is another facet in which MAs and data analysts converge. MAs often possess deep industry-specific knowledge, whereas data analysts seek to acquire relevant domain expertise to the analysis. This shared quest for domain knowledge fosters a cross-disciplinary understanding and collaboration. The emergence of big data technologies further emphasises this convergence. MAs and data analysts are increasingly required to work with vast and complex datasets, necessitating proficiency in technologies that facilitate large-scale data processing, storage, and analysis. Collaboration forms the core of convergence with both MAs and data analysts working collaboratively within cross-functional teams. This collaboration is indispensable for aligning data-driven insights with organisational strategies and ensuring effective implementation (Moll & Yigitbasioglu 2019; Möller et al. 2022; Spraakman et al. 2020).

The convergence of MAs and data analysts reflects the evolving nature of the BI&A. Their overlapping skills emphasise the need for adaptability and cross-functional collaboration in data-driven decision-making. By adopting a comprehensive, unified approach that transcends traditional boundaries, organisations can maximise their data resources and gain significant advantages.

6.5 THE INFLUENCE OF MAPS INFERENCE CAPABILITY ON ORGANISATIONAL PERFORMANCE

This study also seeks to understand the influence of firms' capabilities and accountants involve in the practice on overall firm performance. First, the MAPs inference capability is expected to have a significant and positive influence on organisational performance. The positive and significant relationship found supports the hypothesis (β=0.361). Primarily, MAPs are utilised by organisations to facilitate the generation and analysis of information in many disciplines to support decision-making. Although MAPs capabilities have not been examined in the literature (Adu-Gyamfi & Chipwere 2020; Alabdullah 2019; Cleary 2015; Kalifa et al. 2020; Pedroso et al. 2020), it has been established that the use of MAPs can have a noteworthy and favourable influence on the overall performance of organisations. Some enablers and elements contribute to the establishment of a beneficial connection, such as the alignment of strategic objectives throughout the organisation (Lachmann et al. 2013; McLellan & Moustafa 2008), managers' performance which, in turn, has an impact on both managerial and organisational performance (Pedroso et al. 2020). The examined capabilities of MAPs refer to their capacity to offer valuable information for a range of objectives, including but not limited to planning, decision-making, control, and performance monitoring. The inference capability of MAPs has a positive and significant effect on performance. The capacity for inference refers to the competence of

MAPs to furnish data that may be utilised to deduce the causal connections between actions and outcomes as well as to facilitate the processes of learning and feedback.

An illustration of this concept may be seen in the utilisation of a balanced scorecard, which serves as a tool for elucidating the interconnections between the financial, customer, internal process, and learning and growth views. Furthermore, it facilitates the alignment of these perspectives with the strategic objectives of the organisation. Hence, MAPs capabilities have the potential to enhance organisational performance by providing pertinent and dependable information for diverse objectives. However, the capabilities of MAPs may also be influenced by other factors, including the quality of information, the expertise and knowledge possessed by managers and accountants, the prevailing organisational culture and structure (Schneider et al. 2015; Uyar & Kuzey 2016; Youssef & Mahama 2021). The finding that MAPs inference capability has a significant positive influence on organisational performance ($\beta = 0.361$) aligns with and extends the RBV of the firm, which posits that firm-specific capabilities can be a source of competitive advantage and improved performance (Barney 1991; Peteraf 1993). This result suggests that inferential capability embedded in a firm's MAPs represents a valuable, rare, and inimitable resource that can enhance firm performance.

This finding is consistent with prior studies that found a positive relationship between the adoption of sophisticated MAPs and firm performance (Alvarez et al. 2021; Macinati & Anessi-Pessina 2014; Uyar & Kuzey 2016). However, by focusing specifically on the inferential capability of MAPs, this study extends the RBV by identifying a specific dimension of MAPs that drives the performance. Inferential capability allows firms to derive causal insights from accounting data, facilitating organisational learning and enabling more effective decision-making (Chong & Eggleton 2003). This capability is likely to be particularly valuable in dynamic environments, where firms need to rapidly adapt to changing conditions (Pavlatos & Kostakis 2015).

Relating these findings to the UAE context, the positive impact of MAPs inference capability on performance suggests that UAE firms can benefit from investing in the development of sophisticated MAPs. The UAE's business environment is characterised by increasing competition and technological disruption (Siddiqui & Afzal 2022), making the inferential insights provided by advanced MAPs particularly valuable.

However, realising these benefits may require overcoming certain challenges specific to the UAE. Many UAE firms, especially small and medium-sized enterprises, currently rely on basic MAPs focused on financial reporting rather than decision support (Appelbaum et al. 2017). Upgrading these systems to incorporate inferential capabilities requires investment in technology and human capital. The hierarchical and centralised structures common in UAE firms (Suliman 2013) may also impede the effective use of inferential insights, as decision-making power is concentrated at the top.

To fully harness the performance benefits of MAPs inference capability, UAE firms may need to couple investments in advanced MAPs with organisational changes that empower managers at various levels in order to act on the insights generated. This may involve training programs to build analytical skills, as well as structural changes to decentralise decision-making. The UAE Government's emphasis on promoting innovation and digital transformation (UAE government Official Portal 2021) could provide a supportive context for firms to make these changes.

The positive impact of MAPs inference capability on performance in UAE firms supports the RBV's contention that firm-specific capabilities can drive competitive advantage. However, realising this potential may require not only investing in advanced MAPs but also making complementary organisational changes to fully harness the power of inferential insights. As UAE firms navigate an increasingly dynamic business environment, the ability to derive progressive causal insights from accounting data will likely become an increasingly important driver of performance.

6.6 THE INFLUENCE OF MAS’ ANALYTICAL SKILLSET ON ORGANISATIONAL PERFORMANCE

It is also expected that MAs’ Analytical Skillset will have a significant and positive influence on organisational performance. The positive and significant influence of MAs’ Analytical Skillset on performance ($\beta = 0.740$, p=0.001) support this hypothesis. The examined Analytical Skillset are highly connected to the data analysts’ Analytical Skillset, such as the ability to conduct statistical analysis, working with big data technologies, using data visualisation, dashboarding and reporting to communicate findings to stakeholders, data cleaning and processing, and collaborating with cross-functional teams. MAs are currently conducting research on the Analytical Skillset of data analysts, which is consistent with the literature

(Appelbaum et al. 2017; Bergmann et al. 2020; Möller et al. 2022; Spraakman et al. 2020). This would expand the scope of analysing available financial and non-financial data to include new tools and skills to enhance and reinforce performance. This is consistent with Spraakman et al. (2020), who found that MAs have gained new roles in data preparation and in the presentation and communication of results.

From the RBV theoretical perspective, MAs' Analytical Skillset represents a valuable human capital capability that directly contributes to competitive advantage. According to Barney et al. (2011), human capital capabilities are particularly valuable when they are rare, difficult to imitate, and non-substitutable. The sophisticated analytical capabilities that MAs have developed align with these criteria, as they combine technical expertise with domain-specific accounting knowledge that is developed over time and embedded in organisational contexts. As Peteraf and Barney (2003) suggest, human capabilities that create greater economic value than competitors' resources are primary drivers of competitive advantage. The strong path coefficient ($\beta = 0.740$) indicates that MAs' Analytical Skillset is indeed creating substantial value for UAE organisations. The substantially positive coefficient suggests that these capabilities are particularly effective in translating into performance improvements, more so than the direct effect of BI&A resources themselves.

In the UAE context, the strong relationship between MAs' Analytical Skillset and organisational performance reflects the country's increasing focus on developing human capital as part of its economic diversification strategy. The UAE Vision 2021 and UAE Centennial 2071 plans emphasize the development of knowledge-based capabilities and technical skills to reduce reliance on natural resources (UAE Government Official Portal 2021). The findings suggest that UAE organisations are successfully developing valuable human capital in the form of analytically skilled MAs who contribute directly to performance improvements. This is particularly relevant given the UAE's strategic emphasis on becoming a global hub for finance and business services, where sophisticated accounting and analytical capabilities are crucial competitive factors (Siddiqui & Afzal 2022).

The UAE's multicultural business environment, with professionals from diverse international backgrounds, may also contribute to the development of unique analytical skillsets among MAs working in the region. This diversity of perspectives and expertise creates potential for rare and valuable capability combinations that align with the RBV's emphasis on unique resource configurations (Barney 1991). Additionally, the UAE government's substantial investments in education and professional development, particularly in digital skills and financial expertise, appear to be yielding returns in terms of enhanced organisational capabilities and performance (Youssef & Mahama 2021). These contextual factors suggest that MAs' Analytical Skillsets in the UAE may be particularly valuable as they develop in response to the unique demands and opportunities of this rapidly evolving economic environment.

6.7 THE MEDIATING EFFECT OF MAPS INFERENCE AND MAS' ANALYTICAL SKILLSET ON BI&A AND PERFORMANCE

The RBV contends that a combination of a firm's resources and capabilities can enhance competitiveness (Barney 1991; Wernerfelt 1984). In this study, BI&A, which refers to the technologies, systems, practices, and applications that analyse critical business data to help an organisation better understand its business and market (Chen et al. 2012), is considered a resource. On the other hand, MAPs inference capability, which represents the ability to draw insights from management accounting information, is considered a capability. The RBV provides a suitable framework for examining how these factors interact to influence organisational performance. In this study, we examined the mediating effect of MAPs capabilities on the relationship between BI&A and organisational performance. Our results show that MAPs capabilities significantly mediated this relationship. The inference capability of MAPs showed competitive partial mediation. In other words, MAPs capabilities explain how or why BI&A influences organisational performance.

These findings answer our research question and support our hypothesis that MAPs inference capability is an important factor in explaining how BI&A influences organisational performance. Our findings are consistent with those in the literature, suggesting that MAPs are essential for effective BI&A use and value creation (A. Ahmed et al. 2019; Bordeleau et al. 2020; Möller et al. 2020, 2022; Raffoni et al. 2017). Previous studies have emphasised the importance of MAPs in BI&A use. For example, Uyar and Kuzey (2016) found that MAPs mediate the relationship between BI systems presented in cost management systems and organisational performance. Our study shows that enhancing MAPs inference capability is even more important for the BI&A impact. The partial mediation of inference capability raises the need to develop and enhance it to leverage BI&A for organisational performance. Accordingly, enhancing the capabilities of MAPs and adopting and implementing them would strongly contribute to organisational performance. This led us to consider the different factors and enablers that enhance MAPs capabilities and their outcomes. For example, adopting modern management accounting practices, such as activity-based costing (ABC), target costing, BSC, total quality management, just-in-time, theory of constraint, and process reengineering are widely regarded as more appropriate for making informed decisions (Rashid et al. 2020).

Similarly, improving the MAPs capabilities could include the use of high-quality data. Regarding BI&A and MAPs, data quality appears to have two distinct dimensions as stated by Rikhardsson and Yigitbasioglu (2018). First, activities, such as performance measurement and compliance assurance, adhere to the standard criteria of data accuracy, validity, comprehensiveness, and dependability. The other term pertains to decision support, focusing on the relevance of timeliness and suitability for an intended purpose. Decision-makers require timely information, frequently in real time, and with a limited timeframe to make decisions. Furthermore, information can be derived from extensive datasets in various formats from a multitude of data sources. Given these circumstances, it is highly unlikely and not financially feasible to guarantee that the data meets the standard criteria for data quality. It is crucial to ensure that the data can be readily accessed, altered, and organised. Moreover, it is crucial to have the ability to utilise various analytical techniques and tools, and to visualise the outcomes at every stage of the process.

The findings of this research also highlight the critical role of MAs' Analytical Skillset in fully mediating the relationship between BI&A and organisational performance. This full mediation underlines the pivotal position of MAs in translating BI&A resources into tangible benefits for the organisation. MAs possess a unique blend of expertise in financial analysis, data interpretation, and strategic decision-making (Wolf et al. 2020). These skills enable them to effectively leverage BI&A tools and insights to drive organisational success. By analysing and interpreting the vast amounts of data generated through BI&A initiatives, MAs can provide valuable recommendations for optimising resource allocation, improving operational efficiency, and identifying new growth opportunities (Oesterreich & Teuteberg 2019).

Moreover, MAs serve as a vital link between the technical aspects of BI&A and the strategic objectives of the organisation (Moll & Yigitbasioglu 2019). They act as translators, converting complex data into actionable insights that align with the organisation's goals. By communicating these insights to key stakeholders, including top management and cross-functional teams, MAs ensure that BI&A initiatives are strategically aligned and support data-driven decision-making (Bhatta & Hiebl 2022). The concept of full mediation implies that the presence of MAs' Analytical Skillset is indispensable for BI&A to significantly impact organisational performance. Without the expertise of MAs, the potential benefits of BI&A may remain untapped, as the organisation lacks the necessary bridge to effectively leverage BI&A solutions (Odia 2019). This finding emphasises the critical importance of investing in the development and nurturing of MAs' Analytical Skillset to maximise the return on BI&A investments.

Previous research has acknowledged the evolving role of MAs in the context of BI&A (Rikhardsson & Yigitbasioglu 2018). However, this study contributes to the literature by providing empirical evidence of the full mediation effect of MAs' Analytical Skillset in the BI&A organisational performance relationship. This novel insight highlights the indispensable nature of MAs' expertise in translating BI&A resources into improved organisational outcomes.

To conclude this section, this research underlines the vital importance of MAPs inference capability and MAs' Analytical Skillset that are partially mediating and fully mediating, respectively the relationship between BI&A and organisational performance. By leveraging their expertise in financial analysis, data interpretation, and strategic decision-making, MAs as well as MAPs inference capability serve as the essential link between BI&A and improved organisational outcomes. Organisations must prioritise the development and nurturing of MAPs' inferential capability and MAs' Analytical Skillset to fully realise the potential of their BI&A investments and drive sustainable success in the era of data-driven decision-making.

6.8 RESEARCH CONTRIBUTIONS

6.8.1 Methodological Contributions

Several studies in AIS literature have examined various dimensions of resources under the RBV framework. For example, Ruivo et al. (2014) investigated the impact of ERP capabilities on organisational performance, considering ERP use, collaboration, analytics, and training as key resources. Prasad and Green (2015) examined the influence of AIS capabilities on organisational performance by treating AIS planning and development, AIS operations and support, and AIS use as key resources. Alomari et al. (2018) explored the relationship between AIS success factors, including system quality, information quality, and service quality, and organisational performance, viewing these factors as critical resources. Elbashir et al. (2008) studied the role of BI systems in enhancing organisational performance, considering BI infrastructure, BI functionality, and BI-business alignment as essential resources. While previous AIS studies have examined various dimensions as resources under the RBV, this study adopts a different approach by conceptualising and examining MAPs inference capability as a strategic capability.

This research contributes methodologically in several significant ways to management accounting and business intelligence research. First, the study advances methodological innovation by conceptualizing and empirically testing MAPs inference capability as a strategic capability within the RBV theoretical framework. While previous studies have examined various dimensions of resources within accounting information systems (Ruivo et al. 2014; Prasad & Green 2015; Alomari et al. 2018), this research uniquely positions MAPs inference capability as a distinct organisational capability that mediates the relationship between BI&A resources and organisational performance.

Second, the research develops and validates a novel measurement approach for MAPs inference capability. By operationalizing this construct through "the real-time conclusions and insights that can be perceived from conducting the MAPs" across 14 specific management accounting practices, the study provides a robust methodological framework for capturing this previously unmeasured dimension. This measurement approach allows for a more nuanced understanding of how management accounting practices generate value beyond their implementation. The validation of this measurement instrument contributes a methodological tool that future researchers can employ to examine similar capabilities in different contexts.

Third, the study employs a dual unit of analysis approach, examining both organisational-level phenomena (BI&A adoption, MAPs capabilities, firm performance) and individual-level factors (MAs' Analytical Skillsets) within a single integrated model. This methodological approach acknowledges what Saunders et al. (2023) describe as the nested nature of organisational research, where individual capabilities are embedded within broader organisational systems. By simultaneously analysing both levels, the research provides a more comprehensive understanding of how BI&A influences organisational capabilities and professional practices in management accounting, offering methodological guidance for future multi-level research designs.

Fourth, the research contributes to the field by developing and validating a comprehensive survey instrument that captures the evolving nature of BI&A, MAPs, and MAs' Analytical Skillsets in contemporary business environments. The rigorous pre-testing process involving both academic experts and industry practitioners ensured the instrument's validity and reliability, while the multi-channel data collection strategy maximized response rates. These methodological refinements provide valuable procedural guidance for future researchers investigating similar phenomena in rapidly evolving technological contexts.

Fifth, the study contributes methodologically by integrating BI&A components into a single unified construct. Rather than treating business intelligence and analytics as separate variables, this research consolidates them into a comprehensive BI&A measure encompassing OLAP, data mining, digital dashboarding, and various analytics types (descriptive, diagnostic, predictive, and prescriptive). This integrated approach better reflects the contemporary business environment where these technologies operate as interconnected systems rather than isolated tools (Chen et al. 2012; Rikhardsson & Yigitbasioglu 2018). The validated scale provides researchers with a comprehensive measurement tool that captures the full spectrum of analytics capabilities.

Finally, the application of PLS-SEM analytical techniques to test the complex mediation relationships in the research model represents a methodological strength. The study's detailed reporting of measurement model validation, structural model testing, and mediation analysis procedures offers a transparent methodological template for future researchers investigating similar multi-construct relationships in management accounting and information systems research.

6.8.2 Theoretical Contributions

First, evident research gaps have been noticed in the existing literature on MAPs, particularly in accounting information systems and BI&A studies. Although there is increasing awareness of the impact of Business Intelligence and Analytics on performance, only one view (Uyar & Kuzey 2016; Youssef & Mahama 2021), and the majority are conceptual studies that have examined the function of MAPs in this relationship. Based on a thorough examination of the current body of research, it is appropriate to present factual data on the consequences of BI&A in the context of MAPs. This study aims to expand upon previous research by presenting and rigorously examining a comprehensive framework that encompasses contextual variables, BI&A, MAPs capabilities, and the Analytical Skillset of MAs. The objective of this study is to determine how this framework can enhance organisational performance. To the best of our knowledge, no previous study has integrated these concepts into a unified framework. This study developed a comprehensive theoretical framework and conducted an empirical analysis to investigate the structural connections between the constructs. By filling in gaps and serving as a framework for future research, it enhances the potential for a more in-depth exploration of BI&A and MAPs capabilities. This study makes several theoretical contributions as follows:

a. The research framework is supported by the ideas of resource-based view. This study utilises the resource-based view theory to present data supporting the crucial elements related to the utilisation of BI&A, MAPs capabilities, and MAs' Analytical Skillset to enhance the performance of firms in the UAE. The literature was thoroughly examined, and the framework presented in this study aims to improve future organisational performance by incorporating the resource-based view theory.

b. The framework developed in this study provides a better understanding of the key MAPs that influence performance as well as the main capabilities we need to focus on and enhance. While the broader role of MAPs inference in mediating organisational resources and performance might be studied (Uyar & Kuzey 2016), there is a gap in understanding the specific capabilities of MAP that are enhanced or crucial when integrating BI&A. The research framework provides a methodology that can be utilised by businesses to effectively utilise key components. This study offers a significant examination of the existing body of literature to improve performance and identify deficiencies. This study conducted a comprehensive analysis of the different components within the framework and the theoretical model outlined in chapter two using a critical literature assessment.

c. The existing academic research reveals a significant deficiency regarding the capabilities of MAPs, namely their inference capabilities in conjunction with BI&A. This research aims to address this gap by providing a novel theoretical approach in numerous significant aspects, such as emphasising the potential of MAPs within the framework of BI&A. This study highlights the unexamined relationship between MAPs and BI&A. The fundamental usefulness of MAPs' inferential power is augmented when combined with BI&A tools and processes.

d. There may be limited research comparing the specific skills of MAs and data analysts in BI&A settings. Both professionals might overlap in certain areas, such as data handling or software usage, but differ in other areas, such as financial modelling or data visualisation. This study contributes to the theoretical understanding of the technical skills required by MAs. As BI&A tools become more integrated into organisational decision-making processes, the current research shows how MAs evolve relative to data analysts and become more data centric. Additionally, while both MAs and data analysts may play mediating roles between BI&A and organisational performance, the subtle aspects of their mediation may differ. The literature may lack a detailed comparison of these mediation dynamics and their subsequent impacts on performance.

e. Incorporating both MAPs inference capability and the MAs' Analytical Skillset contribute to the theory through expanding the scope of strategic capabilities. By examining MAPs inferential capability and MAs' new Analytical Skillset as strategic capabilities, this research broadens the scope of the RBV theory within the management accounting domain. It demonstrates that not only tangible resources but also intangible capabilities, such as the ability to draw insights from management accounting information and the skills of MAs, can serve as sources of competitive advantage. Furthermore, the research provides a detailed knowledge of how the inferential capabilities of MAPs and the skills and duties of MAs contribute to the creation of value. The study enhances our understanding of how BI&A contribute to organisational success by investigating their role as mediators. This analysis provides a more detailed insight into how these skills lead to improved outcomes for firms, hence expanding the explanatory capacity of the RBV hypothesis.

These theoretical contributions are significant because they introduce MAPs inference capability as a novel construct within RBV theory, empirically validating its role as a mediator between BI&A and performance. The study is the first to integrate BI&A, MAPs capabilities, and MAs' Analytical Skillset into a unified framework, revealing their complex interrelationships. The research uniquely demonstrates how BI&A transforms management accounting through both organisational capabilities and individual skillsets. By identifying specific mechanisms through which technological resources create value in emerging economies, this study addresses critical gaps in understanding how BI&A adoption translates into performance improvements, providing a more nuanced theoretical explanation for previously inconsistent findings in the literature. This study enhances academic literature by revealing the intricate functions and capacities of MAPs, particularly when examined within the comprehensive framework of BI&A, and by emphasising their direct influence on enhancing organisational performance.

6.8.3 Practical Contributions

The research findings offer valuable practical insights that can serve as strategic guidelines for organisations. The key finding indicates that for enterprises to optimise the advantages gained from their intelligence and analytics systems, it is crucial to concentrate on improving the capabilities of these specific MAPs. An intentional endeavour of this nature can result in the maximisation of performance results.

Moreover, the changing roles and skill sets of MAs are evident and have become data driven. Our research reveals that MAs are rapidly adopting analytical skills linked to data analyses. The merging of these skill sets has had significant consequences. Organisations should acknowledge and adjust to this change by ensuring that their MAs have the necessary analytical and technical skills. Customised training programs in line with the requirements of contemporary BI&A technologies can effectively address any current deficiencies in skills.

Finally, the importance of BI&A in improving capabilities and enhancing skills is emphasised. The report highlights that investments in BI&A are not only about gaining insights from data but also about improving the skills of MAs and boosting the fundamental capabilities of MAPs. Accordingly, firms are strongly recommended to pursue strong integration between data analytics tools and their management accounting procedures. These synergies can facilitate the implementation of efficient procedures, eliminate unnecessary repetitions, and enhance decision making by providing deeper insights.

Overall, the findings of this study offer organisations a more distinct understanding of how to effectively utilise BI&A, enhance the skills and abilities of their MAs, and strengthen their management accounting methods to achieve exceptional performance.

6.9 LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Several limitations must be acknowledged when interpreting the results of this study. One limitation of this study is its limited scope in the UAE, which restricts the applicability of the findings. Initially, UAE offered a significant research environment for BI&A as well as AI studies. Its government initiatives, swift digital transformation, diverse multinational business landscapes, and its economic power in the Middle East offer unique opportunities for scholarly investigation. This dynamic environment facilitates examination of BI&A's impact on business practices and urban development in emerging economies, contributing to broader discourses on technological innovation and economic transformation (Adewusi et al. 2024; and Adeniran et al. 2024). While the UAE presents an interesting context in which to study BI&A implementation, it also limits the generalisation of the findings. Future research should test and implement research methodologies in different geographical contexts to enhance generalisability.

The current study is restricted to medium and large organisations in the UAE, which may impact the generalisability of findings to other organisational contexts. However, it's important to acknowledge that the study employed a dual unit of analysis, examining both organisational and individual levels. At the organisational level, the research investigated how BI&A adoption affects firm-level capabilities and performance, while at the individual level, it examined how BI&A influences MAs' Analytical Skillsets and capabilities. This multi-level approach provided richer insights but also introduced complexity in data aggregation and analysis (Saunders et al. 2023). Future research could expand this investigation to small and medium-sized enterprises to conduct comparative studies across different organisational sizes, while maintaining this valuable dual-level analytical approach to capture both individual and organisational dimensions of BI&A implementation and its impacts. SMEs play a vital role in Dubai's and the UAE's economy. According to the (Dubai Government 2019) report, SMEs constitute approximately 99.2% of all establishments in Dubai and employ approximately 51%

of Dubai's workforce and contribute up to 46.4% of Dubai's added value. Similarly, SMEs in the UAE contribute around 60% of the country's GDP and provide over 86% of private-sector employment (Ministry of Economy 2019). SMEs play a crucial role in most economies by contributing significantly to employment, innovation, and economic growth (OECD 2023). However, research on MAPs and BI&A has often focused on medium and large enterprises, leaving a gap in the understanding of how these practices impact SMEs (Lavia López & Hiebl 2015; Massaro et al. 2016). Studying SMEs can provide valuable insights into how these important economic actors can leverage MAPs and BI&A to improve performance and competitiveness.

This study was limited by its exclusive use of a quantitative research design to investigate the association between variables in large organisations. While quantitative research enables the measurement and analysis of data, it often overlooks the contextual aspects of natural settings and does not explore detailed interpretations of many individuals. Therefore, future investigations may employ a qualitative research framework to unveil novel variables and attain a more profound comprehension of the intricacies surrounding these variables.

The next constraint was that new instruments were created to assess the constructs of BI&A and MAPs. Although the empirical findings verified the satisfactory validity and reliability of these instruments, additional studies are necessary to further validate and enhance their effectiveness. While the current research has investigated the role of MAPs as mediators, future studies could explore their potential as moderators to examine how they impact the strength or direction of the association between BI&A and performance. Within the same limitation, future research could decompose the eight components of BI&A into subcomponents to assess the level and extent of each application.

Another limitation was that the hypotheses were evaluated using only 192 suable observations. This was due to the challenges in collecting data at the organisational level. Therefore, it is recommended to include a larger number of samples in future tests to enhance the statistical power. While the PLS technique maximises the observed variance in the dependent variable and requires fewer samples (Chin 1998), it is recommended that future research be undertaken with larger samples to enhance the statistical power, despite our current sample size being sufficient to detect substantial effects.

The research concentrated on many industries within the UAE, assessing 14 primary MAPs, the implementation of which may vary depending on the industry. For instance, manufacturing industries commonly employ activities, such as target costing and product lifecycle analysis, but the service industry may not rely on them as extensively. Accordingly, future research may focus on a single industry using the most convenient MAPs within this industry.

Finally, firm size and industry are potentially significant variables in the implementation of BI&A and MAPs. However, this study did not consider these as control variables, which could potentially impact the results.

6.10 CONCLUSION

The study examined the crucial impact of BI&A and MAPs on organisational performance. This study then examined the analytical skillset of MAs, as well as their impact on the relationship between BI&A and performance. The study has gone through the following phases:

I. During the initial phase, an extensive literature assessment was conducted to identify the research gap, elucidate the constructs, and formulate the theoretical model.

II. During the second step, a questionnaire was developed and evaluated using feedback from the pretests and pilot tests.

III. Finally, both the measurement and structural models were examined to assess their reliability and validity and to evaluate the causal linkages using the responses obtained from the main survey.

The increasing incorporation of BI&A in many organisational functions has resulted in complex ramifications, especially within the UAE's business environment. Our research inquiry aimed to clarify the complex links between BI&A, MAPs, and overall organisational performance. A significant finding was the unequivocal impact of BI&A on MAPs. Our results clearly indicate that BI&A enhances the capabilities of MAPs while simultaneously increasing their inference. Based on existing literature, these improvements can be ascribed to BI&A's ability to consolidate extensive data sources, therefore providing MAs with superior predictive and analytical instruments (Davenport & Harris 2017).

A significant finding from our work is the intermediary function of MAPs. Consequently, BI&A may have the capacity to influence organisational outcomes. This highlights the crucial function of MAPs in converting analytical insights from BI&A into implementable strategies to enhance performance. This is seen in the mediating function of MAPs capabilities between both BI&A and performance. This aligns with the proposition by (Appelbaum et al. 2017; Oesterreich & Teuteberg 2019; Pervan & Dropulić 2019; Richards et al. 2019; Uyar & Kuzey 2016; Vallurupalli & Bose 2018; Youssef & Mahama 2021) that the strength of BI&A is truly harnessed when paired with effective management practices.

Furthermore, the adoption of BI&A has resulted in a significant transformation in the responsibilities and competencies of MAs. They are not only adopting analytical duties similar to data analysts but also acting as intermediaries to effectively bridge the gap between BI&A findings and organisational imperatives. This evolution mirrors literature suggesting that the modern management accountant surpasses mere numerical analysis to become a strategic collaborator in corporate decision-making. (Franke & Hiebl 2023; Spraakman et al. 2020). Finally, although the relationship between MAPs and performance is significantly positive, it is essential to recognise that this relationship depends on various factors, including organisational adaptability, the training provided to accountants, and the integration of BI&A tools with traditional accounting practices.

This study underlines the importance of MAPs in the BI&A-driven landscape of the business sector in the UAE. As enterprises initiate digital transformation, the integration of BI&A and MAPs is essential for achieving optimal organisational efficiency. Future study may investigate the specific mechanisms via which MAPs enhance the interplay between BI&A and performance, as well as how businesses in the UAE might manage their operations to maximise the benefits of this partnership.

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APPENDIX A

QUESTIONNAIRE

Dear Participants,

I am conducting research in the accounting information systems area. Specifically, the purpose of my study is to understand the tools in business intelligence and analytics used and the management accounting practices in your organisations.

As a valued participant, your insights are crucial to the success of this research. Your responses to the questionnaire will provide valuable data that will be used to develop a deeper understanding of the topic and contribute to the advancement of knowledge in this field.

Participation in this survey is entirely voluntary, and all responses will be kept confidential. Your anonymity is guaranteed, and any information gathered will only be used for research purposes.

The survey will take approximately 10-15 minutes to complete, and your responses will be greatly appreciated. Please answer all questions as honestly and accurately as possible, as this will help ensure the validity and reliability of the data collected.
Thank you in advance for your valuable contribution to this research. If you have any questions or concerns about this study, please do not hesitate to contact me.

Thank you for your participation

Hesham Salama (PhD candidate)
Assoc Prof. Sofiah Md Auzair (supervisor)
Faculty of management and economics
Universiti Kebangsaan Malaysia

Yours sincerely,

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SECTION 1: DEMOGRAPHIC DATA

Job title	
CEO	○
Controller	○
Manager	○
Management Accountant	○
Financial analyst	○
Business analyst	○
Budget manager	○
Treasurer	○
Others	○

Current qualification				
	□ Post-graduate	□ Professional Certificate	□ Bachelor	□ Other

Level of experience					
	<1 year	1 - 5 years	5 - 10 years	10 - 15 years	Above 15 years

The Company's Main location:							
	Abu Dhabi	Dubai	Sharjah	Ajman	Al Fujairah	Umm Al Quwain	Ras Al Khaima

Industry type				
Banking/finance/insurance	○			
Consulting/professional service/IT	○			
Health care	○			
Hospitality/travel/tourism	○			
Media/entertainment/publishing	○			
Telecommunications	○			
Education	○			
Transport/Logistics	○			
Agricultural/mining/construction	○			
Manufacturing	○			
Retail/wholesale/distribution	○			
Number of employees	<100	100-500	500-1000	>1000
Annual turnover (AED)	<10 m	10m -100m	100m - 500m	>500m

SECTION 2 Business intelligence and analytics

To what extent are the following being practiced in your firm?

Questions	Never Always				
1: Online Analytical Processing (OLAP) ***(Use the multiple categories-based data to drill down, roll up, slice, or pivot for presentation, tracking, or analysis.)***	1	2	3	4	5
2: Data mining ***(Clean and extract usable data from a larger set of raw data)***	1	2	3	4	5
3: Data warehouse ***(provide a central repository)***	1	2	3	4	5
4: Visualisation ***(use interactive dashboard scorecards and visualisation of multidimensional financial and non-financial data)***	1	2	3	4	5
5: Descriptive analytics ***(The IT tools provide data on <u>what</u> is happening in my business e.g. financial statement analysis)***	1	2	3	4	5
6: Diagnostic analytics ***(The IT tools that shows <u>why</u> it is happening, e.g., root-cause analysis, correlations cause and effect relationship, etc.)***	1	2	3	4	5
7: Predictive analytics ***(The IT tools used to predict and forecast the future statistics such as trend analysis, forecasting future cashflow.)***	1	2	3	4	5
8: Prescriptive analytics ***(The analytical IT tools that recommend one or more solutions such as investment decision or fraud detection.)***	1	2	3	4	5

SECTION 3 Inferential Capability of Management Accounting Practices (MAPs).

To what extent the following practices <u>facilitate extraction of meaningful insights</u> and support company's decision-making?

Management Accounting Practices	Low			High	
Budgeting practices	1	2	3	4	5
Forecasting practices	1	2	3	4	5
Performance evaluation based on financial metrics	1	2	3	4	5
Performance evaluation based on non-financial metrics	1	2	3	4	5
Cost-Volume-Profit analysis	1	2	3	4	5
Product profitability analysis	1	2	3	4	5
Discounted cash flow to evaluate investments	1	2	3	4	5
Activity-based costing	1	2	3	4	5
Cost of quality reporting	1	2	3	4	5
Target costing	1	2	3	4	5
Customer profitability analysis	1	2	3	4	5
Industry analysis	1	2	3	4	5
Value chain analysis	1	2	3	4	5
Product life cycle analysis	1	2	3	4	5

SECTION 4 Management accountant's Roles

Kindly indicate the extent to which you conduct the following roles and possess the following skills.

		Never →				Always
1	Data collection and preprocessing (Gathering data from various sources like databases and cleaning it by handling missing values, duplicates, and inconsistencies)	1	2	3	4	5
2	Data exploration and analysis (Analysing patterns and trends in large datasets to uncover insights and facilitate decision-making).	1	2	3	4	5
3	Statistical analysis (Using statistical methods to draw conclusions about the data)	1	2	3	4	5
4	Data visualisations, dashboarding and reports to communicate findings to stakeholders (e.g., Excel, Tableau, Power BI, or SQL)	~~1~~	~~2~~	~~3~~	4	~~5~~
5	Design and implement experiments to test hypotheses and optimize processes or products.	1	2	3	4	5
6	Analytical thinking and problem-solving skills contribute to addressing business challenges.	1	2	3	4	5
7	Possess domain knowledge relevant to my industry or specific area of operation.	1	2	3	4	5
8	Working with big data technologies (e.g. NoSQL)	~~1~~	~~2~~	~~3~~	4	~~5~~
9	Build predictive models and evaluate their accuracy and effectiveness.					
10	Collaborating with cross-functional teams (Working with other departments like marketing, finance, or IT to help them leverage data for decision-making and supporting their data-related needs - e.g. create key performance indicators (KPIs) and new measurement methodologies.)	1	2	3	4	5

SECTION 5: Performance

Kindly evaluate your organisation's performance relative to your competitors concerning each of the subsequent statements in the last two years:

	Very Low →				Very High
Financial perspective (the company experiences:)					
profitability and increased revenues	1	2	3	4	5
cost reduction	1	2	3	4	5
Customer/market perspective (the company experiences:)					
Efficiency in customer loyalty	1	2	3	4	5
Efficiency in attracting new customers	1	2	3	4	5
Market share evolution of the company	1	2	3	4	5
Level of customer satisfaction	1	2	3	4	5
Insight into customer behaviour and purchasing patterns	1	2	3	4	5
Process capabilities perspective (the company experiences:)					
Reduction in the time for servicing orders	1	2	3	4	5
Efficiency of the inter-organisational management processes with suppliers	1	2	3	4	5
Efficiency of the inter-organisational management processes with customers	1	2	3	4	5

Human capacities aligned with business goals	1	2	3	4	5
Technological capacities aligned with business goals	1	2	3	4	5
Analyses that can be shared in real-time across departments	1	2	3	4	5
Learning and growth perspective					
Staff with growth potential for competencies in process management	1	2	3	4	5
Levels of workforce committed to the process performance goals	1	2	3	4	5
Level of improvement in the management of process know-how	1	2	3	4	5

The end of the survey
Thank you for your valuable participation

APPENDIX B

MISSING VALUES

Elements	Valid	Missing	Minimum	Maximum
BI&A1	204	0	1	5
BI&A2	204	0	1	5
BI&A3	204	0	1	5
BI&A4	204	0	1	5
BI&A5	204	0	1	5
BI&A6	203	1	1	5
BI&A7	204	0	1	5
BI&A8	201	3	1	5
INF_MAP1	204	0	1	5
INF_MAP2	204	0	1	5
INF_MAP3	204	0	1	5
INF_MAP4	204	0	1	5
INF_MAP5	201	3	1	5
INF_MAP6	204	0	1	5
INF_MAP7	204	0	1	5
INF_MAP8	204	0	1	5
INF_MAP9	204	0	1	5
INF_MAP10	204	0	1	5
INF_MAP11	204	0	1	5
INF_MAP12	199	5	1	5
INF_MAP13	204	0	1	5
INF_MAP14	204	0	1	5
RS_1	204	0	1	5
RS_2	204	0	1	5
RS_3	204	0	1	5
RS_4	204	0	1	5
RS_5	204	0	1	5
RS_6	204	0	1	5
RS_7	204	0	1	5
RS_8	204	0	1	5
RS_9	202	2	1	5
RS_10	204	0	1	5
PERFORM_1	203	1	1	5
PERFORM_2	203	1	1	5
PERFORM_3	203	1	1	5
PERFORM_4	202	2	1	5

PERFORM_5	204	0	1	5
PERFORM_6	204	0	1	5
PERFORM_7	204	0	1	5
PERFORM_8	200	4	1	5
PERFORM_9	200	4	1	5
PERFORM_10	204	0	1	5
PERFORM_11	204	0	1	5
PERFORM_12	202	2	1	5
PERFORM_13	204	0	1	5
PERFORM_14	200	4	1	5
PERFORM_15	200	4	1	5
PERFORM_16	204	0	1	5

APPENDIX C

EXTRACTION SUMS OF SQUARED LOADINGS

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	35.643	46.899	46.899	35.643	46.899	46.899
2	7.510	9.882	56.781			
3	4.911	6.461	63.242			
4	3.742	4.923	68.165			
5	2.513	3.306	71.472			
6	2.413	3.175	74.647			
7	1.911	2.515	77.161			
8	1.623	2.135	79.297			
9	1.544	2.031	81.328			
10	1.297	1.707	83.035			
11	1.148	1.511	84.545			
12	1.088	1.431	85.977			
13	.965	1.270	87.246			
14	.918	1.209	88.455			
15	.816	1.074	89.529			
16	.696	.916	90.445			
17	.658	.866	91.311			
18	.617	.812	92.123			
19	.602	.792	92.915			
20	.558	.735	93.650			
21	.500	.657	94.307			
22	.435	.573	94.880			
23	.419	.551	95.431			
24	.376	.495	95.926			
25	.341	.448	96.374			
26	.308	.406	96.780			
27	.285	.375	97.155			
28	.263	.346	97.501			
29	.237	.312	97.812			

30	.234	.308	98.120			
31	.203	.268	98.388			
32	.177	.233	98.621			
33	.164	.215	98.836			
34	.133	.175	99.012			
35	.123	.162	99.174			
36	.103	.135	99.309			
37	.099	.131	99.440			
38	.084	.110	99.550			
39	.074	.097	99.647			
40	.061	.080	99.727			
41	.045	.059	99.786			
42	.037	.048	99.834			
43	.030	.039	99.874			
44	.027	.036	99.909			
45	.025	.034	99.943			
46	.023	.030	99.973			
47	.014	.018	99.991			
48	.006	.008	99.999			
49	.001	.001	100.000			
50	6.615E-6	8.703E-6	100.000			
51	1.502E-6	1.977E-6	100.000			
52	2.998E-7	3.944E-7	100.000			
53	9.076E-15	1.194E-14	100.000			
54	6.340E-15	8.342E-15	100.000			
55	4.304E-15	5.663E-15	100.000			
56	3.943E-15	5.188E-15	100.000			
57	3.446E-15	4.534E-15	100.000			
58	2.765E-15	3.638E-15	100.000			
59	2.570E-15	3.382E-15	100.000			
60	2.413E-15	3.175E-15	100.000			
61	1.990E-15	2.618E-15	100.000			
62	6.614E-16	8.703E-16	100.000			
63	4.722E-16	6.213E-16	100.000			
64	1.344E-16	1.768E-16	100.000			
65	-2.419E-16	-3.183E-16	100.000			
66	-7.937E-16	-1.044E-15	100.000			
67	-1.105E-15	-1.454E-15	100.000			
68	-1.820E-15	-2.395E-15	100.000			
69	-1.942E-15	-2.555E-15	100.000			

70	-2.598E-15	-3.418E-15	100.000			
71	-3.230E-15	-4.250E-15	100.000			
72	-3.728E-15	-4.905E-15	100.000			
73	-4.040E-15	-5.315E-15	100.000			
74	-4.769E-15	-6.276E-15	100.000			
75	-7.061E-15	-9.291E-15	100.000			
76	-9.674E-15	-1.273E-14	100.000			

Extraction Method: Principal Component Analysis.

APPENDIX D

DESCRIPTIVE RESULTS OF PERFORMANCE

	Variables	Mean	SD
Financial perspective	Profitability and increased revenues	**3.953**	0.9283
	Cost reduction	**3.745**	1.1033
Customer/market perspective	Efficiency in customer loyalty	**3.578**	1.0305
	Efficiency in attracting new customers	**3.661**	1.2428
	Market share evolution of the company	**3.536**	1.1662
	Level of customer satisfaction	**3.667**	1.0044
	Insight into customer behaviour and purchasing patterns	3.443	1.1518
Process capabilities perspective	Reduction in the time for servicing orders	3.405	1.0715
	Efficiency of the inter-organisational management processes with suppliers	**3.527**	1.0705
	Efficiency of the inter-organisational management processes with customers	3.479	1.0383
	Human capacities aligned with business goals	**3.542**	1.1341
	Technological capacities aligned with business goals	3.417	1.2035
	Analyses that can be shared in real-time across departments	3.354	1.2982
Learning and growth perspective	Staff with growth potential for competencies in process management	3.417	1.0552
	Levels of workforce committed to the process performance goals	**3.593**	1.0723
	Level of improvement in the management of process know-how	3.333	1.1225

APPENDIX E

MULTICOLLINEARITY ANALYSIS

Variables	Tolerance	VIF
BI&A	0.417	2.395
Inference	0.121	2.273
Analytical Skillset	0.369	2.707

APPENDIX F

CONVERGENT VALIDITY – OUTER LOADINGS FOR INFERENCE MAPS CAPABILITY

Construct	Items	Outer loadings	Cronbach's Alpha	CR	AVE
BI&A	BI&A1	0.74	0.913	0.914	0.567
	BI&A2	0.734			
	BI&A3	0.705			
	BI&A4	0.77			
	BI&A5	0.837			
	BI&A6	0.713			
	BI&A7	0.76			
	BI&A8	0.759			
Inference Capability	INF_MAP1	0.819	0.949	0.957	0.562
	INF_MAP2	0.836			
	INF_MAP3	0.915			
	INF_MAP4	0.989			
	INF_MAP5	0.660			
	INF_MAP6	0.647			
	INF_MAP7	0.564			
	INF_MAP8	0.613			
	INF_MAP9	0.431			
	INF_MAP10	0.638			
	INF_MAP11	0.716			
	INF_MAP12	0.771			
	INF_MAP13	0.923			
	INF_MAP14	0.761			
Performance	PERFORM_1	0.809	0.967	0.969	0.646
	PERFORM_2	0.648			
	PERFORM_3	0.774			
	PERFORM_4	0.836			
	PERFORM_5	0.727			
	PERFORM_6	0.773			
	PERFORM_7	0.916			
	PERFORM_8	0.659			
	PERFORM_9	0.791			
	PERFORM_10	0.781			
	PERFORM_11	0.862			
	PERFORM_12	0.840			
	PERFORM_13	0.958			

	PERFORM_14	0.751			
	PERFORM_15	0.755			
	PERFORM_16	0.907			
Analytical Skillset	RS_1	0.693	0.921	0.925	0.54
	RS_2	0.732			
	RS_3	0.725			
	RS_4	0.738			
	RS_5	0.558			
	RS_6	0.825			
	RS_7	0.854			
	RS_8	0.774			
	RS_9	0.671			
	RS_10	0.740			

APPENDIX G

STANDARD ERRORS

Descriptive Statistics

	N	Mean		Std. Deviation
	Statistic	Statistic	Std. Error	Statistic
SMEAN(MAP1)	204	4.307	.0800	1.1089
SMEAN(MAP2)	204	4.286	.0824	1.1423
SMEAN(MAP3)	204	4.401	.0657	.9099
SMEAN(MAP4)	204	3.802	.0813	1.1267
SMEAN(MAP5)	204	3.555	.1050	1.4556
SMEAN(MAP6)	204	4.000	.0919	1.2740
SMEAN(MAP7)	204	3.862	.0890	1.2331
SMEAN(MAP8)	204	2.984	.1074	1.4881
SMEAN(MAP9)	204	2.709	.1059	1.4669
SMEAN(MAP10)	204	2.958	.1134	1.5715
SMEAN(MAP11)	204	2.792	.1067	1.4788
SMEAN(MAP12)	204	2.927	.1022	1.4160
SMEAN(MAP13)	204	3.667	.1000	1.3855
SMEAN(MAP14)	204	3.109	.1164	1.6126
SMEAN(BI&A1)	204	3.719	.1048	1.4522
SMEAN(BI&A2)	204	3.729	.0951	1.3183
SMEAN(BI&A3)	204	3.583	.0941	1.3038
SMEAN(BI&A4)	204	3.839	.0910	1.2616
SMEAN(BI&A5)	204	3.500	.1052	1.4580
SMEAN(BI&A6)	204	2.906	.0952	1.3190
SMEAN(BI&A7)	204	3.036	.0984	1.3628
SMEAN(BI&A8)	204	2.705	.1038	1.4388
SMEAN(INF_MAP1)	204	3.865	.1016	1.4077
SMEAN(INF_MAP2)	204	3.948	.0930	1.2893
SMEAN(INF_MAP3)	204	4.073	.0856	1.1867
SMEAN(INF_MAP4)	204	3.719	.0866	1.1995
SMEAN(INF_MAP5)	204	3.313	.1050	1.4554
SMEAN(INF_MAP6)	204	3.724	.1005	1.3925
SMEAN(INF_MAP7)	204	3.641	.0887	1.2284
SMEAN(INF_MAP8)	204	2.984	.1097	1.5194
SMEAN(INF_MAP9)	204	2.958	.1107	1.5344

SMEAN(INF_MAP10)	204	3.063	.1102	1.5268
SMEAN(INF_MAP11)	204	2.854	.1078	1.4933
SMEAN(INF_MAP12)	204	3.166	.1120	1.5517
SMEAN(INF_MAP13)	204	3.542	.0993	1.3761
SMEAN(INF_MAP14)	204	3.063	.1112	1.5405
SMEAN(COMP_MAP1)	204	3.757	.1053	1.4594
SMEAN(COMP_MAP2)	204	3.807	.0993	1.3764
SMEAN(COMP_MAP3)	204	4.078	.0760	1.0531
SMEAN(COMP_MAP4)	204	3.677	.0792	1.0973
SMEAN(COMP_MAP5)	204	3.359	.1055	1.4619
SMEAN(COMP_MAP6)	204	3.325	.1041	1.4421
SMEAN(COMP_MAP7)	204	3.333	.0975	1.3511
SMEAN(COMP_MAP8)	204	2.964	.1101	1.5260
SMEAN(COMP_MAP9)	204	2.942	.1002	1.3887
SMEAN(COMP_MAP10)	204	3.022	.0999	1.3841
SMEAN(COMP_MAP11)	204	2.958	.1036	1.4356
SMEAN(COMP_MAP12)	204	3.167	.1050	1.4556
SMEAN(COMP_MAP13)	204	3.333	.1008	1.3968
SMEAN(COMP_MAP14)	204	3.167	.1040	1.4411
SMEAN(ACCU_MAP1)	204	3.849	.0917	1.2711
SMEAN(ACCU_MAP2)	204	3.786	.0855	1.1851
SMEAN(ACCU_MAP3)	204	4.177	.0685	.9489
SMEAN(ACCU_MAP4)	204	3.819	.0723	1.0022
SMEAN(ACCU_MAP5)	204	3.422	.1091	1.5123
SMEAN(ACCU_MAP6)	204	3.651	.1004	1.3911
SMEAN(ACCU_MAP7)	204	3.547	.0942	1.3056
SMEAN(ACCU_MAP8)	204	3.089	.0998	1.3833
SMEAN(ACCU_MAP9)	204	3.081	.1031	1.4286
SMEAN(ACCU_MAP10)	204	3.038	.1032	1.4303
SMEAN(ACCU_MAP11)	204	2.943	.1108	1.5356
SMEAN(ACCU_MAP12)	204	3.154	.1103	1.5290
SMEAN(ACCU_MAP13)	204	3.318	.1033	1.4319
SMEAN(ACCU_MAP14)	204	3.089	.1062	1.4714
SMEAN(RS_1)	204	4.219	.0678	.9401
SMEAN(RS_2)	204	4.057	.0743	1.0293
SMEAN(RS_3)	204	3.448	.0892	1.2353
SMEAN(RS_4)	204	4.042	.0895	1.2400
SMEAN(RS_5)	204	2.984	.0959	1.3282
SMEAN(RS_6)	204	3.932	.0902	1.2493
SMEAN(RS_7)	204	3.635	.0878	1.2161

SMEAN(RS_8)	204	2.750	.0957	1.3263
SMEAN(RS_9)	204	3.089	.0968	1.3410
SMEAN(RS_10)	204	3.927	.0853	1.1823
SMEAN(PERFORM_1)	204	3.953	.0670	.9283
SMEAN(PERFORM_2)	204	3.745	.0796	1.1033
SMEAN(PERFORM_3)	204	3.578	.0744	1.0305
SMEAN(PERFORM_4)	204	3.661	.0897	1.2428
SMEAN(PERFORM_5)	204	3.536	.0842	1.1662
SMEAN(PERFORM_6)	204	3.667	.0725	1.0044
SMEAN(PERFORM_7)	204	3.443	.0831	1.1518
SMEAN(PERFORM_8)	204	3.405	.0773	1.0715
SMEAN(PERFORM_9)	204	3.527	.0773	1.0705
SMEAN(PERFORM_10)	204	3.479	.0749	1.0383
SMEAN(PERFORM_11)	204	3.542	.0818	1.1341
SMEAN(PERFORM_12)	204	3.417	.0869	1.2035
SMEAN(PERFORM_13)	204	3.354	.0937	1.2982
SMEAN(PERFORM_14)	204	3.417	.0762	1.0552
SMEAN(PERFORM_15)	204	3.593	.0774	1.0723
SMEAN(PERFORM_16)	204	3.333	.0810	1.1225
MAPs	204	3.6290	.09833	1.36252
BI&A	204	3.3958	.09456	1.31028
Inference	204	3.5495	.09877	1.36865
Roles_Skills	204	3.6667	.08495	1.17715
Performance	204	3.6146	.07320	1.01424
Valid N (listwise)	204			

APPENDIX H

CROSS LOADINGS – INFERENCE MAPS CAPABILITIES

	BI&A	Inference	Performance	Analytical Skillset
BI&A1	**0.74**	0.465	0.519	0.564
BI&A2	**0.734**	0.498	0.442	0.581
BI&A3	**0.705**	0.471	0.356	0.615
BI&A4	**0.77**	0.479	0.428	0.676
BI&A5	**0.837**	0.616	0.456	0.654
BI&A6	**0.713**	0.43	0.432	0.612
BI&A7	**0.76**	0.617	0.425	0.533
BI&A8	**0.759**	0.635	0.368	0.558
INF_MAP1	0.532	**0.819**	0.605	0.6
INF_MAP2	0.589	**0.835**	0.573	0.596
INF_MAP3	0.625	**0.916**	0.647	0.661
INF_MAP4	0.659	**0.991**	0.718	0.672
INF_MAP5	0.45	**0.66**	0.466	0.421
INF_MAP6	0.39	**0.646**	0.506	0.466
INF_MAP7	0.331	**0.563**	0.45	0.405
INF_MAP8	0.531	**0.614**	0.327	0.492
INF_MAP9	0.387	**0.43**	0.215	0.328
INF_MAP10	0.462	**0.638**	0.425	0.458
INF_MAP11	0.559	**0.716**	0.438	0.463
INF_MAP12	0.619	**0.771**	0.457	0.553
INF_MAP13	0.625	**0.924**	0.659	0.655
INF_MAP14	0.51	**0.759**	0.545	0.512
PERFORM_1	0.341	0.557	**0.747**	0.599
PERFORM_2	0.476	0.507	**0.715**	0.491
PERFORM_3	0.422	0.555	**0.769**	0.583
PERFORM_4	0.383	0.641	**0.799**	0.588
PERFORM_5	0.406	0.603	**0.741**	0.501
PERFORM_6	0.481	0.56	**0.80**	0.592
PERFORM_7	0.437	0.56	**0.861**	0.735
PERFORM_8	0.305	0.552	**0.639**	0.436
PERFORM_9	0.42	0.544	**0.776**	0.607
PERFORM_10	0.467	0.612	**0.806**	0.566
PERFORM_11	0.468	0.576	**0.848**	0.675
PERFORM_12	0.44	0.531	**0.813**	0.673
PERFORM_13	0.557	0.626	**0.959**	0.767
PERFORM_14	0.518	0.442	**0.787**	0.65
PERFORM_15	0.495	0.437	**0.776**	0.651
PERFORM_16	0.634	0.572	**0.961**	0.763
RS_1	0.534	0.473	0.554	**0.694**

RS_2	0.587	0.526	0.559	**0.73**
RS_3	0.557	0.595	0.581	**0.725**
RS_4	0.611	0.485	0.549	**0.739**
RS_5	0.424	0.451	0.45	**0.557**
RS_6	0.629	0.579	0.667	**0.825**
RS_7	0.683	0.514	0.659	**0.854**
RS_8	0.661	0.514	0.556	**0.774**
RS_9	0.64	0.517	0.418	**0.671**
RS_10	0.495	0.542	0.663	**0.739**